Decision making in Liner Shipping by cost assessment under uncertainty

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Abstract

Container shipping has revolutionized global transportation since the 1960s. Through specialization and standardization, the unit costs for transport could be reduced further and thus the demand for transport volume increased. Due to economic growth in the world, especially in emerging economies such as China, demand continued to grow and container line companies rose steadily over the years. Due to the financial and subsequent economic crisis from 2008, the market collapsed and freight rates fell. As a result, the transport capacities that had been developed for years and were still under construction could not be utilized any more, so the logic consequence would have been to reduce the size of the fleets. Instead, shipping companies tried to drive the market again by falling prices and to achieve economies of scale and thus reduce costs by building new container vessels with greater capacities. The problem of overcapacity still persists globally. With transport strategies such as slow steaming, container shipping companies were able to adapt to changing conditions, and the problem of overcapacity has been reduced, but persisted. Currently, freight rates for transports from Asia strongly increase since summer 2020. However the sustainability of this development is uncertain, as such developments are not visible in other parts of the world. The continuous existing problem of overcapacity still puts companies under intense pressure, which has led to unprecedented bankruptcies respectively to multiple acquisitions.

These problems cannot be solved through further specialization or technical advances in shipbuilding, but only by improvement of the existing transport strategies. In this thesis, three sub-problems of liner shipping are illumi-

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nated, approaches are developed and their use are demonstrated. The first approach is the selection of cargo for transport, with the repositioning of the empty containers being included in this consideration. The uncertainties are modeled by fuzzification. The next approach considers the cost of bunker fuel. The existing criticism on the current models of the dependence between speed of the vessel and the consumption is evaluated and is integrated into a new model. The effects of delays and their importance as well as the advantages of reliability are listed and the necessary costs to ensure a certain level of reliability are determined. The last approach deals with the question of which vessels with which characteristics should be used in the services. Usually, the vessels are assessed solely by considering the charter costs, while another here used approach includes the costs of fuel, depending on the reliability.

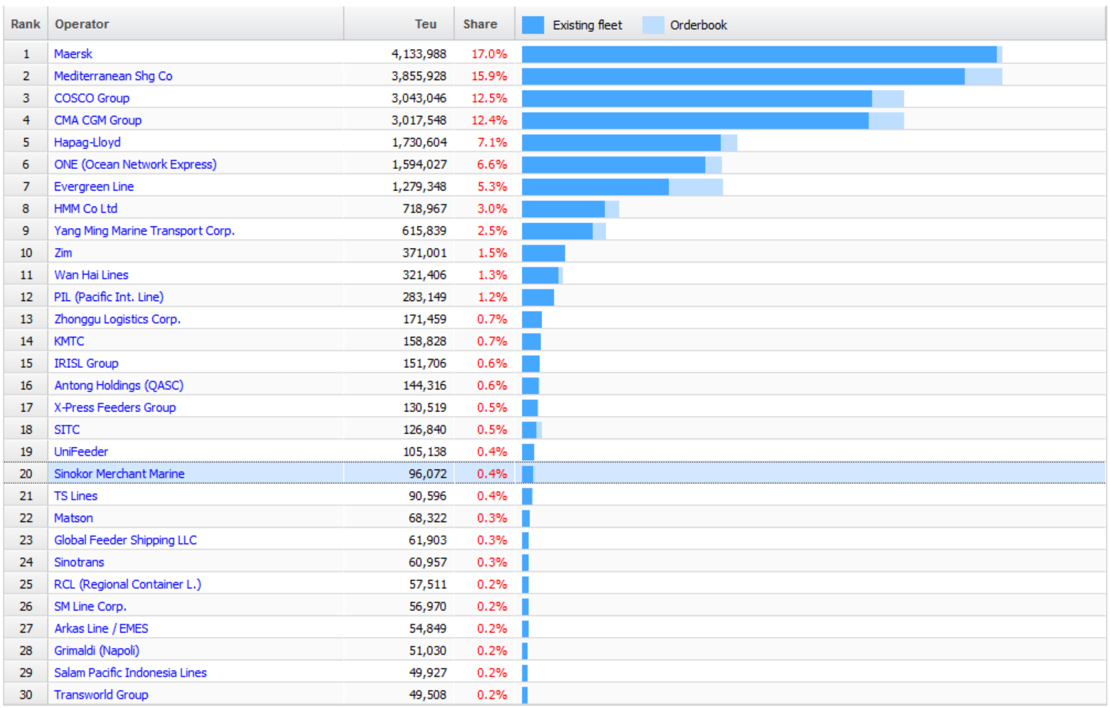
At the end a model is presented, which weights positive and negative consequences of a good reliability. With these methods, some potential in container shipping can be exploited and the efficiency of services and the profit can be increased. All of these results are calculated using computer models that can also be used in the long-term, so that they are supported by computer-based tools in the process of service planning and their decisions are enhanced.

Contents

1. Introduction

In the British Museum in London a Roman document from 236 AD can be found which can be considered as an ancient bill of lading, as mentioned by Stopford (2008). In this bill, the Roman shipowner Aurelius Herakles and his client Aurelis Arius agree the conditions for the transport of vegetable seeds from the port of Grove to the port of Oxyrhynchus. This comprises price, the terms of payment, the voyage data and additional fees for any delays, conditions being just the same as nowadays. A document like this is still the basis for a contract of parties in shipping transportation, like Stopford (2008) outlines, which is reflected in the design of the bills of lading actually used. The questions and challenges for terms of transportation have not changed to date, which illustrates one of the most important characteristics of sea transportation: *Since centuries the basic concept has remained the same.*
However, three aspects in maritime shipping do have changed tremendously. First, the vessels have been specialized, and special services have been created, e.g. bulk vessels, container vessels and others. Bulk vessels carry bulk freight like corn or coal and transport cargo of only one owner from one port to another port on demand. This service is called tramp shipping. In contrast, container vessels are mainly deployed in liner shipping, where cargo of various owners is transported on predefined, repetitive routes between named ports. Thereby, several vessels are used on the same route to guarantee a regular service with a determined schedule (see Stopford (2008), Notteboom (2012), Wang and Meng (2012c) and Abioye et al. (2019)).
Secondly, the vessels and their technology including the size and propulsion have been developed. Pascali (2017) describes the evolution from wind to coal and later to heavy fuel oils and the impacts on efficiency. Ducruet et al. (2018) show that each change in proportion technology or vessel size provoked an enormous boom in the cities of the transport network. By exploiting the economy of scales, prices for transportation fell for the benefit of the shipping industries and their clients, discussed by Wang and Meng (2012b). In long-term, this led to market concentration and division into fewer and bigger companies and to the establishment of conferences at which companies agreed on prices and quantities. However, these were banned in the early 2000s because they gave the companies too much market power, as discussed in Stopford (2008). As a result, alliances were established in which companies could realize synergy effects. Currently, each of the top 20 companies belongs to one of the three biggest alliances in the market, which makes

the concentration obvious. The current global market situation is shown in detail in Figure 1, taken from Alphaliner (2021). Basing on the market share of the top thirty liner shipping companies, the Herfindahl-Hirschmann Index (HHI) is 997.3. This is below the critical value of 1000, which identifies the market as highly competetive, as Roberts (2014) states. As a consequence, the price is determined by supply and demand and only marginally by the participants.



Rank	Operator	Teu	Share
1	Maersk	4,133,988	17.0%
2	Mediterranean Shg Co	3,855,928	15.9%
3	COSCO Group	3,043,046	12.5%
4	CMA CGM Group	3,017,548	12.4%
5	Hapag-Lloyd	1,730,604	7.1%
6	ONE (Ocean Network Express)	1,594,027	6.6%
7	Evergreen Line	1,279,348	5.3%
8	HMM Co Ltd	718,967	3.0%
9	Yang Ming Marine Transport Corp.	615,839	2.5%
10	Zim	371,001	1.5%
11	Wan Hai Lines	321,406	1.3%
12	PIL (Pacific Int. Line)	283,149	1.2%
13	Zhonggu Logistics Corp.	171,459	0.7%
14	KMTC	158,828	0.7%
15	IRISL Group	151,706	0.6%
16	Antong Holdings (QASC)	144,316	0.6%
17	X-Press Feeders Group	130,519	0.5%
18	SITC	126,840	0.5%
19	UniFeeder	105,138	0.4%
20	Sinokor Merchant Marine	96,072	0.4%
21	TS Lines	90,596	0.4%
22	Matson	68,322	0.3%
23	Global Feeder Shipping LLC	61,903	0.3%
24	Sinotrans	60,957	0.3%
25	RCL (Regional Container L.)	57,511	0.2%
26	SM Line Corp.	56,970	0.2%
27	Arkas Line / EMES	54,849	0.2%
28	Grimaldi (Napoli)	51,030	0.2%
29	Salam Pacific Indonesia Lines	49,927	0.2%
30	Transworld Group	49,508	0.2%

Figure 1: Market share of liner shipping companies in January 2021, taken from Alphaliner (2021). A clear market concentration can be seen, although according to the Herfindahl-Hirschmann Index this distribution is considered to be highly competitive.

Thirdly, the strategies for planning the transportation became more diverse in consequence of more knowledge, experience, scientific advancement and actual developments. An overview of strategies in the last decades is given by Ronen (1983), Ronen (1993), Christiansen et al. (2004) and Christiansen et al. (2013). The different services of a liner shipping company are permanently checked and adjusted in dependence of changing conditions such as demand and supply of freight capacities, development of bunker fuel price, characteristics of usable vessels. Accordingly, the liner manager decides continuously to leave or change a service, e.g. to change speeds, to add, replace or remove a vessel or a port from the service. For these decisions, consequences and dependences are included in the three time horizons short-, medium- and long-term. Wang et al. (2013) criticize that the design of container services is done mostly manually, according to managers' experience and currently used strategy. Instead, an automatization of finding possibilities for the services will provide significant advantages. McLean and Biles (2008) explain the components and the interaction of factors in liner shipping and Bae et al. (2013) describe how the proper ports for a schedule are chosen. Additionally, the cargo that promises the greatest profit must also be selected. Zurheide and Fischer (2015) present a model to evaluate the available freight and choose the optimal cargo mix for transportation due to the limited capacity. For planning reasons terminal operators in ports often offer so-called *berth windows*, i.e. weekly time slots are reserved for concrete liner shipping companies. Accordingly, the line coordinators have to be in time for the berth windows and include this in the transportation strategy, see Wang et al. (2014) and Alharbi et al. (2015). A successful example for a transportation strategy is *slow steaming*, first used by the company *Maersk* in 2008 (see Aydin et al. (2017)), as a consequence of an increase of bunker price and a big idle fleet, as Meyer et al. (2012) state. Vessels were added to a liner shipping service, but the number of port calls remained, so the average speed was reduced. The positive effects were a reduction of bunker consumption and thereby costs, as well as of overcapacity, as Cariou (2011) and Yin et al. (2014) state. Wang and Meng (2012a) describe slow steaming as a trade-off between time charter and bunker fuel costs. Although, in this strategy no new technology was introduced and no innovative vessels were constructed, the costs decreased significantly, shown by Maloni et al. (2013) and Woo and Moon (2014). In summary, Psaraftis and Kontovas (2013) underline that a change of transportation strategy impacts the cost structure and the balance sheet of the shipping company.

The thesis deals exclusively with specialized, container vessels in liner service with current ocean going vessel size and propulsion operating with heavy fuel oil. Basing on these current constraints various decion making issues under uncertainty in the planning process are considered in order to identify potential for improvement. The relevant questions deal with e.g. the decision-making criteria for cargo and equipment transportation, more realistic calculation of bunker fuel consumption and proactive including delays in decision-making in order to reduce bunker fuel consumption and increase reliability. Another important issue is the improvement of sustainability in liner shipping. Approaches to reducing fuel consumption and increasing efficiency reduce greenhouse gas and sulfur oxide emissions accordingly.

The thesis is structured as follows:
Subchapter 1.1 describes the current problem of liner shipping industry and the resulting continuous crisis since the financial crisis of 2008. At the end of this subchapter, Table 1 presents a summary of the three articles on which this thesis is based. In Subchapter 1.2.1 the contribution and methodology of the articles from Westarp, A. Graf von and Schinas (2016) (Chapter 2), Westarp, A. Graf von (2020) (Chapter 3) and Westarp, A. Graf von and Brabänder (2021) (Chapter 4) are briefly summarized. Thereby, the focus is set on methods and results, that can be used for short-, mid- and long-term benefits for liner shipping companies. Beside these benefits of the three articles the combination of their results promise a high potential. To higlight the potenital further options examples for combination enhancement of the approaches by combination that excees the articles is shown in Subchapters 1.3.1 and 1.3.2. In summary, this work represents a decision-making paper based on uncertainties.

1.1. Overcapacity as the main problem of modern Container Shipping Companies

The aspect of specialization of the vessels and its benefits for the shipping industry is expounded by Stopford (2008). Thereby, the invention and use of containers in the shipping industry turned out to be quasi revolutionary leading to the greatest increase in efficiency in shipping transportation, as Notteboom (2012) demonstrates. As a result Gelareh and Meng (2010) and Zondag et al. (2010) report that the container transport shows an increase of transport volume by 10% every year between 1985 and 2005. Notteboom (2012) lists various benefits by containerization, such as reduction in damage to the goods and a simplification of further transportation. However, the major advantage of containerization is the reduction of port lay time of the vessels, because the goods are not stowed on board, but are already stowed in the containers and ready for loading, as soon as the vessel enters the port. Many authors like Zondag et al. (2010) or Notteboom (2012) determine two important factors for the success of containers. Firstly, the container industry took benefit from the increased demand of transportation volume due to globalization, which was stimulated by the container industry itself. Secondly, more and more commodities were containerized as expressed in Figure 2 taken from Notteboom and Rodrigue (2008).

in %	Country	1980	1985	1990	1995	2000	2003	2005
Hamburg	Germany	32.0	42.6	66.2	81.7	93.1	95.4	96.4
La Spezia	Italy	34.4	40.3	76.1	88.0	90.3	93.2	93.2
Le Havre	France	58.9	67.7	71.2	66.8	80.4	86.9	90.3
Algeciras	Spain	71.8	69.4	70.8	79.2	88.5	89.4	89.7
Leixoes	Portugal	22.0	28.7	37.1	63.5	75.4	85.1	87.7
Rotterdam	The Netherlands	57.4	65.8	69.9	73.9	77.7	79.1	83.1
Bremerhaven	Germany	35.6	47.1	58.7	73.4	81.9	82.9	82.8
Valencia	Spain	35.4	68.5	60.3	68.6	74.8	79.1	79.7
Antwerp	Belgium	21.5	29.0	38.0	50.9	64.8	75.0	77.6
Bordeaux	France	32.3	34.4	43.4	31.3	42.4	67.5	76.1
Thessaloniki	Greece	1.2	3.1	14.3	43.8	42.8	68.8	73.9
Barcelona	Spain	30.0	61.3	71.0	74.3	73.9	73.4	73.1
Lisbon	Portugal	32.2	47.3	58.0	65.8	69.5	72.9	72.0
Piraeus	Greece	20.4	36.5	45.8	65.3	74.8	76.3	68.6
Genoa	Italy	36.5	46.0	45.2	49.7	65.0	61.7	63.0
Bilbao	Spain	26.4	33.0	53.1	46.7	49.2	58.1	58.9
Marseilles	France	32.3	42.4	50.5	46.9	53.2	54.2	56.9
Zeebrugge	Belgium	30.6	22.5	23.3	30.0	41.5	51.0	55.0
Rouen	France	23.1	40.4	36.7	31.8	32.9	36.5	42.0
Amsterdam	the Netherlands	21.0	21.6	30.2	40.5	25.9	22.9	29.7
Trieste	Italy	34.4	46.7	55.4	28.9	27.4	18.8	29.6
Dunkirk	France	14.6	14.7	10.5	11.5	27.9	13.9	15.0
Zeeland Seaports	the Netherlands	11.1	10.0	4.4	3.1	2.3	4.3	4.3

Figure 2: Development of containerization for some of the most important European ports in percentage of total freight from 1980 to 2005, taken from Notteboom and Rodrigue (2008). During this period the containerization has increased dramatically until its limit was largely reached.

However, the degree of containerization is limited. Notteboom and Rodrigue (2008) estimate a maximum of containerization of about 75 % of total world freight cargo. Currently, most of the commodities are already transported in containers or are shipped in special vessels. Steenken et al. (2004) report that 60 % of the world's deep-sea general cargo is containerized, and in economically strong region up to 100 %. Thus, the expectations for further specialization are limited as Legorburu et al. (2018) indicate.
The containers are also specialized and differ in length (mostly 20 feet and 40 feet) and technology (e.g reefer containers for chilled and frozen goods, tank containers for liquids, flat racks for oversized commodities). The various regions connected by container shipping have different climate zones, economic growth rates, degree of industrialization and production of goods and, thus different demand of container types. This leads to an unbalanced surplus

and deficit of container types, which must be resolved by transporting empty containers, so-called *empty repositioning*.
The second aspect deals with the development of the vessels. Over the centuries the target of new propulsion and fuels has been to increase speed and reliability, e.g. by becoming independent of the wind as Pascali (2017) indicate. Currently, in a period of increasing fuel prices, the focus of research shifted on fuel saving as Ronen (1982) highlights. The aims of economy and ecology meet here as Mansouri et al. (2015) and Koilo (2019) state. During this period, long- and short-term economic strengthening of emerging economies, e.g. China, resulted in growing demand for transportation services. To meet the greater need, the liner shipping companies saw the solution in more and larger vessels, up to so-called *ultra large container vessels* with more than 10,000 TEU. As in 1996 *Regina Maersk* was launched, it was by all means the biggest container vessel with a capacity of 6,400 TEU as listed in Marine Traffic (2020). However, already *Emma Maersk*, launched in 2006, offered a capacity of 15,000 TEU (Marine Traffic (2020)). This shows the demand for bigger vessels, the liner shipping companies called for in the beginning of this century. During this boom periode more than 50% of the current fleet were in the order books of the yards, expecting of further continuous, unlimited growth. The financial crisis of 2008 put an end to this growth as the world economy decreased and the demand for transportation volumes collapsed. While other sectors recovered in the short or medium term, liner shipping industry faced huge overcapacity in tonnage, as Grzybowski, Kim (2017) and Wilmsmeier and Monios (2020) explain, and has been caught in a continuous crisis since then. Due to high costs for the investments in the fleets and high fixed costs, the liner shipping companies hesitated to reduce the transport capacity (see Song et al. (2019)). This led to an oversupply of vessels and thus, a decrease of their price as well as the price for transportation. The usage of slow steaming effectuated a decrease of overcapacity, however, also a disadvantage of efficiency, as Wang (2016) describes. So, the possibilities to take advantage of this were limited. These developments exacerbated the problem of overcapacity, reducing the profits and facing the shipping companies with a cost pressure. The liner shipping companies found themselves in a so-called *prisoner's dilemma*. This scenario, well-known from game theory, describes a set up in which all market participants could be more effective in mid and long-term by cooperation. In this case relinquishing new vessels would have eased the problem of overcapacity, like Kou and Luo (2016) state. However, the liner shipping company

decided to order new vessels of larger size to reduce costs, as summed up by Kou and Luo (2016). This is an unlogical behavior in the terms of the *prisoner's dilemma*, as this exacerbated further the difficulties of overcapacity.

However, this can be explained by the hope that lower costs could be

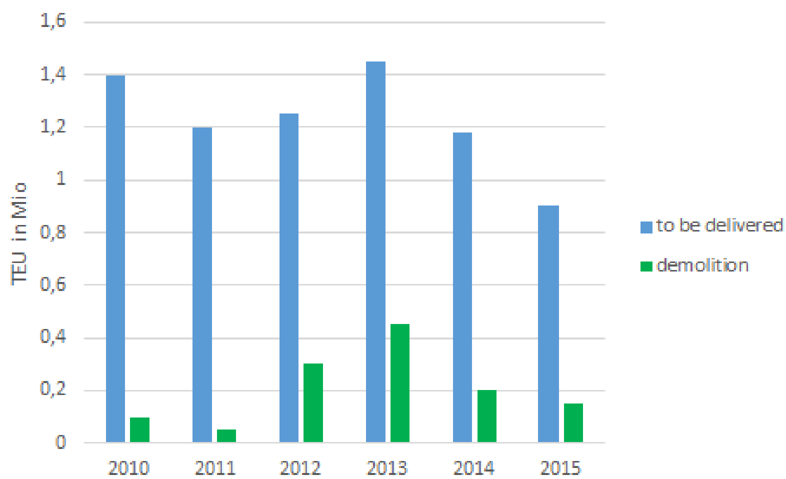


Figure 3: Delivered newbuildings (blue) and demolition (green) for the periode of 2010 to 2015 in Mio TEU. The values of the newbuildings are always significantly higher than those of the demolition (Source: Sand (2013), data from 2010 to 2012 are actual data, from 2012 are of forecast and from 2014 and 2015 are estimated)

achieved by full use of the economy of scale, and so being able to keep up with low transportation prices. As the economy of scales can only be effective, when vessels are almost fully utilized, this turned out to be difficult. To achieve high utilization, the prices were reduced, but the effect was limited, since all companies acted this way. A targeted reduction in capacities through scrapping could only have taken place in consultation between all companies, but such agreements, which took place in the 1950s, are now prohibited for antitrust reasons (see Stopford (2008) and Owen and Po-wan (2018)). However, global alliances between companies were founded to leverage effects of synergies, such as shared use of liner services and higher utilization of capacity (see Midoro and Pitto (2000) and Huang (2016)). Although alliances of container shipping have a lot of leeway, they are regulated and monitored so, that large alliances do not distort competition (see Owen and Po-wan (2018)). Notteboom et al. (2017) describe the growing influence of

the few largest alliances on port operators with regard of port calls or handling charges, which leads to a quasi-oligopoly. In order to limit this power, various regulations were drawn up, including the prohibition on negotiating overcapacity. So, the companies had to deal with the cost pressure due to overcapacity on their own (see Georgieva (2019)). As liner shipping companies were forced to further optimization, larger vessels were built. This becomes clear, as *Emma Maersk* was 2006 the biggest container vessel of the world with 15,000 TEU, while *HMM Algeciras*, the actual biggest vessel, has a capacity of about 24,000 TEU (see Marine Traffic (2020)), which is an increase of about two thirds. In result, a vicious cycle of falling prices and rising overcapacity began, described in Song et al. (2019). The volumes of newbuilding in TEU are always larger than of the demolition, shown in Figure 3. In addition, the approach of achieving lower transport costs per unit by building larger vessels is reaching its limits, as Ulrich (2017) describes. According to the analysis of Ulrich (2017), vessel sizes beyond the current level bring only minor advantages, but mean very high investment costs for port operators. So this attempt is not efficient any more.
Because of this pressure, the shipping industry underwent dramatic changes between 2014 and 2017, causing merges and acquisitions of large companies with world-wide engagement and even bankrupts (Yap and Zahraei (2018)). This led to dissolutions of global alliances and to formations of new alliances, and in long-term to a concentration of shipped cargo (Aymelek et al.). The ratio of the top ten global companies raised from 64 % in 2013 to 82 % in 2017 (Yap and Zahraei (2018)). Hoffmann et al. (2017) highlights that 72.3% in 2017 were transported only by the three biggist alliances. Clemente and Vicens (2019) attribute this to the fact that the current vessel sizes offer so much space that individual companies cannot fill them alone and cope with the risks. Alliances that are too small are threatened by excessively high costs and acquisitions of companies by members of larger alliances, as Crotti et al. (2019) discuss. Kim (2017) considers the formation of larger alliances as the only possible answer to the current problem in the shipping industry. However, mergers, bankrupts and alliances do not solve the core problem of overcapacity, as the vessels of the amalgamated companies were kept in service, and the vessels of the bankrupt companies were bought cheaply by competitors (Song et al. (2019)). Crotti et al. (2019) show the susceptibility of the stability of alliances due to overcapacity and cascading effects. Haralambides (2019) shows that diseconomies of scale in ports can ruin the advantages of alliances in respect of economies of scale. Song et al.

(2019) give the example of Hanjin Shipping, one of the largest liner shipping companies and part of one of the largest alliances in the world, which had to declare bankrupt due to pressure from overcapacity and mismanagement. Yap and Zahraei (2018) underline the persistently poor conditions for liner shipping despite the formation of alliances. By 2020 the formation of alliances in the EU should be limited, but being aware of this background, the EU-Commission extended this permission until 2024 (Hütten (2019)). However, requirements are imposed that customers must benefit from the advantages acquired, but the reproach arises that this does not happen sufficiently, and benefits for customers, e.g. lower transport fees, are demanded. This puts further pressure on companies, as (Hütten (2019)) states. The current corona pandemic and the associated decline in world trade have further exacerbated the crisis and led to highest volume of idle container vessel fleet ever since with a value of 2.46 million TEU (Hand (2020)). In summary, the strategy to reduce costs due to larger vessels and to return to profitability failed, and cannot be seen as a solution for the current high economic pressure of the liner shipping companies.
As shown above, further specialization is not expected and improvement of the vessel technology would lead to newbuildings and therefore would increase the overcapacity additionally.
Accordingly, hope to overcome the crisis is now focused on the third aspect, the optimization of decision-making processes. McLean and Biles (2008) underline the importance of operational performance for the effectivity of a service. This is the core of this thesis. The current state of science and computer technology allow mathematical calculations basing on algorithms and applications, which can map reality with more details and knowledge of the relevant interactions and uncertainties, as discussed by Wang and Meng (2012c). Generally the decision maker is confronted with a lack of data and uncertainties due to economic conditions as short-term economic fluctuations or unpredictable developments in the markets. Additionally, uncertainties arise during the voyages and time in ports, such as weather conditions, technical problems, strikes, outbreaks of epidemics. As a result, a solid basis is missing to evaluate important issues. Decisions seem to be right, but often they base on insufficient data and might have bad consequences, as Yao et al. (2012) state on the example of bunker fuel consumption and Chang et al. describe on various themes.
The field of possible improvement is various. So, in this work new approaches are introduced that focus on the large cost blocks in order to improve the re-

sults on the basis of new predictions. The two largest cost blocks in shipping are bunker fuel costs and loading costs including empty repositioning. Accordingly, it is reasonable to examine these blocks for potential cost savings. Obviously, bunker consumption forecast methods exist, but their practicality and validity is discussed intensively in practice and literature (see Kristensen and Lützen (2012) and Psaraftis and Kontovas (2013)). Hence, there is a great need to improve the existing models so that reality is better mapped, otherwise any investigation of bunker fuel costs would be not reasonable.

Current sub-problems for liner shipping companies, discussed in the thesis:

- In order to evaluate which containers should be accepted for shipment, currently the variable contribution margin is used. The costs for empty repositioning are usually included basing on the past performance, as done by Shen and Khoong (1995), Won et al. (2011), Dang et al. (2012) and Long et al. (2012). However, in this mindset the empty containers are not considered as a consequence of transported cargo. The resulting problem is that containers promising the highest revenue are transported, but the profit of the voyage might be ruined by unexpected high costs for empty repositioning, discussed in Edirisinghe (2016).

- Bunker costs can make up 75 % of the operational expenses, Ronen (2011), with large fluctuations, Notteboom and Vernimmen (2009). Psaraftis and Kontovas (2014) estimate a great potential for savings due to optimization of speed and thus consumption. He et al. (2017) regard speed optimization as the fundamental problem in maritime transportation. In this context, the correct determination of the bunker fuel consumption in dependence of speed is of significant importance. Typically, this is calculated with a so-called *speed-consumption-curve*, formulated in different ways by e.g. Ronen (1982), Fagerholt et al. (2010) Du et al. (2011) and Wang and Meng (2012a). This curve consists of speed as the only variable and parameters depending on each vessel. However, the current used speed-consumption-curves are critically discussed, e.g. in Kristensen and Lützen (2012) and Psaraftis and Kontovas (2013). Psaraftis and Kontovas (2013) show a dependence of the parameters on the variable speed, which is in contradiction to definition of the parameters. Unexpected deviations in bunker fuel consumption may occur due to unrealistic speed-consumption-curves. Additionally, the events of delays make it difficult to give a close estimation for the bunker fuel consumption. Notteboom (2006) consider the trade-off between bunker fuel costs and reliability. Other authors, like Nair et al. (2012), Zhang and Lam (2014) and He et al. (2017), include environmental aspects in this trade-off. However, in literature relations between speed and reliability are insufficiently examined. One reason might be the study by Notteboom (2006) who describes that 93,6 % of the delays occur in ports. This study using data from 2004 seems to be still the basis for evaluation of delays, so no forward-looking measures for avoiding delays at sea can be found in current literature.

- As described above, the liner shipping services and the used vessels, the strategy for speed etc. is permanently checked and their efficiency is rated. If the decision manager determines that another vessel promises higher profit than a current used, it is inserted instead. Currently, this decision mostly depends on the time charter costs of the vessels. However, only by taking also the bunker consumption into account, it is possible to rate the vessel by actual daily costs.

All problems are somehow related to overcapacity.

1.2. Contribution, methodology and classification of the published articles from Chapter 2, Chapter 3 and Chapter 4

1.2.1. Contribution and methodology

The overall aim of this thesis is the evaluation of procedures that enable more profound operational, financial or environmental decisions. In this subchapter the contributions of the articles Westarp, A. Graf von and Schinas (2016), Westarp, A. Graf von (2020) and Westarp, A. Graf von and Brabänder (2021) are highlighted and the methodology is briefly explained. Article Westarp, A. Graf von and Schinas (2016), Chapter 2, deals with the problem of empty repositioning, as described in Subchapter 1.1. By including empty repositioning in the planning process and avoiding empty imbalances from the start, long-term significant savings in handling costs are investigated. For the assessment of the costs a linear model is constructed. Since the conditions in reality are volatile, the objective function as well as some objective constraints are fuzzified, as described in Westarp, A. Graf von and Schinas (2016). For reason of simplification a form of the triangular function is used, however, other fuzzy functions could be easily implemented.

Table 1: Bibliographic summary of the three focus articles

	Article 1	**Article 2**	**Article 3**
Chapter	Chapter 2	Chapter 3	Chapter 4
Title	A fuzzy approach for container positioning considering sustainable profit optimization	A new model for the calculation of the bunker fuel speedconsumption relation	Support of the speed decision in liner operation by evaluating the trade-off between bunker fuel consumption and reliability
Authors (estimated contribution)	Arnd Graf von Westarp (90 %) Orestis Schnias (10 %)	Arnd Graf von Westarp (100 %)	Arnd Graf von Westarp (50 %) Christian Brabänder (50 %)
Research questions	*Research question 1*: How can empty repositioning be included in the selection of cargo for liner container services? *Research question 2*: Are fuzzy optimization suitable to include uncertainties?	*Research question 3*: How can the criticism on the speed-consumption curves be taken up and converted into a new, generally applicable approach? *Research question 4*: Can the advantages of the approach be demonstrated with statistical criteria?	*Research question 5*: Can the reliability be controlled by consumption? *Research question 6*: How can speed profiles be found that optimize the consumption?
Methodology	Fuzzy linear programming	Exponential regression statistical criteria (AIC, BIC, Cook's Distance)	Discrete simulation statistical distribution
Addressee	line managers from liner shipping companies, vesselowners		
Status	published	published	published
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In summary, the consideration of empty repositioning lowers the profit in short-term, but the new approach provides financial more attractive solutions avoiding expensive empty repositioning costs in mid- and long-term.
The base of each analysis is good data quality. As discussed in Chapter 1.1 the common used speed-cunsumption curve is intensively criticized. So, Westarp, A. Graf von (2020) introduces a method to estimate the bunker fuel consumption in dependency of the speed, shown in Chapter 3. The fundamental result is the establishment of an universal valid speed-bunker fuel consumption model for all speeds. This approach uses exponential regression on real data of three vessels. Mathematically, it is proven that the model delivers values with less aberrations to reality than the common currently used one, especially at high and low speeds. For that determination of this the statistical criteria Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC) and Cook's Distance are applied. Decisions which are basing on the new function are expected to be closer to reality than the old approach.
Article Westarp, A. Graf von and Brabänder (2021), Chapter 4, broaches the issue of the trade-off between optimization of bunker consumption and reliability. The idea is to propose the built-up of spare time during the voyage, the so-called *buffer*, for reaction on unpredictable events. The tool is a discrete event simulation, as thus it is possible to evaluate very complex relations with many possibilities. This obviously leads to simplifications, but the results can still be evaluated. Basing on the modular structure of the simulation, it is easy to adopt other circumstances, such as bad weather, technical problems etc. like defined in Westarp, A. Graf von and Brabänder (2021). The effecting delays were modeled statistically by the use of the Bernoulli coefficient. Additionally, the effects of delay in several different scenarios are demonstrated.

1.2.2. Classification of the articles in decision theory and time frame

To classify the work correctly, three approaches are pursued. First, the method is described. While in the first and the third article deductive approaches are used, in the second article an inductive appraoch is chosen.
Second, the work is embedded in the decision theory through broader analytics spectrum. A distinction is made between descriptive analysis, predictive analysis and prescriptive analysis. The first article, presented in Chapter 2, contains a prescriptive analysis, which is about finding an optimal solution.

For the second work, presented in Chapter 3, data was collected from vessels in form of so-called *Noon Reports*, which indicate technical data such as position of the vessel, average speed, bunker fuel consumption since last report, propeller slip. This can be seen as part of a descriptive analysis and was used to determine parameters by exponential regression. In the third article shown, in Chapter 4, a predictive analysis was carried out by using a simulation. The aim was the research of the influence of delays on bunker fuel consumption and reliability by simulating realistic delays.
Third, the work is classified on the basis of Stadtler and Kilger. In the Supply Chain Planning Matrix (SCP-Matrix) two different dimensions are used. One dimension is the supply chain, devided into four sections: procurement, production, distribution and sales. Since all articles concentrate on transportation and logistics, they can be located in the distribution section.
The second dimension is the time frame, where a distinction is made between short-term, medium-term and long-term. These different time horizons are used to interpret the results of the articles.
So, the first article shows effects of operational planning options in different time horizons. Neglecting the empty container positioning in the process of the decision about the containers to be transported can lead to higher revenues in short-term, but are associated with disproportionately high costs in the long-term. While the selection of containers is always done short-term, the results could also be used for mid- and long-term concerning tactical and strategic decisions. medium-term changes in the service such as changing the port order, adding or dropping ports can be examited with the demonstrated model in the article. Additionally, tactical decisions about changing the vessel types can also be illuminated, due to the significant impact of draft, size, equipment like number of refer plugs on board, on the revenue as well as on the costs. By further development of the results long-term strategies like targeted marketing improvement on special products, ports or regions can also be evaluated. Moreover, long-term financial impact of tactical measures, such as the development of new services, can also be assessed more realistically through including more important aspects.
The gains of the second article also cover the three different time frames. In short-term, it is expected that daily bunker fuel consumption will be assessed more precisely and thus, forecasts as well as analyzes of past data enhance operational planning. In case, the current consumption are regulary higher than the model predict, this could be a hint for an undiscovered technical problem of the vessel or high biofouling on the hull of the vessel. Tactical

decisions to provide vessel types in certain services can be based on more accurate figures in medium-term. In medium-term the results of a voyage can be better estimated, weaknesses can be identified and proactive countermeasures can be taken. In long-term, strategic decisions on the charter and vessel procurement politics can be supported by evaluating the vessels on basis of the present and future needs. Basic evaluation of vessels can be performed, and therefore, more realistic costs are covered. In the current corona crisis, e.g. a significant decrease of demand for capacity leads to additional overcapacity (Hand (2020)). Because of this slow steaming is used more often and vessels move more frequently in a range of lower speeds, in which the exponential function, from the article in Chapter 3, is much more precise than the common used models.
Also the third article offers results at different levels of the dimension time frame in Stadtler's matrix. In short-term the vessel can regulary gain the optimal speed to follow the bunker fuel consumption- and reliability strategy of the company, that can be monitored. In medium-term the planning of the voyage can be improved and reliability can be enhanced leading to lower costs and higher reliability. For medium-term tactical decision it is possible to determine the most bunker fuel consumption efficient vessel types at requested speeds by comparing different vessel types for a certain service. On long-term the results offer an approach for the decision which service profile leads to more profitable results. Strategic decisions could be adjusted, e.g. whether a premium carrier strategy with high realibility or low fare carrier strategy offering discount costs or any other marketing aims are more successful. In addition, it is possible to find berth windows that support the company's strategy to improve the results.

1.3. Combination of the results of the three articles and enhancement of planning strategy

Each article enables liner shipping companies to increase the quality of decisions in their day-to-day business. However, by combining these ideas even more complex tasks can be evaluated on a more detailed level. In the following two examples for these enhancements are given. In subchapter 1.3.1 a way to evaluate two different type of vessels are evaluated on a real service. By combining the realistic bunker consumption curve shown in Chapter 3 with the findings about impacts of delays in Chapter 4 it is possible to evaluate costs including time charter, bunker fuel costs and different levels of reliability. The second example presented in Subchapter 1.3.2 assess a realistic service based on the core results of all three articles. In this service, profit is optimized considering reliability by implemanting the realistic bunker consumption curve, uncertainties (e.g. markt fluctuations), equipment imbalance and the effects of delays.

1.3.1. Evaluation of vessels on basis of realistic bunker fuel consumption and effects of delays

A fundamental and frequently arising problem is deciding which vessel to charter or provide for a specific service. Currently, the common approach is to charter the vessel with the lowest time charter costs of all available vessels which satisfies the needs of the service, e.g. length over all, wideness, top speed, TEU capacity, reefer plugs, draft, flag. These different demands for the services require vessel types with different characteristics. The entirely of the planned characteristics is called *vessel design*. A better assessment would be possible by considering not only time charter costs, but also cost for bunker fuel consumption. Generally, a vessel is provided in different services and changing services over its life cycle. However, a vessel chartered for a certain service typically remains there for the first year, reported by Shintani et al. (2007). Additionally, it would be useful for liner shipping companies to evaluate whether a reallocation of the fleet would be reasonable at a certain time, including risks like delays. Here, reliability should also be considered due to two reasons: Firstly, Qi and Song (2012) report, that a low reliability leads to a high dissatisfaction of the clients and damage the reputation of the liner shipping company. Secondly, operational problems and consequently financial problems arise, so-called *cascading effects* of delays, as Song et al. (2015) and Abioye et al. (2019) describe. This means that delays do not vanish by arrival at the next port. In contrast, they can shift to the next route and cause further delays. So, Song et al. (2015) concludes that reliability is most important. Furthermore, they claim that, although slow steaming allows a better level of reliability, liner companies implement speed instructions which prohibit upspeeding to catch up delays. Over 200 sources, also in recent times like Aydin et al. (2017), quote the remarks of Notteboom (2006), that 93,6% of all delays occur in ports basing on about 200 data points in 2004. However, in the past 16 years the situation in liner shipping industry has changed dramatically, especially in bunker fuel prices. For the years between 2004 and 2007 this shown by Notteboom and Vernimmen (2009). In 2004 the bunker price in Rotterdam is 155 USD per

metric ton and 505 USD per metric ton in 2007, an increase of 226 %, as Notteboom and Vernimmen (2009) state. The price remained volatile and fluctuated between 200 USD per ton and 700 USD per ton in the following years, as Bunkerwire platts (2020) state. Therefore, bunker consumption has not been in the focus of the liner shipping companies during the time of the study Notteboom (2006). Masters of vessels tended steaming the vessels up at the beginning of the voyage in order to avoid later problems and delays. Additionally, the situation in the ports is much easier to monitor and delays are more difficult to hide, as more parties collaborate. On high seas usually only one or two parties (for example vesselowner and charter) interact, who have no interest to promulgate any form of delays. At last, delays are easier noted in the port, as a vessel is called delayed when arriving later than announced in the schedule, which McLean and Biles (2008) call *Estimated Time for Arrival (ETA)*. A schedule at which point a vessel has to be on the high seas does not exist. Abioye et al. (2019) consider that delays often occur at sea today and mention methods to measure them. Notteboom (2006) himself knows the existing problems of his analysis in 2006 and claims that the reason for the limited number of delays on high seas is that the vessels can be speeded up. However, this limitation is often not mentioned and the changed situation in the circumstances, especially the increase of bunker fuel price, is usually not considered in citations. So, a new research with new figures is necessary for all further analysis.
The general aim of this subchapter is to evaluate vessels in terms of operational costs by combining the research results of Westarp, A. Graf von (2020) and Westarp, A. Graf von and Brabänder (2021). The fundamental idea is to evaluate vessels not only on base of time charter costs, but also consider bunker fuel consumption, which are the largest operational costs, as already mentioned. Hereby, the speed-consumption-curve formulated in Westarp, A. Graf von (2020) is used to get realistic results. The delays with the relating costs will be also integrated by the formulas for delays from Westarp, A. Graf von and Brabänder (2021). In the end the time charter costs are added to map the costs completely.

The new model to evaluate a vessel type in respect to the costs is:

$$C_{tot} = BC(v) + TC \tag{1}$$

thereby is:

- C_{tot} Total cost in USD
- BC Bunker fuel consumption costs in USD, dependent on speed
- v Speed of the vessel in knots
- TC Time charter costs in USD

In this calculation the bunker fuel consumption depends on the speed-profile S with a build-up of buffer, which is given by (as defined in Westarp, A. Graf von and Brabänder (2021)):

- A the point in time until the buffer is built up
- B the point in time after the buffer is reduced
- H maximum buffer to be built up until point A
- R remaining buffer when arriving at next port

This speed profile and the occuring events causing in total a delay of l hours lead to a reliability strategy r. So, these dependencies can be summarized with the following Equation 2:

$$C_{tot} = BC(r(v(S(A, B, H, R), l))) + TC \tag{2}$$

The bunker fuel consumption $Bcon$ is calculated with the speed-consumption-curve (taken from Westarp, A. Graf von and Brabänder (2021)) in Equation 3:

$$Bcon(v) = \frac{ae^{bv}}{cv} \tag{3}$$

whereby:

- a and b are parameters, examined by exponential regression and show the characteristics of the vessel
- c ist the number of hours, usually a value of 24
- v is vessel speed

The total bunker fuel costs are calculated in Equasion 4:

$$BC(v) = p \cdot \Sigma_i Bcon_i \tag{4}$$

Hereby p is the bunker fuel prize and $Bcon_i$ is the bunker fuel consumption in the descrete intervall i.

Five different cases are calculated and are shown in Table 3. The first case only considers the time charter costs. This is the currently most often used approach. The second case includes besides the time charter costs also the cost for the so-called *proforma schedule*. A proforma schedule is the template of the schedule, respecting all berth windows, but considering no delays or interruptive events. The third (α reliability $\geq 70\%$), the fourth (α reliability $\geq 80\%$) and the last case (α reliability $\geq 90\%$) demand different levels of reliability α, so as defined in Westarp, A. Graf von and Brabänder (2021).

It is assumed that a liner shipping company checks the so-called NERA 1 service of Hamburg Süd, connecting Central Europe and China (shown in Figure 4 a) eastbound and b) westbound). The current (status from 1st of May 2020) port order is:

Ningbo (China) - Shanghai (China) - Xiamen (China) - Yantian (China) - Tanjung Pelepas (Malaysia) - Colombo (Sri Lanka) - Suez Canal (Eygpt) - Felixstowe (United Kingdom) - Bremerhaven (Germany) - Rotterdam (Netherlands) - Tangier (Marocco) - Suez Canal (Eygpt) - Salalah (Oman) - Hong Kong (China) - Yantian (China) - Xiamen (China) - Ningbo (China)

The round voyage (from Ningbo to Ningbo) is 21,834 nautic miles (nm). Following the same split of voyage as Wang et al. (2013) a time in port of 500 hours and a sea time of 1,852 hours is assumed. The round voyage lasts up to 98 days (=14 weeks). Therefore, 14 vessels are needed for a weekly service. A probability of an event leading to a delay is 0.65 % per hour. In case of an delay the interruption is 5 hours (5%), 10 hours (20%), 15 hours (50%), 20 hours (20%) or 25 hours (5%) hours long.

Now, it should be investigated which of the two vessel types introduced in Westarp, A. Graf von (2020) is optimal for this service.

It should be noted that the two vessels, which are taken for this scenario, are too small for this service in reality. However, due to the commitment with the data provider in Westarp, A. Graf von (2020), this special combination of real vessels with a real service creates fictitious scenario. This approach

Figure 4: a) NERA 1 eastbound (above) and b) NERA 1 westbound (down)

is chosen to provide on the one hand real data, on the other not to communicate the identity of the real vessels. Both vessels have about the same capacity but very different designs. Psaraftis and Kontovas (2010) write that the adoption of the needs for slow steaming is reflected in two steps. In the first step the existing vessels simply reduce the speed. In the second step vessels are constructed for lower speed with, e.g. smaller engines. On one hand these new designs reduce the fuel consumption for slow speeds, but on the other hand they also reduce the most economical speed and therefore, increase the bunker fuel costs for higher speeds. Here, although both vessels were constructed in 2007, the beginning era of slow steaming, it seems, that one vessel is of an old design and the other one of a new design. In Figure 5 the speed-consumption-curves are demonstrated. The speed at which both vessels consume the same amount of bunker fuel can be calculated by using the parameters from Table 2, which is 15.7 kns. Vessel I has a higher basic consumption below this point, but on higher speeds disproportionately less. This shows that Vessel I is of the old design and Vessel II is of the new with a high efficiency at low speeds.

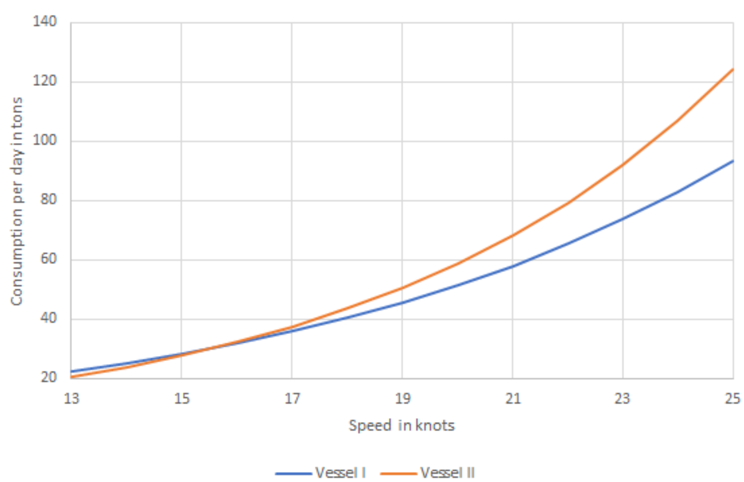

Figure 5: Bunker fuel consumption of the two vessels, Vessel I (blue) and Vessel II (orange). At low speeds Vessel I has a higher consumption up to a value of 15.7 kns and a lower one at higher speeds.

For this purpose the needed assumptions are considered:

- Delays in port can be caught up in the port
- Only delays on the ocean legs are considered
- Data, like the probability of delay, destribution of length of delay, bunker price, time charter costs etc., are correctly assumed
- Minimum and maximum speed are correct
- Speed consumption curve is correct
- Bunker fuel price of 350 USD per ton

In Table 2 the data of the vessels including TC are provided, taken from Westarp, A. Graf von (2020). The different results are summed up in Table

Table 2: Specification of the vessels taken from Westarp, A. Graf von (2020) in comparison

Vessel Type	a	b	TC per day in USD
Vessel I	4.738	0.1193	8,200
Vessel II	2.954	0.1494	8,000

Table 3: Costs in Mio USD p. a., considering time charter (TC), proforma bunker fuel consumption (BFC) and different levels of reliability α. The sign of the Delta shows whether Vessel I (-) or Vessel II (+) are less expensive

Vessel Type	only TC	TC and proforma BFC	TC, realistic BFC and $\alpha \geq 70\%$	TC, realistic BFC and $\alpha \geq 80\%$	TC, realistic BFC and $\alpha \geq 90\%$
Vessel I	41.787	76.966	84.409	**86.471**	**89.717**
Vessel II	**40.768**	**76.294**	**84.301**	87.451	91.267
Delta	1.019	0.672	0.108	-0.980	-1.550

3. Basing on the given data Vessel II is less expensive than Vessel I, taking only time charter into account . The second case (consideration of time charter with proforma bunker fuel consumption) and the third case (time charter with a minimum of α reliability 70 %) lead to the same result. In the case of a α reliability $\geq$80 % and α reliability $\geq$90 %, Vessel I is more effective, because catching delays by speeding up requires high speeds. Somewhere between a reliability of 70 % and 80 % is the break even point where the deployment of both vessels would have the same financial result. Any demanded reliability higher than this point makes Vessel I more effective. Obviously, the higher difference in time charter shifts the break even point to a higher reliability, while a lower bunker fuel price reduces this point. Therefore, the final decision which vessel to deploy bases on the strategy of the liner shipping company. This approach helps the company to find the optimal solution following its own reliability-cost strategy and shows that it is possible to include delays and reliability strategy in the calculation.
A number of aspects have been neglected in these calculations:

- Firstly, speeding up is the most used method to repair a schedule. Notteboom (2006) demonstrates different possibilities to repair the schedule at a given example of port congestion. Li et al. (2016) report measures of a damaged schedule. Brouer et al. (2013), Li et al. (2016) and Abioye et al. (2019) show different possibilities which schedule contingency measures exist and how they can be used.

- Secondly, in this thesis currently only port to port-relations are considered. Cascading effects of the shift of delays on next sea stretches are neglected.

- Thirdly, also delays which occur in the port are neglected. Obviously, the delay of a round voyage is not the sum of port to port stretch delays.

These simplifications enable the evaluation costs of different vessels including effects of reliability in liner shipping services. Therefore, the question which vessel type should be deployed can be answered more sophisticated. Also, a closer evaluation of vessels charter on long-term charter by including bunker fuel costs is possible. Additionally, a closer awareness of risks can help to eliminate or at least reduce them. This can not only be used to include risks, but also offers possibilities for planning or improving a service. This simulation also helps shipping companies to evaluate the costs to reach a certain berth window. By shifts of berth windows, risks can be transferred on successive routes, thereby balancing the risks and reducing costs. The risks on a route between two ports are currently assessed as equal distributed. Since the location of the interruption is very important for the consideration of the costs, a location-based risk distribution could be useful. In the last years fluctuations of the bunker price lead to a high risk of the liner shipping companies, described by Notteboom and Vernimmen (2009). Further information on this risk will help liner shipping companies to detect a proper hedging policy. Currently, the buffer in a liner shipping service is only a measurement to avoid delays in the port. With the shown results it is possible to see speed and buffer as financial factor.
The environmental impact of the shipping industry is getting more and more in the focus of public and politics. Mansouri et al. (2015) describe that companies that act in an environmentally responsible manner are also economically more successful in the long-term. Linder (2018) reports of liner shipping companies that take voluntary part in projects that reduce emissions. Although, container shipping has the lowest carbon footprint per ton (see Koilo (2019)), the total emissions are high. So, already about ten years ago Corbett et al. (2009) and Psaraftis and Kontovas (2013) discussed the effects of a so-called emission-tax on CO_2. Such a tax could be implemented

easily in this model by adjusting Equation 2 to include the effects and analyze the situation by adding a term of CO_2-tax-costs CTC (see Schinas and Westarp, A. Graf von (2017)).

$$CTC = BFC(v) \cdot E \cdot Tx \tag{5}$$

- $BFC(v)$ is the bunker fuel consumption in tons dependent on speed v.
- E is the ratio of emitted tons of CO_2 to consumed tons of bunker fuel. The value of 3.17 is common, e.g. Psaraftis and Kontovas (2013).
- Tx is a coefficient for the amount of tax per ton emitted CO_2 in USD.

Cariou (2011) evaluate how many vessels are under slow steaming (35.4 % of all services world wide), and these services alone save 55 % of the fuel consumption at sea. In ECA zones there are stricter limits for emissions from merchant vessels, which has a massive impact on marine routes, as Chen et al. (2018) argue. ECA-zones or other environmental requirements can also be implemented easily in the model in Equation 2. Yang et al. (2012) describe possibilities to NOx and SOx in shipping industry. Delays are not considered there, but also here the developed approach can be adjusted. Gu and Wallace (2017) state the importance of so-called scrubber in order to comply with the ECA-Zone regulations, but their analysis concludes this is vastly overestimated. This shows the importance of research of measures for lowering emissions to avoid missinvestments. Additionally, an effective planning of services and evaluation of the vessels like in this thesis is essential to lower bunker fuel consumption to reduce emissions effectively.
Safety and security costs can also be assessed by the algorithm. Although it is relatively quiet in the pirate areas at the moment, security teams may be needed again. These costs are also dependent on the speed and thus the bunker consumption of the vessels.

1.3.2. Evaluation of Liner Shipping Services on basis of realistic bunker fuel consumption under uncertainty and empty repositioning

While Subchapter 1.3.1 deals purely with the cost aspects, a more comprehensive approach is provided in this subchapter. Not only the cost depend on the level of reliability, but also the revenue is affected as the clients rely on good service. Although, customers will not be willing to pay more for

a higher level of reliability, a shipping company can only accept some time-sensitive commodities if they offer appropriate reliable services. In case these commodities are paid better not only the volume of cargo increases but also the contribution margin.
So in this subchapter the aim is finding the service level and thus, the available cargo which optimizes the revenue. Thereby, any consequences of any delays in ports are not considered. The focus is on reliability on the ocean crossing stretches, its costs and impacts on the cargo flow. For terms of simplification not a network (like in Westarp, A. Graf von and Schinas (2016)), but just one liner shipping service is evaluated. Additionally, for the same reason the ports at each region are clustered and only the two routes between the regions are considered, shown in Figure 6. As the approach examines only ocean crossing stretches, revenues and costs of coastal movement are assumed not to differ and are not dependent on the reliability on the sea. This also applies to the time charter costs. One problem of the use of the clusterization could be that the transport of cargo within the region is neglected, so that more cargo on the voyage could exceed the capacity of the vessel. However, the first port that is approached in a region is always the one with the largest discharge of cargo. So no problems with the capacity of the vessel will arise. Is not planned to compare different vessels to find the optimal one for a service but to develop the best use of one vessel in short-term.

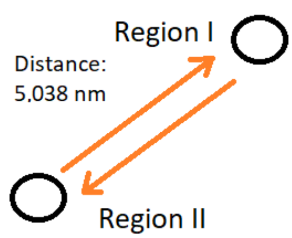

Figure 6: Illustration of the Problem set up

For this purpose, the findings from the articles Westarp, A. Graf von and Schinas (2016), Westarp, A. Graf von (2020) and Westarp, A. Graf von and Brabänder (2021) are combined with each other. The aim is to depict realistically the factors of speed and cargo flows depending on the reliability of the service. Therefore, the algorithm contains two parts as shown in Figure 7. With the combination of Westarp, A. Graf von (2020) and Westarp, A. Graf von and Brabänder (2021) as already done in 1.3.1 the impact of bunker costs can be well estimated. In order to indicate the contribution margin (CM) the fuzzy approach from Westarp, A. Graf von and Schinas (2016) is here used again.

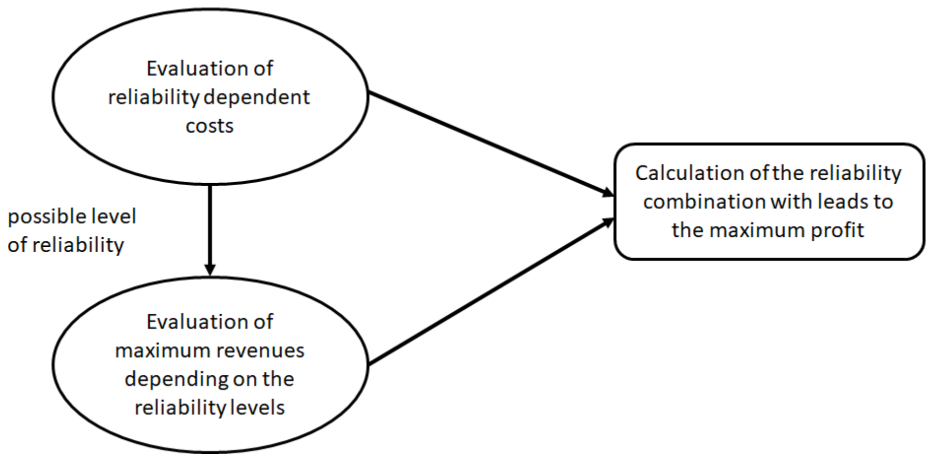

Figure 7: Explaination of the procedure

The mathematical model of Westarp, A. Graf von and Schinas (2016) is considered as a base, however as another focus is set the model is adjusted. The changes apply to both the objective function and the objective constraints. As a single service instead of a network is modeled, the variable for different services s is not needed as well as factors for transshipment. The variables loading and discharge costs are balanced with the freight rates to contribution margin $CM_{i,j,t}$. Additionally, due the clustering the index o for origin port and d for destination port are not necessary. As it is not wise to call a draft limited port as first or last port in the service it is assumed that no weight restriction needs to be followed. The different weights are reflected in the different TEU restrictions in $TEUC_{i,j}$. Hereby, it is important to note that the profit P is not the total profit, as system costs SC do cover only bunker expenses for ocean crossing, but no coastal costs and time charter.

$$\max P = \sum_{\forall i,j,t} CM_{i,j,t} \cdot x_{i,j,t} - BFC \tag{6}$$

subject to the following constraints:

$$TEUC_{i,j} \geq \sum_{i,j,t} x_{i,j,t} \cdot TEU_t \tag{7}$$

$$PlugC_{i,j} \geq \sum_{i,j,t} x_{i,j,t} \cdot PLUG_t \tag{8}$$

$$AV_{i,j,t} \geq x_{i,j,t} \tag{9}$$

$$x_{i,j,t} = x_{j,i,t} \tag{10}$$

$$x_{i,j,t} \geq 0 \tag{11}$$

thereby is:

- P is the profit for the transport on ocean stretches in USD without considering coastal costs, time charter costs or coastal revenues
- $AV_{i,j,t}$ are the available full containers of type t from port i to port j
- $CM_{i,j,t}$ is the contribution margin for one full container of type t from port i to port j in USD per unit
- $Plug_t$ is the number of plugs one container of type t uses
- $PlugC_{i,j}$ is the plug capacity between port i and port j
- BFC are the bunker fuel costs on the ocean stretches in USD
- TEU_t is the number of slots one container of type t uses.
- $TEUC_{i,j}$ is the TEU capacity between port i and port j
- $x_{i,j,t}$ is the number of units transported from port i to port j of type t

The objective function of the problem, which can be modeled as an LP, is given in Equation (6). The product of contribution margins $CM_{i,j,t}$ and transported volumes $x_{i,j,t}$ leads to the revenues. The bunker fuel costs on the ocean stretches are all considered costs BFC in the model. Therefore, the profit, with the limits described above, is the difference of revenue and costs. The five additional objective constraints are expressed by Equation (7) to (11). Equation (7) ensures that the TEU capacity $TEUC_{i,j}$ of the regarded vessel are not violated and Equation (8) considers the limitations of the plug capacity. The prevention that the number of containers picked up in a port $x_{i,j,t}$ is larger than the number of available containers in the port $AV_{i,j,t}$ is shown in Equation (9). Equation (10) is the balanced constraint that ensures that the number of containers of each type which leaves each region $x_{i,j,t}$ is the same as the containers arriving in that region $x_{j,i,t}$. The last one Equation (11) denotes the apparent constraint of non-negativity of the volume $x_{i,j,t}$. A real number n is mapped by a function $\zeta(n) \rightarrow$ [0,1]. A triple of number a, b and c where $a \leq b \leq c$, in such a way that:

1. $\zeta(n) = 1$ if $n = b$
2. $\zeta(n) = 0$ if $n \leq a$ or $n \geq c$
3. $\zeta(n) = \frac{\arctan(n-b)+d}{f}$
4. $\zeta(n) = \frac{\arctan(b-n)+d}{f}$

The parameters $b = 75$, $d = 1.53$ and $f = 3.06$ are chosen to fulfill the constraints shown in Constraint 1 and 2. The model is fuzzified by calculation of $CM_{i,j,t}$ and $AV_{i,j,t}$ by the function ζ in Constraint 3 and 4. To defuzzify the data in this thesis the defuzzification of center of gravity is used. Therefore the value of n is calculated with the the following equation:

$$n = \frac{\Sigma_i \zeta_i n_i}{\Sigma_i \zeta_i} \tag{12}$$

Hereby, the functions ζ_i are the functions from the Constraints 3 and 4 with discrete nodes n_i in the intervall between a and c.
Unfortunately, liner shipping companies are rather strict with their data, especially with market and CM numbers. One reason is the strict enforcement of antitrust compliance regulations which forbid to share, exchange or publish data depending on the legislation between six months and one year. However, also for older data liner shipping companies are not willing to share their information. Therefore, realistic but no real data are assumed. Additionally, the relationship between reliability and CM respectively reliability and volume are pure estimation of an expert in this field. For a practical application further research is needed to get reliable data and relations.

Needed assumptions:

- For this purpose is it assumed that any delay that occurs can be caught up in the region, and the vessel leaves a region without any delays.

Table 4: Specification of the vessel in comparison

Vessel Type	a	b	TEU @14tons	Reefer plugs
Vessel I	4.738	0.1193	1,400	150

- Data like the probability of delay, distribution of length of delay, bunker price, etc. are assumed realistically.
- Vessel characteristics like minimum and maximum speed as well as number of TEU and values of CM are estimated realistically.

Vessel I from Westarp, A. Graf von (2020) and Subchapter 1.3.1 is used, see data of Table 4, and thereby the capacities have been changed to ensure anonymity of the vessel. For CM and available volume the assumptions of Table 5 are considered. For the northbound it is assumed that volume of dry standard containers and deep frozen reefers is independent of the reliability. For time sensitive dry cargo and chilled reefer cargo there is an 5% increase in average CM and between 50% and 100% increase in volume depending on the container type. Southbound the reefer market is not important, therefore the focus is on dry time sensitive cargo. An increase in CM about 25% and in volume about 25% respectively 50% is taken in the model.
For the distance of 5,038 nm following Sea Distances (2020) the distance between Le Havre (France) and Rio de Janeiro (Brazil) on the northbound legs 300 hours and on the southbound leg 335 hours for schedule are assumed. The different voyage times result from the intense reefer leg, the northbound, which requires higher speeds. This can also be seen in real services, e.g. SAEC (Hamburg Süd (2020)). To simulate the delay a probability of 0.25% per hour on the northbound leg and of 0.4% per hour on the southbound leg is assumed. For the length of the delay the same discrete assumptions as in Subsection 1.3.1 are considered.
Table 5 shows the market conditions in relation to the offered reliability. For standard dry and frozen reefer cargo it is assumed that no effects occur. The focus is set on time sensitive dry and chilled reefer cargo. Basing on the length, distance, risk of delay and distribution of the delays 10,000 possible voyages considering the potential different delays are created. The same speed profiles introduced in Westarp, A. Graf von and Brabänder (2021) are used to discover the dominate strategies. As for northbound and southbound different strategies are possible those strategies providing a reliability of 70% to 90% are combined to find the profit maximizing results. Figure 8 shows

Table 5: Volume and CM in dependency of reliability

	dry				reefer			
	standard		time sensitive		chilled		deep frozen	
	20'	40'	20'	40'	20'	40'	20'	40'
volumen southbound in units								
50% reliability	350	400	100	200	5	5	10	15
100% reliability	350	400	150	250	5	5	10	15
volumen northbound in units								
50% reliability	300	320	50	50	75	40	100	120
100% reliability	300	320	100	75	125	75	100	120
CM southbound in USD								
50% reliability	350	700	400	800	350	700	350	700
100% reliability	350	700	500	1,000	350	700	350	700
CM northbound in USD								
50% reliability	200	450	350	850	650	1,400	500	1,050
100% reliability	200	450	367.5	892.5	682.5	1,470	500	1,050

the results for this case in a 3D- figure. Thereby the reliabilities on the northbound respectively on the southbound leg are on the x- and y- axis while the profit is on the z-axis, colored dependent on the value. The profit optimum is southbound at a reliability of 81,40% and northbound at 79,21% with a value of about 364,500 USD. This is about 10 % higher than the value of the minimum. This shows the significance of the effect of reliability and its interaction with other parameters is in this model.

In this subchapter the used data like CM, dependency, volume, the fluctuation in the data have to be reviewed critically. Due to a lack of information in this area precise studies are necessary to examine these dependencies. Being aware of these circumstances the focus of this thesis was not on the results of the calculation but on the methodology and the algorithm. For this reason too, the ports of a region were clustered, only the consumption of fuel was taken into account in the system costs SC and the further costs and revenues from coastal shipping or time charter were not considered. In a model with a network of several ports in the different regions, like in Westarp, A. Graf von and Schinas (2016), these aspects would have to be taken into account again and could offer further interesting insights, especially with

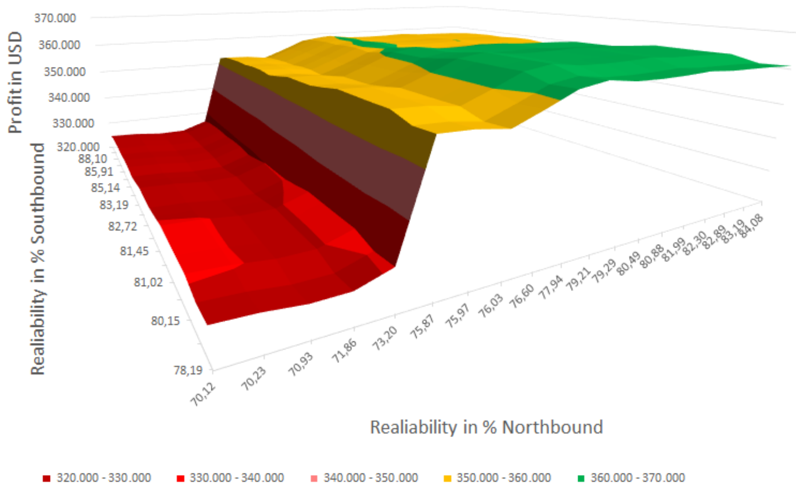

Figure 8: Illustration of profit in dependency of southbound and northbound reliability. A dramatic increase of profit is obvious at a reliability of about 75 % southbound. The maximum is at a value of 81,40% southbound and 79,21% northbound

regard to transshipment and coastal operations, which is described e.g. in McLean and Biles (2008) with 4 services, 64 vessels and 20 different ports. In such a model, the effects of cascading delays would also be important and should be examined from this perspective. In practice, the use of higher CM and volumes, depending on the reliability, is only slightly developed. A liner shipping company that offers this service in an aim-oriented manner can secure higher CM and thereby bring an advantage in competition. How this is built up and advertised among customers is not part of this work.

2. A fuzzy approach for container positioning considering sustainable profit optimization

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A fuzzy approach for container positioning considering sustainable profit optimization

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ABSTRACT

Liner companies are forced to operate efficiently due to regulatory and market competition patterns and requirements. Container positioning is a vital part of their strategy. Instead of minimizing costs of moving empty units as preferred in the literature, this paper presents a formulation that optimizes the trade-off between full and empty units. Paradoxically, carrying empty instead of full units in some cases leads to more profitable operations. This paper considers these as well as the derived CO_2 footprint aspects. Owing to the seasonality and incompleteness of data, a fuzzy optimization approach is chosen.

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1. Introduction: statement of the problem

Undoubtedly, containers have revolutionized liner shipping, but the immense problem of equipment positioning has arisen. Different commodities have necessitated different container types, causing local imbalances of demand and supply of equipment. Theofanis and Boile (2009) estimate the number of unused stored containers to be 1.5 million TEU globally. These imbalances can be solved by repositioning the empty units. The process is described in detail in Rodrigue et al. (2013). Cheung and Chen (1998) and Choong et al. (2002) present models for repositioning, distinct from the transportation of full containers. Theofanis and Boile (2009) provide reasons for the imbalance of containers and analyze the logistical management and strategies of liner shipping companies, while Sherali and Suharko (1998) present an approach that deals with a related issue regarding the repositioning of empty rail cars. Most commonly, the problem of empty unit positioning is considered a mixed-integer linear programming (MILP) multi-commodity flow problem to evaluate the optimal cargo mixture with respect to all relevant costs and constraints (see Aversa et al. (2005), Meng and Wang (2011), and Shintani et al. (2007)).

In the present article, a pure linear programming (LP) approach is chosen in order to keep the calculation uncomplicated and fast. However, it is simple to extend this LP formulation to an MILP one, if necessary. Chang et al. (2015) uses a bi-level structure comprising an upper level for optimizing operational profits and a lower level for repositioning empty containers and minimizing transportation costs. Cheung and Chen (1998) and Choong et al. (2002) merely concentrate on minimizing the transit costs for a predefined, distributed number of empty containers.

Thus, most of the literature describes the overall problem as "static," i.e. all costs, parameters, and constraints are well defined and the cargo mixture is a priori determined. But in reality, the local demand and surplus for empty units are

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dynamic, as they depend on the flow of transported units. The cargo flow is chosen by the shipping companies on the basis of the so-called contribution margin (CM). The CM is defined as the difference between all variable revenues, such as the gross freight rate or bunker adjustment factor surcharge, as well as all variable costs, such as cargo handling or storage expenses. However, when shipping companies decide on the cargo flow of both full and empty units, the demand and the related cost of repositioning of the empty containers are practically unknown. Thus, the total variable costs cannot be estimated; hence, the derived CM is uncertain. In this paper, the CM is not regarded as a reliable indicator; it will be treated as a fuzzy variable (see Section 2.2).

In order to reduce this imbalance, some companies such as Maersk involve their clients in savings or extra costs for repositioning (MAERSK Line, 2015). However, to change the cargo flows in the preferred way, the companies need to know the exact reactions of clients and competitors, which is not always possible or a realistic assumption. Another approach is to block some capacity for empty units, which is not efficient either, due to the uncertain fluctuation of the market in terms of both prices and demand. Therefore, it is only possible to react a posteriori to imbalances of equipment.

In the short term, which means only one voyage, equipment imbalances are negligible. The algorithm that provides the optimal short-term solution is called *imbalanced* algorithm in this paper. For sustainable and efficient operations, it is necessary to generate an algorithm that maximizes the profit for longer periods, the so-called *balanced* algorithm. First, this might be regarded as the dual problem of the well-known LP of cost minimization. In this case, however, the costs would have been fixed, as mentioned in Choong et al. (2002) and Cheung and Chen (1998). This does not describe real-world conditions. As opposed to this conventional concept, the new approach takes a holistic view and regards the demand of repositioning empty units as a consequence of the imbalance of full-unit shipments. Consequently, changes in the cargo-flow of laden units directly alter the need for empty positioning. Therefore, the cargo flows of full units are optimized with respect not only to their revenues, but also to costs and capacity effects on empty positioning. In contrast to the rest of the literature known to the authors, in this work profit is optimized in a single holistic step.

Other essential parameters such as available cargo between ports or freight rates fluctuations are quite uncertain due to many external effects, namely dynamically changing market patterns. The effort to develop parametric programming to deal with the related uncertainty would be enormous. In contrast to Chang et al. (2015), who uses an LP formulation, in this work a crisp model is presented vis-á-vis the fuzzy linear optimization (FLP) approach, in order to highlight the benefits of fuzzification. Fuzzification is explained in the works of Xu and Zhou (2011) and Bojadziev and Bojadziev (2007). This innovative approach to position empty units with FLP is also a contribution of this work.

The conception presented is also in accordance with the considerations put forward in Kontovas (2014), where existing formulations of green ship routing and scheduling problems are recited. The implementation of repositioning empty units in his paper leads to a reduction in transportation effort and emission of CO_2. The same effect is shown in this paper.

The present paper is structured as follows: In the following Section 2, the crisp mathematical LP and the FLP models are presented. In the end of this section, the balancing constraint Eq. (11) is added to the model to expand the *imbalanced* short-term profit-maximizing LP or FLP model into a *balanced* mid- and long-term profit-maximizing model. In Section 3, a numerical example is introduced and solved by the fuzzy algorithm. Finally, a comparison is drawn between the *imbalanced* and the *balanced* algorithm. In Appendix A, the different results between the crisp and the fuzzy model are presented. Section 4 concludes the paper with a summary of the results.

2. Problem formulation

2.1. The crisp model

The problem of optimal cargo flows can be interpreted as a multi-commodity flow problem that can be solved by LP. The approach used in this work is developed from the original Dantzig–Wolfe decomposition method (Dantzig and Wolfe, 1960). The formulation of the crisp *imbalanced* problem is described below. The *imbalanced* algorithm solves the commonly considered problem of optimizing profit in the short term.

Objective function:

$$max\ P = \sum_{\forall o,d,t}\left[FR_{o,d,t}\cdot x_{o,d,t} - \left(SC + \sum_{\forall i,j,s} SF_{i,j,s}\cdot x_{o,d,t}^{i,j,s} + \sum_{\forall i} t\nu_i \cdot f_i + lc_o \cdot x_{o,d,t} + dc_d \cdot x_{o,d,t}\right)\right] \tag{1}$$

subject to:

$$TEUC_{i,j,s} \geqslant \sum_{o,d,t} x_{o,d,t}^{i,j,s}\cdot TEU_t \tag{2}$$

$$PlugC_{i,j,s} \geqslant \sum_{o,d,t} x_{o,d,t}^{i,j,s}\cdot PLUG_t \tag{3}$$

$$TONC_{i,j,s} \geqslant \sum_{o,d,t} x_{o,d,t}^{i,j,s}\cdot w_{o,d,t} \tag{4}$$

$$AV_{o,d,t} \geqslant x_{o,d,t} \tag{5}$$

$$x^{i,j,s}_{o,d,t} \geqslant 0 \tag{6}$$

where

- $AV_{o,d,t}$ is the available full containers of type t from origin port o to final destination port d.
- dc_d are the discharge costs to discharge one unit at port d.
- f_i are the transshipment costs to be paid for every unit that changes the transportation service in port i.
- $FR_{o,d,t}$ is the freight rate of one unit transported from port o to port d of type t.
- lc_o are the load costs to load one unit at port o.
- $PLUG_t$ number of plugs one container of type t uses.
- $PlugC_{i,j,s}$ is the plug capacity between port i and port j on vessel system s.
- SC are the constant system costs.
- $SF_{i,j,s}$ are the ad hoc third-party feeder costs, which are only paid for used space from port i to j at system s.
- TEU_t is the number of slots one container of type t uses.
- $TEUC_{i,j,s}$ is the TEU capacity between port i and port j on vessel system s.
- $TONC_{i,j,s}$ is the TON capacity between port i and port j on vessel system s.
- tv_i are transshipment units that change the transportation system in port i.
- $w_{o,d,t}$ is the average weight of one unit of type t from origin port o to final destination port d.
- $x_{o,d,t}$ is the number of units transported from port o to port d of type t.
- $x^{i,j,s}_{o,d,t}$ is the number of units transported from port o to port d of type t on edge from port i to port j on service s.

The objective function of the problem, which can be modeled as an LP, is given in Eq. (1). The first term describes the revenue, which is the product of freight rate and volume shipped. The second part consists of the five cost components, namely fixed system costs, third-party costs, transshipment costs, load, and discharge costs.

Five additional constraints are expressed by Eqs. (2)–(6). Eq. (2) ensures that the TEU capacity of a vessel in every port is not violated. Eq. (3) considers limitations of the plug capacity of a vessel while Eq. (4) sets the weight limitations of the vessel and the draft limitations of the port. Eq. (5) ensures that the number of containers onboard is less than the number of available containers in the respective connection among ports. The last one, Eq. (6), denotes the apparent constraint of non-negativity.

2.2. The fuzzy model

Due to the seasonality and the constantly changing market conditions, some components are unknown or hard to predict. As described in Section 1, parametric programming fails due to the numerical effort required. Therefore, the crisp model introduced in Section 2.1 will be modified in an FLP. The theoretical pattern is presented by Zimmermann (1978, 1991) and Rommelfanger (1996).

In the fuzzy model, it is assumed that beside the freight rates FR_{odt} and available cargo AV_{odt}, the average weight w_{odt} of the units is also fluctuating (see also the preamble and the amendment to SOLAS by the International Maritime Organization (2014)). Fuzzification follows the procedures described by Zimmermann (1991).

The fuzzy model uses the same structure of the crisp model. In order to model fluctuations (fuzzification), the objective function (1) and the constraints (4) and (5) are replaced by the objective function (7) and the constraints (8) and (9) respectively.

The new objective function:

$$max\ P = \zeta(FR_{o,d,t}) \cdot x_{o,d,t} - \left(SC + SF_{i,j,s} \cdot x^{i,j,s}_{o,d,t} + tv_i \cdot f_i + lc_o \cdot x^{i,j,s}_{o,d,t} + dc_d \cdot x^{i,j,s}_{o,d,t}\right) \tag{7}$$

New constraints:

$$TONC_{i,j,s} \geqslant \sum \zeta(W_{o,d,t}) \cdot x^{i,j,s}_{o,d,t} \tag{8}$$

$$\zeta(AV_{o,d,t}) \geqslant x_{o,d,t} \tag{9}$$

A real number x is mapped by a function $\zeta(x) \to [0,1]$. A triple of numbers a, b, and c, where $a \leqslant b \leqslant c$ is such that:

1. $\zeta(x) = 1$ if $x = b$
2. $\zeta(x) = 0$ if $x \leqslant a$ or $x \geqslant c$
3. $\zeta(x) = \frac{(x-a)}{(b-a)}$ if $a < x < b$
4. $\zeta(x) = \frac{(c-x)}{(c-b)}$ if $b < x < c$

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To defuzzify the necessary fuzzy numbers in this paper, the fuzzy average approach is used. Hence, the following standard equation is used for defuzzification, as described by Xu and Zhou (2011). For reasons of simplification, it is assumed that the numbers of the triple are not weighted.

$$x_{max} = \frac{a+b+c}{3} \tag{10}$$

Obviously, x_{max} does not have to be an integer. However, the impact of x_{max} as a fractional number is marginal compared to an integer number.

2.3. The balancing constraint

Thus far, the *imbalanced* model is described. In order to extend this model to the *balanced* algorithm, an additional constraint has to be implemented. The number of containers of a certain container type t that leave a port i has to be the same number as the containers of this type that arrive in port i. This equation ensures that in the end the number of equipment in every port is the same as in the beginning.

$$\sum x_{o,d,t}^{i,j,s} - \sum x_{o,d,t}^{j,i,s} = 0 \quad \forall i,j,t \tag{11}$$

3. Numerical example

3.1. Test scenario

To illustrate the difference between the *imbalanced* and the *balanced* algorithms, an easily generalizable test scenario is provided. Fig. A.1 in Appendix A illustrates graphically the numerical test example. The scenario is constructed in such a way that it is on the one hand realistic and representative of all types of services, and on the other hand simple enough, allowing the reader to focus on the significant issues and the results. The test scenario is comprised of two regions: Region I with three ports, A, B and D, and Region II with two ports, C and E. Additionally, Table A.1 with the volumes, Table A.2 with the average weight per unit, and Table A.3 with the CM values realistically reflect that demand and supply of different types of containers are most often not in line in different regions. All tables can be found in Appendix A. Due to the imbalance in cargo flow, either a high demand for repositioning for empty units or a decline in the transportation of certain imbalanced container types is expected.

The network system consists of three liner shipping services. The first service, which is marked in green,[1] is provided by the network's own vessels as a standalone service offering the port rotation $A \to E \to C \to A$. On a service of the competitor, marked in red, some space is structurally bought, meaning that the slots have to be paid in any case whether they are used or not. With this second sling (port rotation) $A \to B \to C \to D \to A$), the port coverage increases, so a ship can call B and D directly. Moreover, ports A and C offer transshipment opportunities. Additional space is bought on a line between ports B and E. However, on this service slots have to be paid only if they are used. By this third service, ports B and E also become possible transshipment ports. Detailed data are presented in Appendix A.

3.2. Imbalanced algorithm

The *imbalanced* algorithm ignores the imbalance, aims for the best-paying cargo, and is thus expected to gain higher short-term profits than the *balanced* algorithm. This is the traditional way of choosing cargo. Only space that cannot be used for profitable cargo (CM > 0) is filled up with empty containers.

The maximum total profit is predicted to be USD 334,400 per round voyage for transportation of 3587 TEUs, as per Table C.11. At this point, it should be highlighted that the figures have been slightly rounded, which is why some marginal rounding errors are expected. This is an inherent feature, as the $x_{o,d,t}^{i,j,s}$ are not integers. Table B.7 suggests the sum of $(569 + 42) + 2(1113 + 375) = 3587$ TEUs (see also Table C.11), i.e. 611 20′ units (569 dry and 42 reefer) and the 1488 40′ units (1113 dry and 375 reefer), as per Table B.7. For evaluating capacity constraints, the cargo flow on the edges is illustrated in Table B.6, and the flow from port to port is presented in Table B.7, both in Appendix B. If $x_{o,d,t}^{i,j,s}$ were integers, then the problem would have the nature of a mixed integer and the computational effort would have to be increased without any real gain in accuracy, especially for relatively large problems. The assumption of relaxing $x_{o,d,t}^{i,j,s}$ does not harm the applicability and integrity of the formulation.

Two more results require further examination. Firstly, edges 8 and 9 are not used at all; this is explained by the comparably high costs for the slot charter agreement. One TEU on the first two services costs USD/TEU 429 $\left(= \frac{total\ \ costs}{TEU\ \ capacity} = \frac{1{,}500{,}000}{(1000+750)\cdot 2}\right)$ at a utilization level of 100%, while a slot on the third service is at a level of USD/TEU 500 per

[1] Service 1: A-B-C-D-A or edges 1-2-3-4; Service 2: A-E-C-A or edges 5-6-7; Service 3: B-E-B or edges 8 and 9.

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leg. As the slots are only paid if they are used, no costs arise. Secondly, the weight allocation is completely used on all edges, except edge 1, while the volume capacity is never completely exploited and the plug capacity only on three stretches. The allocation is agreed on a standard weight of 14 tons per TEU, but as the high average weight of the full containers is greater or equal to this assumption, it is obvious that the weight capacity is reached first. When leaving the regions, the vessels are fully utilized TEU-wise and ton-wise, as well as plug-wise, since cargo is available on the market.

Table B.9 sums up the results of the cargo flow in Table B.7 and illustrates an equipment imbalance arising from the proposed cargo flow. Negative numbers mean that units of a specific container type are more discharged than loaded, while a positive number means more loaded units than discharged ones. As there is no more attractive cargo for this route as shown in Fig. A.1 (see capacity differences) and Table B.6; the unused capacity of 82 TEU and 660 tons can be used to ship empty units. Based on an average weight of 2.5 tons per empty TEU, the TEU capacity is reached first. Therefore, the total empty capacity is 82 TEU (41 empty 40′Dry) can be shipped from Port A to Port B (see Table B.7).

3.3. Balanced algorithm

The *balanced* algorithm, a major contribution of this work, focuses on the optimal cargo mix on board that ensures maximum profit in the long-term approach. However, compared to the *imbalanced* algorithm, constraint Eq. (11) is implemented, which guarantees that there is no equipment imbalance. In the end, due to the choice of cargo flow and empty positioning, the number of each container type in all ports is the same as before the shipments started. Therefore, it is possible that full-paying containers are rejected to make room for non-paying empty units. As the *balanced* algorithm has one additional constraint, the profit of the *imbalanced* algorithm is higher or equal than the result of the *balanced* algorithm. The maximum total profit of the *balanced* algorithm is predicted to be USD 195,700 per round voyage (see Table C.11). The proposed transportation of 2662 units (4190 TEU) contains 110 empty units (33 40′Dry and 77 40′Reefer units) and 2552 full units (respectively 3970 TEU). The full containers can be divided into 1134 20′ units (1038 dry and 96 reefer) and 1418 40′ units (1249 dry and 169 reefer), as per Table B.7. It is also notable that the percentage as well as the absolute number of reefer units transported is less than in the *imbalanced* case. This difference is attributed to the original imbalance of the reefer trade in this example, as only ports C and E offer substantial reefer volumes.

The next point of the analysis is the utilization on the edges that is shown in Appendix B in Table B.6. On edges 2–5 and 7, the total weight capacity is used, but only on edge 2 the total volume capacity is used as well. This is attributed to the transport of empty units on this edge. On all other edges, except edges 3 and 9, empty units are transported; on edges 1, 6, 8, and 9 slots remain available. This implies that empty units replace full-paying cargo on edges 2, 4, 5, and 7 and all region-leaving services are fully utilized in terms of volume and weight. Another point is that edges 8 and 9, which are not used in the *imbalanced* algorithm, are partly used here, although the price for these two edges is still the same and quite expensive. Before the empty units are dispatched, there exists an imbalance, as shown in Table B.8.

3.4. Comparison of the imbalanced and balanced algorithms

The *imbalanced* algorithm has a demand for repositioning 870 units or 1277 TEU, see Table B.9, while the *balanced* algorithm needs only 110 units (220 TEU), as shown in Table B.10. This illustrates that the idea behind the balanced algorithm, where empty positioning is enabled and a mix of full and empty units maximise the profit, matches efficiently operational requirements with linear programming. The *balanced* algorithm enables a total system optimization and addresses (merely or partially depending on the input data and the actual demand) the cost of repositioning empty units at the various demand points. The *imbalanced* algorithm promotes the transport of full units, but in reality this is a typical case of sub-optimization, when the service of empty units should also be taken into account.

There are other ways to transport the empty containers from surplus to shortage areas, for example by extra loader or third-party slot charter. However, the costs of this approach might be high. To illustrate this point, the two cases are compared. The *imbalanced* algorithm has a round voyage profit of USD 334,400 compared to USD 195,700 for the approach of the *balanced* algorithm, as shown in Table C.11. The difference of USD 138,700 can be used to pay for the extra loader to reach the break-even point. As illustrated in Table B.9, the *imbalanced* algorithm leads in the test case to 870 units or 1277 TEU, which have to be repositioned, while in the *balanced* algorithm case the equipment is already regulated. For each unit that has to be positioned in the *imbalanced* case, the budget is USD $\frac{138.700}{870} = 159.43$ USD for the repositioning per unit (or USD $\frac{138.700}{1277} = 108.61$ USD per TEU). This budget is unlikely to cover the costs, especially when compared to the slot costs of 429 USD per TEU in this example, as already calculated in Section 3.2.

3.5. Environmental considerations

Efficient environmental management is a requirement for modern liner services too. Therefore, the analysis cannot be complete without a consideration of the carbon footprint of the solutions. Carbon footprint per ton per miles is given in The European Chemical Industry Council (2011). As the same type of vessels with the same port rotation and same speed are used in both algorithms, it can be said that the CO_2-emission is the same for both cases. However, the empty units, which still have to be transported in the *imbalance* case, need additional vessel services.

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Assuming the carbon footprint values published by The European Chemical Industry Council (2011) of about $f_p = 8\,\frac{grCO_2}{ton \cdot mile}$ for all units and all services (i.e. all connections) and the distances of Table A.4, it is possible to estimate roughly the additional carbon emission. Using this assumption, it is possible to calculate the minimum emission of CO_2 for transporting the empty units as 104 tons in the imbalanced case per round voyage as shown in Table C.11. Additional environmental requirements can be included by constraints, such as Eq. (12):

$$f_p \cdot \sum_{arc}\sum_{type} x_{odt} \leqslant \text{regulatory or operational requirement} \tag{12}$$

where f_p is the carbon footprint per TEU.

4. Conclusion

The advantage of the application of FLP formulations is that the decision-maker can model his/her problem in accordance with his/her current state of information. Not fully known parameters (i.e. fuzzy or fuzzified ones), which annul the crisp character of the objective function or that of some constraints, or introduce constraints in a soft form (i.e. with fuzzy right-side bounds), can be introduced and solved using the fast and accurate algorithms of LP. The literature provides many examples of procedures that seek to calculate a compromise solution of an FLP system; they mainly differ in the assumptions made in order to reduce the FLP to a classical mathematical optimization problem (Rommelfanger, 1996; Zimmermann, 1978, 1991). In that regard, the container positioning problem can be further treated with FLP, as many of the parameters are fuzzy or generally not fully known. The need for fast and accurate algorithms renders the FLP approach invaluable, as the model-maker can use the advantages of both FLP (formulation) and LP (algorithm and solution).

Along with the consideration of the FLP, the novelty of this work extends also to revenue maximization. Contrary to the bulk of the papers available in the literature, the objective of this work is to maximize overall profit from the flow of full and empty units simultaneously. The consideration of CM instead of cost per unit is of fundamental importance in this respect. The dual problem of cost minimization also implies a constant revenue per unit, which is not a valid assumption in the industry.

As already stated, the suggested formulation is based on exact algorithms, which are fast and easy to implement on many computational platforms for further development or use by professionals or academics. Although the crisp model can be considered unrealistic, the suggested fuzzy algorithm enables considering objective function parameters that are not well defined (fuzzy), as well as those of the given set of constraints, suggesting that this formulation is more realistic and useful to the decision-maker. The consideration of empty and full unit flow simultaneously aims to put forward a holistic approach that deals with the repositioning of empty containers along with the dispatching of full units. The suggested approach also enables the examination of the paradox of carrying empty as opposed to full units, which leads to more profitable operations in some cases. In order to analyze the differences between the two approaches, an example an easily generalizable example was presented and tested accordingly. In that respect, a dynamic, flexible, and more realistic approach using fuzzy optimization was considered. The derived results pertaining to the available cargo, average weight, and the given freight rates highlight the merits of the fuzzy *balanced* formulation.

As expected, the *imbalanced* algorithm that ignored the empty positioning shows a higher profit. However, the difference in results between the two approaches is marginal and the question regarding which approach is optimal in the long run

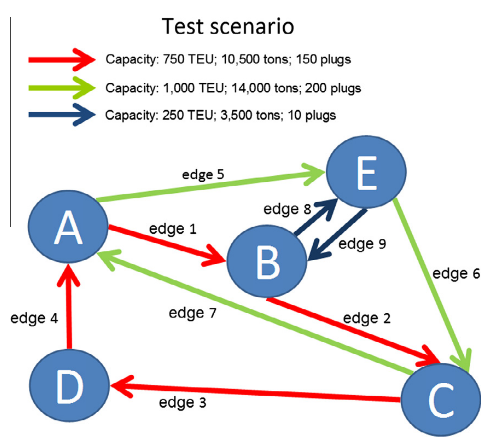

Fig. A.1. Test scenario.

Table A.1
Available volumes for the three different cases (worst case, average case, and best case).

	Port A	Port B	Port C	Port D	Port E
20′Dry					
Port A	–	130/150/160	200/210/250	100/140/160	150/180/200
Port B	90/100/115	–	225/250/260	40/45/60	250/300/350
Port C	310/325/350	250/290/330	–	200/220/250	30/40/70
Port D	70/75/80	120/125/140	150/180/200	–	100/120/130
Port E	250/300/325	120/135/140	40/45/60	80/95/100	–
40′Dry					
Port A	–	60/65/80	230/250/260	125/175/200	150/200/225
Port B	40/50/55	–	150/160/170	40/60/80	240/255/260
Port C	190/205/210	125/135/140	–	175/205/225	35/50/60
Port D	65/75/90	50/60/65	150/160/200	–	180/200/210
Port E	150/160/220	140/200/260	45/55/60	120/140/150	–
20′Reefer					
Port A	–	5/10/20	10/15/20	15/25/30	10–15/25
Port B	0/5/10	–	15/25/35	5/10/20	20/30/35
Port C	150/160/180	120/140/150	–	100/150/180	50/60/65
Port D	0/10/15	0/5/10	0/15/20	–	5/15/20
Port E	150/180/200	180/220/230	120/130/150	110/125/130	–
40′Reefer					
Port A	–	5/10/15	0/5/15	0/10/15	0/5/15
Port B	0/5/20	–	0/10/20	0/10/15	5/10/20
Port C	150/200/210	140/180/200	–	100/125/140	110/120/140
Port D	0/10/15	0/5/10	0/10/15	–	0/5/10
Port E	150/180/200	160/190/230	150/200/210	160/180/190	–

arises effortlessly. Contingent on the needs of the decision-maker, the short- or long-term horizon, the marketing needs depending on or deriving from the balanced or imbalanced approach, the appropriate algorithm can be selected and tested vis-á-vis others as well as for several ranges of parameters. The suggested formulations, both of the crisp and fuzzy LP, provide results in a meaningfully short time and enable scenario analysis or even parametrization, if required. The *balanced* algorithm highlights the importance of the availability of empty units at various ports; the usual *imbalanced* approach considered in most operational cases (as well as in most works available in the literature) could be revisited.

The *balanced* algorithm has two features that increase its competitiveness and attractiveness without ignoring the empty units (i.e. with CM $\leqslant 0$). The first one is the replacing of the full units having relatively lower CM with empty ones, which

Table A.2
Weights per unit for the three different cases (worst case, average case, and best case).

	Port A	Port B	Port C	Port D	Port E
20′Dry					
Port A	–	17/16/15	16/15/14	18/17/16	16/15/14
Port B	17/16/15	–	16/15/14	15/14/13	19/18/17
Port C	17/16/15	16/15/14	–	17/16/15	17/16/15
Port D	19/18/17	16/15/14	16/15/14	–	15/14/13
Port E	19/18/17	15/14/13	18/17/16	17/16/15	–
40′Dry					
Port A	–	30/28/26	30/29/28	31/30/29	30/29/28
Port B	30/29/28	–	31/30/29	31/30/29	30/29/28
Port C	30/29/28	29/28/27	–	29/28/27	29/28/27
Port D	31/30/29	30/29/28	30/29/28	–	31/30/29
Port E	30/29/28	29/28/27	29/28/27	31/30/29	–
20′Reefer					
Port A	–	19/18/17	23/22/21	22/20/18	19/18/17
Port B	18/17/16	–	17/16/15	20/19/18	18/17/16
Port C	19/18/17	21/20/19	–	21/20/19	19/18/17
Port D	18/17/16	16/15/14	15/14/13	–	19/18/17
Port E	18/17/16	17/16/15	16/15/14	18/17/16	–
40′Reefer					
Port A	–	31/30/29	31/30/29	32/31/30	31/30/29
Port B	31/30/29	–	29/28/27	31/30/29	30/29/28
Port C	31/30/29	30/29/28	–	29/28/27	30/29/28
Port D	30/29/28	31/30/29	31/30/29	–	31/30/29
Port E	31/30/29	31/30/29	31/30/29	31/30/29	–

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Table A.3
Freight rates for the three different cases (worst case, average case, and best case).

	Port A	Port B	Port C	Port D	Port E
20′Dry					
Port A	–	350/390/410	500/540/600	270/295/340	630/650/700
Port B	270/280/320	–	540/585/630	290/340/410	580/615/640
Port C	725/750/800	630/655/700	–	480/505/550	325/355/400
Port D	280/315/360	320/325/330	675/690/720	–	600/640/660
Port E	825/860/900	625/650/700	280/305/320	680/710/750	–
40′Dry					
Port A	–	520/560/600	720/760/800	430/460/510	950/1050/1150
Port B	380/410/440	–	1000/1070/1200	290/390/480	930/965/1010
Port C	1100/1275/1450	1000/1040/1100	–	820/855/900	480/525/600
Port D	380/410/460	390/410/460	1100/1225/1400	–	1150/1325/1570
Port E	1450/1500/1600	1000/1075/1125	300/360/420	1100/1225/1300	–
20′Reefer					
Port A	–	420/440/480	450/615/680	320/360/420	680/710/780
Port B	320/355/380	–	600/630/720	380/405/450	610/645/690
Port C	760/800/820	680/720/740	–	350/370/410	360/390/420
Port D	340/355/400	380/415/440	700/720/800	–	710/780/850
Port E	850/880/950	660/685/730	320/345/400	690/745/800	–
40′Reefer					
Port A	–	520/600/700	760/785/820	480/510/550	1100/1190/1250
Port B	380/450/500	–	1090/1125/1200	600/660/690	890/970/1100
Port C	1350/1390/1410	1850/1950/2150	–	860/895/920	640/690/750
Port D	380/440/500	420/440/500	1350/1425/1800	–	1430/1500/1650
Port E	1490/1610/1880	1000/1175/1300	380/405/420	1350/1385/1500	–

Table A.4
Distance table for the five ports in miles.

	Port A	Port B	Port C	Port D	Port E
Port A	–	405	5683	407	6594
Port B	405	–	5435	175	6346
Port C	5683	5435	–	5368	998
Port D	407	175	5368	–	6279
Port E	6594	6346	998	6279	–

Table A.5
Load, discharge, and transshipment costs.

T/S costs	20′Dry	40′Dry	20′Reefer	40′Reefer
Port A	50	50	75	75
Port B	50	75	75	100
Port C	75	75	75	75
Port D	50	50	50	50
Port E	50	50	50	50

balance the system and eventually lead to higher values of the objective function. The second feature is rather knotty in most cases: By filling up the vessel with full units, the boundaries of weight and draft constraints are reached quite fast. Therefore, it might be wiser to leave some full units and instead load some empty ones in order to balance the system and increase the chance of attracting cargo at the relevant ports. All things being equal, one heavy 20-ton full 20′ container can be replaced with eight empty TEUs, with an average weight of 2.5 tons per unit. The opportunity cost of each empty TEU is only a fraction of the profit gained by one full unit. In real-world applications, the demand for empty units is the result of full units transported. While this paper addresses this aspect, the literature considers an a priori well-defined demand for empty units.

Finally, these formulations can be further developed or adjusted in order to accommodate the needs of the respective services. For example, constraints related to the carbon footprint could be included (see Eq. (12)). If necessary, this formulation can be further expanded as a multi-objective goal programming one. Such formulations can help to improve the operational efficiency of liner companies. Liner companies that strive for efficient equipment usage and smart cargo mixtures can reduce the resulting costs and improve their competitive advantage.

Table B.6
Utilization of the edges by using the *imbalanced* and *balanced* algorithms' full and empty units (results are rounded).

Edges	*Imbalanced* algorithm			*Balanced* algorithm		
	TEU	TON	Plugs	TEU	TON	Plugs
Edge 1	668	9840	150	731	10,008	108
Edge 2	703	10,500	35	750	10,500	40
Edge 3	714	10,500	150	709	10,500	48
Edge 4	711	10,500	132	709	10,500	48
Edge 5	930	14,000	30	96	14,000	32
Edge 6	944	14,000	172	941	13,320	60
Edge 7	955	14,000	200	982	14,000	81
Edge 8	0	0	0	79	438	10
Edge 9	0	0	0	85	1377	0

Table B.7
Rounded cargo flows proposed by the *imbalanced* and *balanced* algorithm for full and empty units.

	Imbalanced algorithm					*Balanced* algorithm				
	Port A	Port B	Port C	Port D	Port E	Port A	Port B	Port C	Port D	Port E
20′Dry full										
Port A	–	147	0	0	177	–	147	0	0	177
Port B	0	–	245	0	0	0	–	245	0	0
Port C	0	0	–	0	0	293	0	–	0	0
Port D	0	0	0	–	0	0	0	0	–	0
Port E	0	0	0	0	–	30	98	48	0	–
40′Dry full										
Port A	–	68	0	0	192	–	68	0	0	192
Port B	0	–	160	0	0	0	–	160	0	0
Port C	131	0	–	40	0	111	0	–	118	0
Port D	0	0	46	–	162	0	58	32	–	159
Port E	177	0	0	137	–	177	0	37	137	–
20′Reefer full										
Port A	–	0	0	0	17	–	12	0	0	17
Port B	0	–	25	0	0	0	–	17	0	0
Port C	0	0	–	0	0	28	0	–	0	0
Port D	0	0	0	–	0	0	5	0	–	0
Port E	0	0	0	0	–	0	0	12	5	–
40′Reefer full										
Port A	–	0	0	0	7	–	0	5	0	7
Port B	0	–	10	0	0	0	–	10	0	10
Port C	41	150	–	0	0	0	78	–	0	0
Port D	0	0	0	–	8	0	0	8	–	8
Port E	118	0	0	41	–	0	0	26	17	–
20′Dry empty										
	None	None	None	None	None	None	None	None	None	None
40′Dry empty										
Port A	–	41	0	0	0	–	28	0	0	0
Port B	0	–	0	0	0	0	–	0	0	0
Port C	0	0	–	0	0	0	0	–	0	0
Port D	0	0	0	–	0	0	5	0	–	0
Port E	0	0	0	0	–	0	0	0	0	–
20′Reefer empty										
	None	None	None	None	None	None	None	None	None	None
40′Reefer empty										
Port A	–	0	0	0	0	–	0	0	0	18
Port B	0	–	0	0	0	30	–	29	0	0
Port C	0	0	–	0	0	0	0	–	0	0
Port D	0	0	0	–	0	0	0	0	–	0
Port E	0	0	0	0	–	0	0	0	0	–

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Table B.8
Empty units transported by edges based on the *balanced* algorithms (results are rounded).

Edges	TEU	TON
Edge 1	67	168
Edge 2	57	143
Edge 3	0	0
Edge 4	10	25
Edge 5	36	90
Edge 6	60	150
Edge 7	60	150
Edge 8	60	150
Edge 9	0	0

Appendix A. Data given

This appendix provides all the important details of the test scenario. Fig. A.1 gives a graphical overview of the test scenario.

The bulk of the data is well known or can be estimated appropriately. However, revenue parameters, weight of the containers, and available cargo vary and are uncertain. Based on the fuzzy approach, it is only necessary to generate several relations such as *best case* or *worst case* scenarios. They illustrate different levels of available volume Table A.1, average weight per unit Table A.2, or freight rates Table A.3. Based on these figures, it is possible to calculate expected values. The origin port is always on the left side and the destination port is at the top.

Based on the assumption that the results are especially significant in an environment of high average weights of the containers, a level above 14 tons/TEU is chosen. For empty units, a weight of 2.5 tons TEU is taken. All other weights are shown in Table A.2.

Freight rates are the revenue per unit offered for transport from one port to another. In order to make the model more realistic, these parameters are fuzzy. Three cases are implemented: *worst case*, *average case*, and *best case*. In Table A.3 the freight rates are shown in this order as revenue per unit.

Four types of containers are most commonly used in the maritime industry, based on size and their capacity to cool the commodity. These common containers include the type 20′Dry, 40′Dry, 20′Reefer, and 40′Reefer, hence $t = 4$.

The distances between the ports are well known, as shown in Table A.4.

Weekly services are assumed. The fixed costs are set at USD 1,500,000 per week. As these costs cover the slot fee on slings 1 and 2, only a slot fee for sling 3 has to be defined at a level of USD 500 per TEU. Load and discharge costs each are set at USD 100/move. The transshipment costs depend on the transshipment port as well as on the type of container. Please compare Table A.5. A different fee for full and empty containers is not implemented.

Appendix B. *Imbalanced* and *balanced* results

The results of the *imbalanced* and those of the *balanced* fuzzy formulations are presented in Tables B.6–B.10.

Appendix C. Comparison

Comparing the results of the crisp and fuzzy algorithms is difficult due to the difference in the parameters. Nevertheless, a short overview is provided in Table C.11.

Table B.9
Equipment imbalance resulting from the *imbalanced* algorithm (results are rounded).

	20′Dry	40′Dry	20′Reefer	40′Reefer
Port1	323	−7 (=−48 + 41)	17	−153
Port2	98	51 (=92 − 41)	25	−140
Port3	−245	−35	−25	181
Port4	0	31	0	−32
Port5	−177	−40	−17	144
+ shortage				
− surplus				

Table B.10
Need for transport of empty containers in *balanced* algorithm (results are rounded).

	20′Dry	40′Dry	20′Reefer	40′Reefer
Port1	0	−28	0	12
Port2	0	33	0	−58
Port3	0	0	0	29
Port4	0	−5	0	0
Port5	0	0	0	18

Table C.11
Comparison of results (results are rounded).

	Imbalanced crisp	Balanced Crisp	Imbalanced Fuzzy	Balanced Fuzzy
Maximum profit	333,800	193,500	334,400	195,700
Full TEU shipped	3582	3986	3587	3970
Empty TEU shipped	22	194	82	220
Empty TEU non shipped yet	1322	0	1277	0
Dry TEU shipped	2792	3579	2795	3536
Reefers TEU shipped	790	407	792	434
Additional CO_2 emission for empty repositioning	104	0	104	0

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3. A new model for the calculation of the bunker fuel speedconsumption relation

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A new model for the calculation of the bunker fuel speed–consumption relation

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ABSTRACT

This paper investigates the relationship between bunker fuel consumption and the speed of container ships. Although there are different models existing in the literature and in the industry, they do not always seem to match the actual maritime conditions. The existing models work well in middle speed levels, but they fail at the low- and high-speed ends unless the parameters in the exponent of the function are changed. Besides the problem of missing a general formulation, the parameters seem to change with speed. Therefore, in this paper a new approach is introduced to illustrate the dependance between bunker fuel consumption and speed, and it is tested by formulating the exponent of the function variable. Stochastic criteria are used to compare the new generalized model with common models using real operating data.

1. Introduction

For realistic planning of ship operations, it is of major importance to model the dependance between various ship-related parameters and/or other appropriate variables. Especially, the effects of speed on bunker fuel consumption is important for two reasons.

First, bunker fuel cost, and thus bunker fuel consumption, constitutes the larger part of operational expenses (OPEX) (see Notteboom (2006) and Golias et al. (2009)). The literature provides different values for the percentage of the bunker fuel cost in the total OPEX. The values range from 50% (Gelareh and Meng, 2010) to 60% (Golias et al., 2009) and even up to 75% (Ronen, 2011), showing in any case that bunker fuel costs are the most important component of the total OPEX. Its share depends on several other costs, such as time charter levels, the bunker fuel strategy of the liner company, and the bunker fuel price, as reported by many authors including Stopford (2008).

A second reason is that all calculations for air emissions are based on the bunker fuel consumption, which makes the prediction of this parameter significant. In line with the trend to stricter regulations, this issue will gain in importance in the near future.

Therefore, a realistic and accurate calculation of consumption is of vital significance, as planning and changing of schedule are decided depending on the costs and thus on the consumption. Aberrations between calculations and reality lead to failed decisions, resulting in millions of dollars in losses or avoidable air emissions.

Many authors such as Notteboom (2006), Ronen (2011), and Wang et al. (2013) assume that bunker fuel consumption of the main engine depends on vessel speed and ship characteristics. In general, every vessel, even if it has the same characteristics (i.e. ships built based on the same design from the same shipyard) as others, develops an individual speed–consumption profile. Lewis (1988) claims that three additional factors influence the consumption: maintenance (i.e. the condition of the main engine and other components of the propulsion system, as well as the condition of the hull exposed to the sea and elements), the operating profile (i.e. cargo load, ballast, trim, and bunker fuel quality), and environmental conditions (i.e. weather and sea state). In contrast, Notteboom (2006), Ronen (2011), and Wang et al. (2013) ignore factors such as draught, wind, current, and sea state, which makes their approach questionable. The distance to be steamed requires speed over the ground; however, the data collected to examine consumption is based on the speed through the water, which depends on factors such as wind and sea state. However, for the development of a speed–consumption function, a sufficient volume of data is collected that includes all these effects over the long term. Hence, all factors are implied and already weighted based on their impact. It may be possible to collect data in such a way as to examine the dependance of consumption on these factors. However, the challenge of using these dependencies for future forecasts is that these factors can neither be controlled nor predicted in the long term. The most vital and manageable long-term factors are the speed and the characteristics of a vessel. Assuming that other factors such as sea state and wind do not differ in the long term, the data can be used to predict the future average bunker fuel consumption of a vessel. Therefore, the assumption that the consumption of a vessel is well determined by its speed and design is realistic and reasonable. The design of a realistic, generalized

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speed–consumption function that is valid for all speeds is the main objective of this paper.

The following is structured into five sections. Section 1 presents a short introduction. Section 2 gives an overview of the literature, with a focus on the inconsistency of the existing models and current formulations. In Section 3, the new approach is described and introduced. In Section 4, a comparison of the different formulations is presented and analysed on the basis of a real dataset. Section 5 presents the conclusion.

2. Literature review

Every 10 years, a group of authors publishes papers about vessel's routing and scheduling: Ronen (1983, 1993) and Christiansen et al. (2004, 2013). Gendreau and Potvin (2004) emphasize the importance of fleet management.

Bunker fuel cost is the product of bunker fuel unit price and consumption, the former can be quite volatile depending on supply and demand issues in the bunker fuel market. Fortunately, Stefanakos and Schinas (2014) present a forecast system that seeks to address the volatility.

Most authors tend to agree that consumption is mainly influenced by the characteristics of the vessel and its operating speed; however, determining a formula for the bunker fuel speed–consumption relationship is a topic of active discussion. Wang and Meng (2012a) describe a procedure to generate a bunker fuel speed–consumption function by regression. Several authors such as Ronen (1982), Corbett et al. (2009), Fagerholt et al. (2010), Psaraftis and Kontovas (2010), Ronen (2011), Norstad et al. (2011), Qi and Song (2012), Wang et al. (2013), and Yin et al. (2014) consider a cubic function as a good approximation for the dependance of daily consumption at a specific speed.

Function (1): cubic speed–consumption dependance used in the industry for the main engine, consumption per day in tons

$$f_c(v, Q) = a_{c,Q} \cdot v^3 \tag{1}$$

where:

- $a_{c,Q}$ is a parameter which is calculated for each vessel Q by cubic regression.
- v is the speed in knots.

For reasons of simplicity, this function will be called c-function hereafter.

However, the exponent is a point of widely discussion. For example, the applied exponent of Wang and Meng (2012a) is at a value between 2.7 and 3.3, depending on the vessel size. Du et al. (2011) uses the exponent of 3.5 for feeder container ships, 4.0 for medium-sized container ships, and 4.5 for jumbo container ships.

Function (2): fractional rational description of speed–consumption dependance of the main engine per day in tons

$$f_f(v, Q) = a_{f,Q} \cdot v^{b_{f,Q}} \tag{2}$$

where:

- $a_{f,Q}$ and $b_{f,Q}$ are parameters which are calculated for each vessel Q by fractional rational regression.

This function is called f-function hereafter. Obviously, Function (1) is just a special case of Function (2) for $b_{f,Q} = 3$.

Authors such as Notteboom (2006), Wang and Meng (2012b), and Wang et al. (2013) cluster different vessel designs to estimate the bunker fuel consumption by capacity. Kristensen and Lützen (2013) claim that normally the propulsion power, the resistance, and the total propulsive efficiency are determined empirically and expound ways of calculation. Therefore, since other factors like the shape of the hull below the waterline also influence bunker fuel consumption, Kristensen and Lützen (2013) suggest every vessel design should be investigated individually.

Additionally, Psaraftis and Kontovas (2013) state that a cubic function is invalid for low speed. In the work of Kontovas and Psaraftis (2011), exponents of 4.0, and, in the case of any speed higher than 20 knots, even greater exponents are used.

3. Speed–consumption function

3.1. Development of a new speed–consumption function

As previously noted in Sections 1 and 2, many factors influence the bunker fuel consumption of main engines on container ships. The best way to develop a reliable speed–consumption function is by collecting real data about the speed and the corresponding consumption, and then using regression to detect the function. As described in Section 2, this dependance is mostly used in form of Function (1) or Function (2) with different values for $b_{f,Q}$ dependent on the vessel size. However, two main critical points from the literature still appear. First, all polynomial functions with a fixed exponent are invalid for low speed, shown by Psaraftis and Kontovas (2013). Second, authors such as Kontovas and Psaraftis (2011) explain that in case of higher speed, the exponent also increases.

In this paper, an approach is provided that integrates all these critics by formulating a generalized function with parameters valid for all speeds. Based on the previous discussion, it is concluded that the exponent depends on vessel dimensions and speed. Thus, it is proposed that the speed–consumption function is described as an exponential function, with vessel design as a constant and speed as a variable in the exponent. The basis can be chosen arbitrarily, as this varies only the fit parameters, not the curve itself. In this paper, Euler's number e was taken as the basis to simplify later calculation, so this function will be called e-function hereafter.

Function (3): exponential description of speed–consumption dependance of the main engine per day in tons

$$f_e(v, Q) = a_{e,Q} \cdot e^{(b_{e,Q} \cdot v)} \tag{3}$$

where:

- $a_{e,Q}$ and $b_{e,Q}$ are parameters calculated for each vessel Q by exponential regression.

Fig. 1 shows a comparison between the two Functions, (2) and (3). The curves are similar in the middle, but differences are obvious at the edges. Usually, vessels steam with moderate speed in the middle, but market and environmental conditions or political regulation frames may lead to different basic speeds and the edges of the curves become important. Thus, a generalized function valid for all speeds like the e-function is clearly an advantage. Therefore, the consumption at low and at high speeds will be vital for determining the quality of the regression of the functions.

The use of functions representing daily consumption dependent on speed is common in literature (like the Functions (1), (2), and (3)). As described in Section 1 the aim of this paper is to calculate the consumption of a vessel; not the consumption per day is needed but the consumption on a whole voyage. As in liner shipping the stretches and thus the distances are fixed, it is sensible to evaluate the consumption per nautical mile, not per day. Only then it is possible to determine the consumption on the stretch as a function of the speed. So, an optimal speed can be calculated that minimizes the consumption and thus, bunker fuel costs and emissions.

By dividing the daily consumption from Function (3) by the daily performance in steamed miles, the consumption is given in the form of bunker fuel consumption per nautical mile. This leads to the following function:

Function (4): consumption of the main engine per nautical mile in tons

$$f_e^*(v, Q) = \frac{a_{e,Q} \cdot e^{(b_{e,Q} \cdot v)}}{n \cdot v} \tag{4}$$

where:

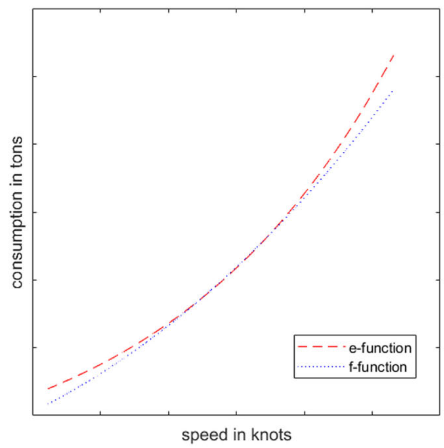

Fig. 1. A drawing of the two functions, e-function (red dashed line) and f-function with constant exponent (blue dotted line). In the middle, the functions are similar, but at the edges they diverge. This shows the main difference between the two functions.

- n is the number of hours in the measured period. In the case of daily data, n equals 24 h.

3.2. Characteristics of the speed–consumption function

A number of authors, such as Ronen (2011) and Du et al. (2011), investigated optimal bunker fuel consumption in a given timeframe and distance. Wang et al. (2013) proved that minimal consumption is achieved by maintaining at a constant speed by using the characteristics of the non-decreasing speed–consumption curve where consumption increases with a higher speed, or conversely, decreases with a lower speed. The latter view is one of the premises used by operators for implementing slow steaming (operating at slower speeds). The described Functions (1), (2), and (3) show these characteristics.

However, Function (4) does not fulfil the requirements in the proof of Wang et al. (2013) as it indicates section-wise decrease of consumption for higher speeds. Therefore, this paper presents a new proof based on the previously noted e-function which is not based on the assumption of a non-decreasing speed–consumption curve.

Obviously, the parameters $a_{e,Q}$ and $b_{e,Q}$ from Functions (3) and (4) are never negative or zero. Fig. 2a illustrates this graphically and explains why $a_{e,Q}$ and $b_{e,Q}$ have to be positive to provide positive consumption with an increasing slope. The next step involves finding a speed that leads to the minimum consumption per nautical mile based on Function (4).

Lemma 3.1. *The slower a vessel sails, the less bunker fuel per nautical mile is consumed on the voyage as long as* $v \geq \frac{1}{b_{e,Q}}$.

The proof of Lemma 3.1 can be found in Appendix and is illustrated in Fig. 2b. The important result of Lemma 3.1 is that for any $v < \frac{1}{b_{e,Q}}$, a speed v' exists with $v < v'$ and $f(v) > f(v')$. Therefore, any speed below $\frac{1}{b_{e,Q}}$ is inefficient, as a decrease in v leads to a increase in consumption, and will not be considered. Thus, the restricted domain for the speed v in this thesis is defined as $v \in \mathbb{R} \mid \frac{1}{b_{e,Q}} \leq v \leq v_{max}$, where v_{max} is the maximum speed of the vessel. The next lemma shows that it is not possible to save the bunker fuel by steaming slow on one stretch of the voyage and speeding up on another part of the voyage.

Table 1
Data for the three vessels used in this analysis.

Vessel	Gross tonnage	Year of build	Flag
Vessel I	18 327	2007	Liberia
Vessel II	18 327	2007	Liberia
Vessel III	15 988	2001	Panama

Lemma 3.2. *The bunker fuel consumption is minimal per nautical mile by proceeding at a constant speed.*

The proof of Lemma 3.2 can also be found in Appendix. So, although the proof of Wang et al. (2013) is not valid for Function (4), it is proved that a constant speed leads to minimal consumption per nautical mile with a given available time.

Combining these ideas leads to the conclusion of Theorem 3.1.

Theorem 3.1. *Independent of the design of vessel, the parameters $a_{e,Q}$ and $b_{e,Q}$ are always strictly positive. Any speed $v < \frac{1}{b_{e,Q}}$ is inefficient. The minimal bunker fuel consumption per nautical mile and total round voyage (RV) is achieved by operating at an optimal speed $v_{opt} = \frac{d}{T}$, while d is the total voyage distance and T is the total voyage time. The greater the number and/or duration of the deviation from the optimal speed, the more inefficient the performance is.*

Theorem 3.1 is proven by Lemmas 3.1 and 3.2. Resulting from Theorem 3.1, bunker fuel consumption is minimized by steaming at a constant speed for the given distance and timeframe.

4. Comparing the different approaches

To evaluate the ability of the three approaches introduced in Sections 2 and 3, namely the c-function, f-function, and the e-function, a test case is created consisting of real data from different vessels. Using different cases of regression helps to examine the optimum parameter for the curves developed for each of the functions. To compare the quality of the resulting curves, three different criteria are used, which are explained later: Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and Cook's Distance.

4.1. Test set-up

The used real data consist of speed and bunker fuel consumption data from the daily reports of three different vessels. To eliminate extreme values, only reports for one whole day (24 h) on sea with a wind speed of less than 4 Beaufort and a current speed of less than 4 knots are considered. These data have been collected between January 2011 and September 2015. The general specifications of the vessels are taken from Equasis (2018) and are provided in Table 1.

MATLAB© 's curve fitting toolbox is used to determine the optimal parameters of each of the three functions. For the three example vessels, the optimal parameters for the different approaches can be found in Table 2.

Fig. 3 shows the data points and the resulting fit of the f- and e-functions for *Vessel II*. As expected, the two functions have similar curves in the middle speed range, where most points are found. However, the two functions diverge at the edges: Here the e-function's gradient is higher at high speeds and the differences from the real data are smaller at both low- and high-speed operating conditions.

4.2. Criteria

In this paper, the decisive aspects are represented by the variances, resulting from deviations between the models and the collected data. To compare the models, different criteria are formulated, which include the variance:

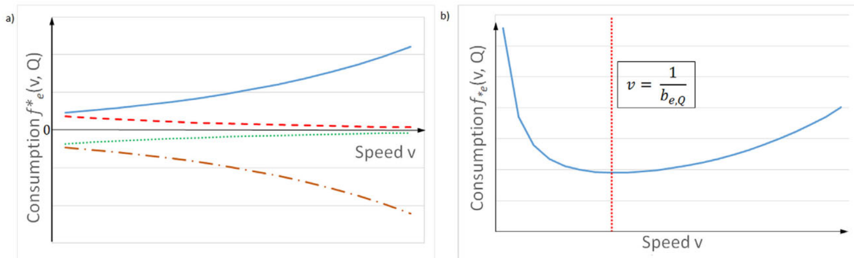

Fig. 2. (a) Only a curve with positive results and rising results with increased speed is realistic. The lines show the speed–consumption dependance in the case of $a_{e,Q}, b_{e,Q} > 0$ (blue solid), $a_{e,Q} > 0$, $b_{e,Q} < 0$ (red dashed), $a_{e,Q} < 0$, $b_{e,Q} > 0$ (green dotted), and $a_{e,Q}, b_{e,Q} < 0$ (orange dash–dot). The green and the orange curves show a negative consumption, while the red curve decrease with increasing speed. Thus, only the blue curve is reasonable. (b) Illustration of Lemma 3.2: The curve shows the consumption dependent on speed. The minimum is at the point where $v = \frac{1}{b_{e,Q}}$.

Table 2
Optimal fit parameters for the three approaches.

Vessel name	Number of data points	e-function		f-function		c-function
		$f_e(v,Q) = a_{e,Q} \cdot e^{b_{e,Q} v}$		$f_f = a_{f,Q} \cdot v^b_{f,Q}$		$f_c = a_{c,Q} \cdot v^3$
		$a_{e,Q}$	$b_{e,Q}$	$a_{f,Q}$	$b_{f,Q}$	$a_{c,Q}$
Vessel I	474	4.738	0.1193	0.1645	1.902	0.00775
Vessel II	527	2.954	0.1494	0.0460	2.359	0.00801
Vessel III	301	5.776	0.1077	0.3138	1.675	0.00770

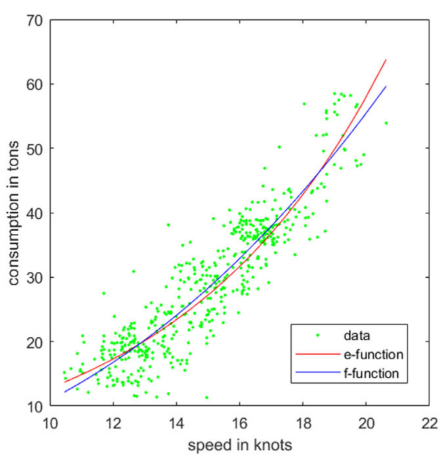

Fig. 3. Fitting curves for e-function (red line) and f-function (blue line) for the case of *Vessel II*. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

- Variances
- Akaike Information Criterion (AIC)
- Bayesian Information Criterion (BIC)
- Cook's Distance

The values for these criteria are calculated and compared to judge the quality of the fits and thus to examine the best model.

Variance of the residuals

The first criterion is the variance of the residuals of all three functions. The variance is examined by using the values of the residuals of the models (as shown by Burnham and Anderson (2004))

$$\sigma^2 = \frac{\sum_i \epsilon_i^2}{p} \tag{5}$$

where σ^2 is the variance *of the residuals*, ϵ_i the residuals, and p the number of data points.

Table 3 shows the results for the different functions, which can be now used to judge the quality of the fits for the three vessels. As described in Sections 2 and 3, the c-function is only a special case of the f-function when the exponent has a value of 3 and so is always dominated by the f-function. Therefore, bigger values of residuals and the variances are expected for the c-function, which can be seen in the table.

For all investigated vessels, the sum of residuals and variances are less for the e-function than for the f-function. This demonstrates the better approximation by the use of the e-function. In order to explore the reasons for this result, further criteria are introduced.

AIC and BIC

Two different criteria are introduced—the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC). These criteria can be defined by (taken from Burnham and Anderson (2004))

$$\text{AIC}(k) = p \cdot \ln(\sigma^2) + 2|k| \tag{6}$$

$$\text{BIC}(k) = p \cdot \ln(\sigma^2) + 2|k|\ln(p) \tag{7}$$

where p is again the number of data points, σ^2 is the variance *of the residuals*, and k is the number of parameter, defined in Sections 2 and 3. Generally, the criteria can be described by Likelihood-Functions, but due to the use of least squares, the variance can be used instead (as shown in Burnham and Anderson (2004)). In general, lower values of AIC and BIC refer to small aberrations between the real data and the function, and thus, the quality of a fit can be recognized by a small value.

However, for the interpretation of the values, the other impacts on the criteria must also be considered.

Table 3
Sum of the residuals and variances of the e-function and the f-function.

Vessel name	e-function		f-function		c-function	
	Sum of residuals	Variance	Sum of residuals	Variance	Sum of residuals	Variance
Vessel I	**1602**	**4.456**	1623	4.510	1899	5.202
Vessel II	**1794**	**4.299**	1823	4.354	2030	4.892
Vessel III	**1378**	**5.608**	1418	5.705	1513	6.135

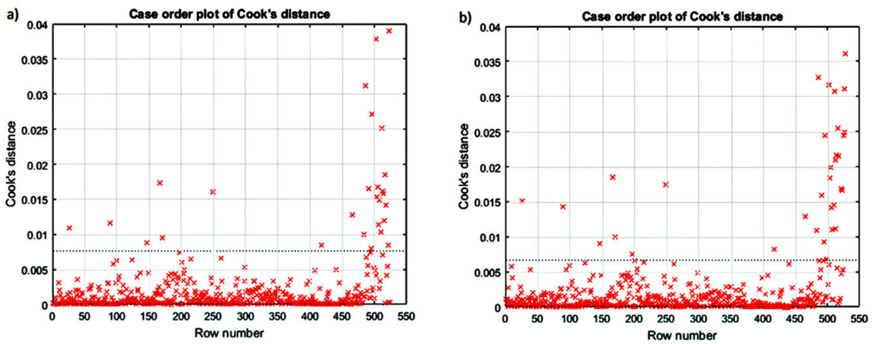

Fig. 4. Cook's Distances for the fit curves (a) e-function and (b) f-function at the example of *Vessel II*.

Table 4
Results for the criteria.

Vessel name	e-function		f-function		c-function	
	AIC	BIC	AIC	BIC	AIC	BIC
Vessel I	**1420**	**1428**	1432	1440	1567	1569
Vessel II	**1541**	**1550**	1554	1562	1677	1680
Vessel III	**879**	**886**	880	887	1077	1078

- As ln(p) is more than 1 for all estimated vessels, BIC is always higher than AIC. For e-function and f-function, k equals 2, while for c-function, k equals 1. Hence, the increase in BIC for c-function is less than for the other functions.
- As the values of AIC and BIC depend on the number of data points p, which varies for the three vessels (shown in Table 2), their heights differ significantly from each other. For Vessel II, the most data points are available, which also means that the values of the criteria are the highest. So, a comparison between the different vessels is not sensible.

In summary, for each vessel the values for the criteria are examined and compared for the three functions, and the lowest shows the best approximation of the data.

Table 4 shows the results for the different fits, which can be used now to judge the quality of the different fits for the three vessels. As already described, the c-function always shows bigger deviations than the f-function, as it is just a special case. Therefore, the values of AIC will always be higher for the c-function than for the f-function. In contrast, BIC favours functions with fewer parameters, and thus, the c-function might have more favourable results. However, in this test case, BIC is less for f-function in the investigated cases. In summary, for the c-function, which is currently the most used function, the quality of data is always inferior to the f-function. Thus, for further analysis, only e-function and f-function will be investigated.

A comparison of the values of AIC and BIC shows lowest values for the e-function, meaning the e-function curve reflects the data best. To clarify this and to examine the differences between the functions, Cook's Distance is calculated in the next subsection.

Cook's Distances

In the literature, Cook's Distances are used to determine points that have a huge effect on the regression curve, such as erroneous measurement and typing mistakes. As a result, Cook's Distances can be used to visualize aberrations between real data and regression curves, e.g. at the edges, and, thus, the quality of the fits.

Mathematically, Cook's Distance D_i is defined as the sum of all the changes in the regression model when point i is removed from it (as formulated in Cook (1977)):

$$D_i = \frac{\sigma^2}{ps^2} \tag{8}$$

where s^2 is the mean squared error of the regression model. Fig. 4 illustrates the results of Cook's Distance for the e- and f-functions. The data is ordered in a row.

As described in Section 3.1, the results are about the same in the middle of the curves. Thus in the middle of the curves the data quality is almost the same for both functions, as Fig. 4a and b show. However, two aspects are observed at the edges. First, the number of points with a big Cook's Distance is higher for the f-function. Second, the Cook's Distances of these points are higher than those using the e-function.

Therefore, it is statistically shown that, based on the three vessel cases, the e-function regression offers a better approximation for the relation between speed and bunker fuel consumption than the f- and c-functions, which are the most prominently used functions in the maritime industry.

5. Conclusion

This paper introduces a new model—the e-function—to establish a relationship between speed and bunker fuel consumption of a vessel as a generalized function. Owing to justified criticism in the published papers, a new universal speed-bunker fuel consumption function is proposed with an exponent including speed as a variable and parameters for the design of the vessel. Here, with the implementation of the e-function, a mathematically elegant way is found, and it is thus possible to evaluate the characteristics of the new function. This novel approach solves the basic problems by a generalized formulation including parameters that are no longer dependent on speed.

To clarify the impact, three cases based on real data are used for numerical examples. Using different criteria such as AIC, BIC, and Cook's Distance, the results unequivocally show that by exponential regression a more precise speed–consumption function is provided in these cases. With the larger size of a ship, these effects increase as well. However, due to a lack of data, a correct evaluation can only be performed at a later stage.

As discussed, a realistic and accurate formulation of the speed–consumption function is of vital importance for the planning and changing of schedules. Failed decisions can result in millions of dollars in losses or increased air emissions.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgement

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Appendix

Proof of Lemma 3.1:

Proof. The function $f(v) = \frac{a \cdot e^{(b \cdot v)}}{c \cdot v}$ is given. To find the minimum of the function, $f'(v) = \frac{a \cdot (b \cdot v - 1) \cdot e^{b \cdot v}}{c \cdot v^2} = 0$. Therefore, the minimum is reached for $v = \frac{1}{b_Q}$. To prove that the point is a minimum $v = \frac{1}{b_Q}$ is inserted in $f''(v) = \frac{(a \cdot b^2 \cdot v^2 - 2 \cdot a \cdot b \cdot v + 2 \cdot a) \cdot e^{b \cdot v}}{c \cdot v^3}$. As the result is always positive, the point $v = \frac{1}{b_Q}$ is always a minimum. Therefore, for any speed below $v \geq \frac{1}{b_Q}$, the function $f(v)$ is strictly monotonically increasing. $\square$

Proof of Lemma 3.2:

Proof. If the first derivation function $f'(v)$ is strictly monotonically increasing and the second derivation function $f''(v)$ has no zero value, then it is obvious that, by splitting up the routes in fast and slow tracks, more bunker fuel will be consumed on the fast track than saved on the slow track and the constant speed is the most efficient per nautical mile. $f'(v) = \frac{a \cdot (b \cdot v - 1) \cdot e^{b \cdot v}}{(c \cdot v)^2} \Rightarrow f''(v) = \frac{(a \cdot b^2 \cdot v^2 - 2 \cdot a \cdot b \cdot v + 2 \cdot a) \cdot e^{b \cdot v}}{c \cdot v^3}$ v, a, and c are still positive. To prove that $f'(v)$ is strictly monotonically increasing, it needs to be shown that $f''(v) = \frac{(a \cdot b^2 \cdot v^2 - 2 \cdot a \cdot b \cdot v + 2 \cdot a) \cdot e^{b \cdot v}}{c \cdot v^3} > 0$. There is no combination that makes $f''(v)$ negative or zero. $\square$

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4. Support of the speed decision in liner operation by evaluating the trade-off between bunker fuel consumption and reliability

Support of the speed decision in liner operation by evaluating the trade-off between bunker fuel consumption and reliability

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Abstract

In liner container shipping, the optimization of bunker fuel costs and reliability can theoretically be achieved by steaming the distance in the available time at average, constant speed. However, in reality bunker fuel costs and reliability are mutually contradictory objectives. Due to incidents (e.g. technical problems on board of vessels, bad weather conditions, piracy) speed ups are necessary to arrive on schedule or at least to mitigate the delay. In this paper, a new approach to liner speed management is proposed. In order to manage the trade-off between bunker fuel consumption and reliability of services, a preventive buffer structure is built up to secure the schedule against delays. However, any analytical calculation of the structure and its effects can only be achieved with disproportionate effort. Therefore, a discrete event simulation is applied. Although a heuristic attempt does not provide the exact solution, reasonable and wide-ranged solutions are offered. Different decision alternatives are outlined, structured and tested to find appropriate speed profiles. For the evaluation of speed profiles three measures of reliability and deviation (α-reliability: ratio of punctual vessels [in%], β-deviation: average positive deviation from the schedule [in hours], γ-deviation: average negative deviation [in hours]) and costs are illuminated.

Keywords: maritime transportation, bunker fuel optimization, speed control, discrete event simulation, steaming, liner container shipping

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1. Introduction

Liner container vessels follow schedules in repeating cycles. In order to minimize the bunker fuel consumption of the main engine, liner shipping companies aspire to steam at constant speed, as proven by Wang et al. (2013). However, any type of event – such as bad weather or an engine breakdown – may affect a liner vessel in two ways. First, the costs of maintaining a schedule can be particular high, because the bunker fuel consumption increases exponentially with speed, as illustrated by Stopford (2008). Second, the schedule reliability suffers in case the vessel is unable to recover the delay. As higher speed leads to higher bunker fuel consumption and better reliability, the problem lies in trading off two objectives: bunker fuel consumption as a function of speed on the one hand and schedule reliability on the other hand. Obviously, both objectives contradict each other and the solution will always be a trade-off between both.
In this paper, a new approach for the liner speed management is proposed: building up and handle buffer to hedge against events that cause delays by implementation of a so-called $speed\ profile$. This speed profile determines the speed during the voyage through four parameters: The time until the buffer is created (A), the adequate amount of buffer (H), the time until the buffer should be kept (B), and the amount of time the vessel should arrive ahead of the berth window (R). These parameters form a speed profile split into three phases: building up the buffer of H hour until point A, maintaining the buffer until point B, and depleting the unused buffer until only R hours of buffer remain. The general concept of speed profiles is illustrated in Figure 1. Thus, the task is to find the optimal speed profile depending on the required costs and reliability.

This paper is structured as follows: In Section 2, a literature review introduces the topics of bunker fuel consumption, steaming under uncertainty, and insights from other transport modes. In Section 3, the methodology and the problem are presented in detail. The required assumptions, data, functions, and parameters are described. In Section 4, a discrete event simulation is set up and thousands of speed profiles are designed and compared. Finally, a conclusion is drawn in Section 5.

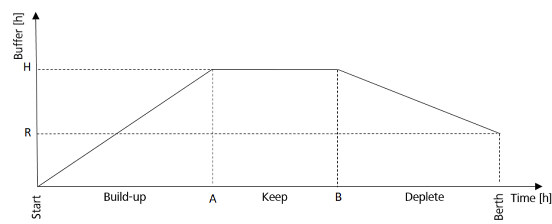

Figure 1: Build-up, maintain-, and depleting the buffer over the voyage

2. Literature review

As the aim of this paper is to describe the trade-off between bunker fuel consumption and the reliability of services, literature about bunker fuel consumption and costs, uncertainty on sea and its consequences, and finally insights from other transportation modes, especially railroads are investigated in this literature review.

Influences on bunker fuel consumption and costs

An overview about the general topic of routing and scheduling of liner ships is given by Ronen (1983), Ronen (1993), Christiansen et al. (2004), and Christiansen et al. (2013). The share of bunker cost of the total operative expenses is widely discussed in the literature, which illustrates the importance of this topic. For example, Gelareh and Meng (2010) state that more than 50 % of the operative expenses consists of the bunker cost of container vessels, Golias el at. (2009) state more than 60 %, and Ronen (2011) estimates more than 75 %. Ng (2019) emphasizes the importance of optimizing speed for reducing shipping costs. As bunker price is volatile, it is difficult to determine the costs, but a forecast system for the bunker price can be used, presented by Stefanakos and Schinas (2014).

In this paper the trade-off between costs, deviation from the schedule and reliability is evaluated, so determining the bunker fuel consumption and thus, costs is vital. Accordingly, the consumption must be described depending on the possible variables. However, this is actively discussed in literature, as Cheaitou and Cariou (2019) note. Aydin et al. (2017) name speed as the decisive variable for bunker fuel consumption. Most authors such as Ronen (1982), Du et al. (2011), Wang and Meng (2012b), Wang et al. (2013), and

Yin et al. (2014) agree that speed and size of vessel are the most influential factors in the bunker fuel consumption of the main engine of a container vessel. Christiansen et al. (2007), Notteboom (2006), Fagerholt (2010), and Ronen (2011) describe the relation between speed and bunker fuel consumption and unanimously agree that sailing above the design speed leads to increasing bunker fuel consumption.

However, Notteboom (2006), Ronen (2011), and Wang et al. (2013) ignore factors such as draft, wind, current, and sea state, which makes their approach questionable. Other authors like Cariou (2011) consider the size of the main engine in the calculation. Psaraftis and Kontovas (2013), Kontovas (2014) and Pasha (2020) emphasize that the usual neglect of payload in the consumption curves is not permissible and include it into their approaches. Abioye et al. (2019) also agree that bunker fuel consumption depends on payload and add various circumstances such as vessel geometric characteristics and weather conditions.

In literature and practice different useful functions are applied to determine the bunker fuel consumption with a focus on the dependence on speed. Li et al. (2016) state that speeding up 8,000 TEU vessels (e.g., from 17 – 19 knots to 20 – 22 knots) increase the bunker fuel consumption by almost 50 %. Authors like Ronen (1982), Corbett at al. (2009), Psaraftis and Kontovas (2010), Ronen (2011), Norstad et al. (2011), Qi and Song (2012), Yin et al. (2014) and Venturini (2017) assume that a cubic function is a good approximation for this dependence and use regression basing on real data to determine parameters in the function. Psaraftis and Kontovas (2013) propose a cubic function for tankers and bulkers. However, some authors such as Kontovas and Psaraftis (2011), Psaraftis and Kontovas (2013) and Venturini (2017) state that a cubic function is invalid for low speeds and high speeds. Additionally, some authors describe deviations from the cubic function depending on the vessel size. Authors such as Notteboom (2006), Wang and Meng (2012b), and Wang (2013) cluster vessels depending on the possible maximum volume. The exponents used by Wang and Meng (2012a) are between 2.7 and 3.3, while Du et a. (2011) use a value of 3.5 for feeder container ships, 4 for medium-sized container ships, and 4.5 for jumbo-sized container ships. This fractional rational function is adopted by Zhen et al. (2016). Psaraftis and Kontovas (2013) propose an exponent of 4 or 5 or even higher. Abioye at al. (2019) use a polynomial speed consumption curve and Westarp (2020) discusses the options to use an exponential speed consumption function.

All the speed consumption functions shown here represent a reasonable approximation and are appropriate for the model in this paper.

Importance of speed on scheduling and liner shipping operations

Many authors agree that speed has a vital impact on scheduling and liner shipping operations, e.g. Dulebenets (2018a), Dulebenets (2018b) and Abioye et al. (2019) state that consumption is highly dependent on speed and describe the possibility of steaming slowly in order to reduce consumption. Dulebenets (2018b) emphasizes the need for a proper efficient speed in liner schedules and concludes that disregarding it leads to avoidable losses. Cheaitou and Cariou (2019) also highlight the importance of speed on revenue and cost and optimize profit in respect of speed. Giovannini and Psaraftis (2019) note that vessel provider tend to steam slower in recession periods when management of costs is more vital. Aydin et al. (2017) give the example of the financial crisis in 2008 when Maersk introduced generally slow steaming. Aydin et al. (2017) and Dulebenets (2018a) emphasize that bunker price influences the optimal speed.

Many authors such as Venturini et al. (2017), Dulebenets (2018a), Dulebenets (2018b) and Cheaitou and Cariou (2019) optimize speed by calculating an average speed on the voyage from one port to another. Abioye et al. (2019) also use constant speed between two ports, but change it in case of a disruption at sea. Additionally, Abioye et al. (2019) doubt that simple calculating an average speed leads to optimal solutions and suggest including the total distance of the voyage. Dulebenets (2018a) implements bounders for minimum and maximum sailing speed, mentioning that sometimes vessels arrive too early at the next port. Venturini et al. (2017) describe berth windows for vessels and explain the possibility to select the most speed efficient ones. The consideration of time windows is also important for the deployment of container vessels, as Ng (2020) illustrates. Ng (2019) and Ng (2020) differentiate between soft and hard berth windows. Aydin et al. (2017) notice that decisions about speed depend on customer requirements and berth windows in the ports. Venturini et al. (2017), Aydin et al. (2017), and Abioye et al. (2019) describe the dilemma that a delay requires steaming faster to reach the planned berth window, which leads to higher consumption. Dulebenets (2018b) also notes that arrival delays at ports may significantly disturb port operations, so the terminal operators offer berth windows and demand container vessels to comply with them. This leads to higher necessary speed and higher consumption. Aydin et al. (2017) highlight that time in and between ports depend on congestions at the ports, handling and weather conditions. In Dulebenets (2018a) it is discussed that the occurrence of delays on sea is uncertain, but he does not develop a strategy to deal with the uncertainty in terms of speed. Dulebenets (2018a) concludes that speed has a high impact on schedule and transit times. Abioye et al. (2019) discuss optimal speed at sea due to a delay in the context of emission control areas (ECA). In this context the use of low sulfur bunker fuel is investigated. Sheng et al. (2019) state that usually speed inside the ECA is lower than outside.

Apart from consumption and schedule speed influence other factors. Giovannini and Psaraftis (2019) and Sheng et al. (2019) describe the effects of speed on freight rates and Sheng et al. (2019) consider the effects on inventory costs. Speed also influences the number of vessels in a service, as commonly a weekly service is used. By reducing the speed, more vessels are implemented in the service, described by Dulebenets (2018b) and Cheaitou and Cariou (2019). This trade-off between number of vessels and speed is also explained by Dulebenets (2018a), Ng (2019) and Sheng at al. (2019). Ng (2020) highlights the importance of the optimal choice of the number of ships for liner shipping. Ng (2019) gives an insight into how the actual selection of the number of ships is limited and indicates critical parameters such as minimum and maximum sailing speeds, distances between ports and port times. Sheng at al. (2019) determine the optimal vessel speed and vessel fleet size for a service operating through ECA. Giovannini and Psaraftis (2019) vary the number of vessels, the speed on the stretches and the frequency to optimize a service, although the authors are aware that deviations from the weekly frequency are unusual. Ng (2019) and Ng (2020) highlight the importance of the sailing frequency.

Until today, the debate about the environmental pollution of shipping has also become increasingly important with a special focus on emissions of greenhouse gases, above all CO_2 and SO_x. Therefore, several authors study the impact of speed on emissions. Venturini et al. (2017) describe a model for speed optimization that leads to less consumption and thus, emission savings. By steaming slowly the emissions can be reduced up to 42 %. Cheaitou and Cariou (2019) describe a model with the optimization of the three objective factors profit, CO_2 and SO_x in respect of speed. Giovannini and Psaraftis (2019) also note the vital impact of speed on emissions.

Uncertainty on sea and its consequences

One reason for an increase in bunker fuel consumption are uncertainties and interruptions at sea. For this reason, the influence of uncertainty and the ways to deal with it are widely researched. Qi and Song (2012) research optimal vessel schedules for liner shipping services with the objective of minimizing the total expected bunker fuel consumption and/or emissions by using simulations that apply approximation methods and consider the uncertainty of time in port. Wang and Meng (2012c) also consider the effects of uncertainty at sea and schedule contingency.

Qi and Song (2012) and Song et al. (2015) describe the problem of bad reliability leading to the dissatisfaction of clients and damaging the reputation of liner shipping companies. Notteboom (2006) presents a general approach to estimate the costs of delay for the customer by using interest and depreciation. Song et al. (2015) and Aydin et al. (2017) also note serious financial consequences for the clients and describe a so-called cascading effect which indicates that delays cause further delays on subsequent voyages if the vessel does not fully recover the delay. Wang and Meng (2012d) point out the problem from the perspective of the automotive industry, where the production has to be stopped in case of missing special parts. Song et al. (2015) simulate the optimal schedule from a tactical perspective, including the optimal number of vessels, but they emphasize that liner shippers are unwilling to steam at maximum speed. Li et al. (2016) and Abioye et al. (2019) state that delays are common in liner shipping. As an example Li et al. (2016) report that in January 2015 only 49 % and in February 2015 only 55 % of the calls in the three East–West trades arrived within an interval of +/- 24 hours. Aydin et al. (2017) report that in 2016 the average percentage of on-time delivery ranges from 55% to 89% depending on the trade and services. Vernimmen et al. (2007) state that only 52 % of the vessels arrive in time. Wang and Meng (2012d) search for optimal shipping services in terms of bunker cost, reliability, integrity, and stability. Some authors like Abioye et al. (2019) suggest speeding up to deal with delays. However, they state that this is generally too slow to catch up the whole delays. All articles in literature who speak about buffer describe the maximum opportunity of catching up delays. This definition of buffer is reactive and is only used after the delays already have occurred.

In this article the idea is to use consequently a higher speed from the beginning to create a buffer proactively before any delays occur. So, in this article buffer means the time that the ship is ahead of schedule if it were traveling at an average constant speed as most authors suggest. To the best of our knowledge, this is the first time that a proactive approach to dealing with delays has been formulated in the literature.

Insights from other transportation modes, especially railroads

The problem of optimal speed is well known in other modes of transportation such as road haulage, rail and aviation. Jaillet et al. (2013) present a mathematical framework to solve routing optimization problems with deadlines and uncertain travel times. Goverde et al. (2016) search for robust, conflict-free, and energy-efficient railway timetabling frameworks. In doing so, Goverde et al. (2016) also test operational speed profiles. The Transportation Research Board (2008) deals with vehicle flow problems on highways and shows how data such as travel time, delay, and reliability, can be evaluated cost-efficiently on a large scale. Higgins et al. (1995) note three types of delays in rail operations – namely terminal delays, track- related delays, and rolling stock-related delays. Higgins et al. (1995) model possible projects to reduce delays and illustrate the effects on the timetable reliability. They use exact and heuristic optimization techniques to minimize the total delays of trains. D'Ariano and Albrecht (2010) describe that the cascading effects also exist in the rail industry and explain how to deal with this problem in real time. They use a heuristic algorithm to optimize the speed. Kroon et al. (2008) demonstrate how to create robust rail timetables against stochastic disturbances by allocating buffer times. The importance of punctuality in railway systems is underlined. They also discuss how to measure delays critically, and explain the trade-off between sufficient buffer time on the one hand and efficient service on the other hand. Brouer et al. (2013) apply techniques and methods from the aviation industry for the recovery of delays of liner vessels by illustrating the commonalities as well as the differences between liner shipping and the aviation industry. Besides adapting the speed of a vessel, other methods of schedule recovery are presented.

3. The problem of finding speed profiles

3.1. Problem description

This paper focuses on the question whether the quality of a liner service can be increased in terms of bunker fuel consumption and reliability by

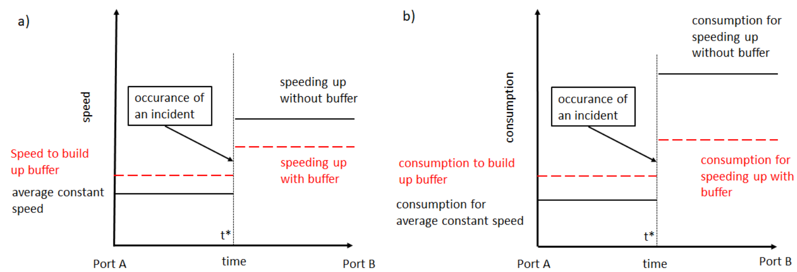

Figure 2: a) Speed changes due to incident without (black solid line) and with buffer (red dashed line). Obviously, without creating buffer the speed is lower at the beginning and disproportional higher after the incident. b) Bunker consumption per day due to incident without (black solid line) and with buffer (red dashed line). The much higher speed after the incident without buffer leads to extremly higher consumption.

the creation of buffer. For the sake of simplicity only voyages between two different ports, starting port A and destination port B, are considered. As discussed in Wang et al. (2013) the minimal bunker fuel consumption can be achieved by steaming at an average constant speed on the whole voyage. However, in case an incident occurs on the voyage at the time point t*, the vessel has to increase the speed to arrive port B in time. This is shown in Figure 2 on the left side with the solid black line. This leads obviously to over proportional higher fuel consumption (presented in the right side of Figure 2). Assuming the same vessel starts at a marginal higher speed than the average optimal constant speed, the bunker fuel consumption is higher (red dashed line). However, the incident at t* only leads to marginal higher consumption. Since incidents do not occur on every voyage, the challenge arises to build up a meaningful buffer in order to achieve low consumption and high reliability at the same time.
While the assessment of costs for bunker fuel consumption of a vessel is easy, reliability is difficult to evaluate. Many different factors such as the network of the liner companies, the productivity of the ports, third party providers of slots on– and off–shore, delays of other vessels, cost structure of the ports and cargo flow are also important to determine the additional costs of delayed vessels. In container liner shipping fixed schedules for round trips are provided. Well planned schedules account for various financial and operational drivers: freight rates, bunker price per ton, the demand rate, and

other operational costs of the ship, such as insurance, tax, personnel, and lubricants (Gudehus et al. (2010)). However, as the research question does not challenge the set-up of the service, but the decisions about speed, it is assumed that the schedule, including ports, port order, berth windows and vessel size are set.
In summary, the approach deals with just two variables, bunker fuel consumption, reliability, but nevertheless, it would be desirable to transform both into monetary units. This approach would have the advantage that there is only one objective to minimize. However, this idea over-simplifies the fact that it is impossible to determine the exact monetary and non-monetary costs of delays. Additionally, these non-monetary factors need to be valuated monetarily, but any approach that satisfies this would require questionable assumptions, as Notteboom (2006) states. Therefore, to avoid handling the costs due to delays in this paper bunker fuel consumption and reliability are two separate variables.

In general, it is cost-optimal to steam at a constant average speed as proven by Wang et al. (2013), so it might be the optimal solution to steam at a constant average speed the whole voyage and to arrive just in time at the next port. However, unplanned events like bad weather and technical problems cause delays at sea and perturb the voyage, so either this delay is recovered by speeding up or the speed is held and the ship does not arrive in time with following problems like missing berth windows or violating deadlines. Speeding up the vessel for the rest of the voyage might be expensive but is the only option to avoid late arrival at the next port. Notteboom (2006) illustrates that about 90 % of all delays occur in ports. This could lead one to believe that the topic is insignificant, however, the study is about 14 years old. Since these days the view onto the topic of bunker fuel consumption has changed. In 2007 – one year after the publication of Notteboom (2006) – the price for bunker fuel started to increase dramatically as shown by Bunkerwire (2020). Before 2007 the vessels were speeded up at the beginning of the voyage in order to perform a high reliability at marginal costs due to these low prices, as stated by Stopford (2008). By speeding up occurring interruptions were already buffered and never became public. Today the liner shipping services are more concerned with lower bunker fuel consumption and enforce stricter the rules of constant required speed, as Zhou et al. (2017) state.

3.2. *Further preconsiderations*

Before the model is constructed, the used speed-bunker fuel consumption function, the used equations for the probability of delays and a discussion between an analytical solution and a discrete model simulation is presented.

3.2.1. *Speed – bunker fuel consumption function*

To describe the effects of different speeds on the bunker fuel consumption it is important to choose a realistic relation function. Any bunker fuel consumption of a vessel is possible in the model, however, in the paper the formulation is used as defined by Wang and Meng (2012a):

$$c = a \cdot v^b \tag{1}$$

where c is the bunker fuel consumption per day, a and b are parameters for each type of vessel, which are determined by regression. Hence, in this paper, three broad classes of vessels are considered: the Panamax class having a capacity of 2,500 TEU, the post-Panamax class having 5,000 TEU, and the neo post-Panamax class having up to 13,000 TEU. Usually, $b > 2$ (see Psaraftis and Kontovas (2013), Wang and Meng (2012a) and Du et al. (2011)), so increased speed leads to significantly higher bunker fuel consumption. Thus, times with high speeds to recover delays result in disproportionately higher bunker fuel consumption, which shows the vital impact of recovering delays by speeding up on general bunker fuel consumption.

3.2.2. *Probability of delay at sea*

The determination of both the probability for some events and the vessel-specific parameters is important to generate realistic results. The simulation model has the following assumptions (normal distributed):

- Discrete random occurrence of delaying events
- Per discrete time unit, there is one event or none
- The probability of event occurrence is constant over all discrete time units
- The probabilities of random event lengths are constant over all discrete time units

A practitioner may find it difficult to estimate the real probability of an event in some arbitrary period of time, e.g. one hour. However, it is assumed that practitioners are able to judge the probability of an event during a voyage from experience. Therefore, this probability P_{total} is used as an input for the simulation model. As a result, the discrete time units can be expressed as a Bernoulli process having the following distribution (see Bronstein and Semendyayev (1991)).

Bernoulli coefficient:

$$1 - P_{total} = \binom{n}{x} \cdot P_{stretch}^{x} \cdot (1 - P_{stretch})^{n-x} \tag{2}$$

Equation 2 is well known and is called the Bernoulli coefficient. In this equation, the number of discrete time units is the number of Bernoulli experiments n. Herein, $x = 0$, since probability $P_{stretch}$ of an delay happening in one concrete period is discrete. Therefore, the Bernoulli coefficient is simplified (Equation 3).

Simplified Bernoulli coefficient:

$$P_{stretch} = 1 - \sqrt[n]{1 - P_{total}} \tag{3}$$

3.3. Design of speed profiles

Hence, the approach of this paper bases on the following idea: Steaming moderately faster than the constant minimal necessary speed for a long time to build up buffer is more effective than steaming at the constant minimal speed in the beginning and, in case of a random delay, very fast. The consumption is less in the first case, while the reliability remains at a comparable level in both cases. By setting a marginally higher speed at the beginning of the voyage, a buffer is created prior to any delay, and so a fast and very expensive recovery is avoided. As events happen randomly and will not occur on most voyages, it is essential to analyze to which extent and when the buffer should be built up. Additionally, it must be decided how long the buffer should remain and how much buffer should be kept until arrival in the port. As described in Section 1, this can be transferred into four parameters for a voyage from origin port O to destination port D:

- A is the point in time after leaving the port [in hours] until the buffer of height H is built up with a constant speed v_{OA}.

- B (with $A \leq B$) is the point in time after leaving the port [in hours] until the buffer is kept by steaming with a constant speed v_{AB}. After B, the buffer is depleted until the vessel arrives at the destination port D at time T with a constant speed v_{BD}.
- H is the buffer [in hours] to be built up until A.
- R is the remaining buffer [in hours] at the destination port D. Obviously, $H \geq R$.

The decision about these four parameters leads to a set of speed instructions on the different route sections of the voyage and creates the different speed profiles. Therefore, a speed profile consists of three phases, each with a constant speed, and thus, two speed adjustments. The reason is that the built-up of buffer needs some time and, at the time (A) the determined buffer (H) is completely built up, the speed can be lowered. In this phase the buffer remains constant, in case of no event occurs. However, when there is no event as the vessel is nearing its destination, the complete buffer is not needed anymore. As the probability of an event causing a delay during the remaining voyage depends on the time that has already elapsed and the time that is still remaining, an event becomes less likely during the remaining voyage. Therefore, some bunker can be saved by lowering the speed until a determined rest of buffer is left (R). Consequently, each developed speed profile has three phases: built-up phase (I), maintaining phase (II), and depleting phase (III), as illustrated in Figure 1. Owing to this, the design of any speed profile can be described entirely by the four parameters.

As already mentioned the four parameters A, B, H and R jointly define a speed profile. However, the question is how to deal with occurred delays. One procedure (without recovery) is to follow the speed profile strictly and to accept any further delays, the other (with recovery) is to adjust the speed in case the delay stride the buffer. Therefore, two version of the same speed profile exist.

Calculation of planned speed of speed profiles

The next step is to calculate the planned speeds for all possible speed profiles with the described three phases. The following equations show the speed for each phase, Equation 4 for built-up phase (phase I), Equation 5 for maintain phase (phase II), and Equation 6 for depleting phase (phase III). The speed during the built-up phase depends on the amount of buffer H and the point in time A when the buffer is completed. The speed can be calculated by Equation 4.

Speed calculation in the build-up phase:

$$v_I = \frac{\frac{D}{T} \cdot (A + H)}{A} \tag{4}$$

where:

- v_I is the planned speed in knots in phase I.
- D is the total distance in nautical miles.
- T is the planned time in hours.

The smaller A, the higher is the speed v_I at which the buffer H is built. The buffer is linearly built up as this is the most efficient way, as proven by Wang et al. (2013).

In the second phase, for time between A and B (where $A \leq B$), the buffer is hold constantly, and the speed is defined by Equation 5.

Speed calculation for the second phase:

$$v_{II} = \frac{D}{T} \tag{5}$$

One special case is for $A = B$, when just after the buffer at maximum level the speed is lowered and the buffer is depleted again, so the phase II is omitted.

In the third phase, the question arises whether the complete built-up buffer is actually still necessary. As most of the voyage is already performed, the risk of any further delay is lower and therefore, some of the buffer can be depleted in order to decrease the bunker consumption by reducing the speed on the phase III. In the special case of $H = R$, the third phase is dropped and all built-up buffer is kept until the next port in case of no delay. Of course this case has a higher level of reliability, but it is also a quite costly version.

The speed in depletion phase is defined in Equation 6.

$$v_{III} = \frac{D - (v_I \cdot A + v_{II} \cdot (B - A))}{T - B - R} \tag{6}$$

In case of $R = 0$, all of the buffer is depleted linearly until the vessel reaches the destination port. Some of the costs are recovered, but this procedure is susceptible to events on the last nautical miles. Furthermore, only a part of the costs of creating the buffer can be saved by reducing the buffer due to the disproportional slope of the speed consumption curve.

A special case is the "principle of hope" speed profile (PHSP). As $A = B = T$ and $H = R = 0$, no buffer is built up and only one phase with one speed is considered. This speed is calculated by Equation 7.

$$v^* = \frac{D}{T} \tag{7}$$

A comparison of Equation 7 with Equation 5 shows $v^* = v_{II}$, as this is the optimal speed for neither building up nor depleting buffer. This approach without recovery is analytically the cost-minimal speed profile, but also minimal reliable.

Handling of delays

The next step is demonstrating how to adjust the speed due to delays. As already mentioned above two different approaches exist:

- The first type contains speed-profiles without recovery following Equation 4, Equation 5 and Equation 6, ignoring any delays. It is expected to find solutions with comparable lower costs, but also lower reliability.
- The second type contains speed profiles with recovery. In case a delay occurs, the speed is adjusted to obtain the planned buffer.

In speed profiles with recovery, the speed is not only adapted with each phase, but with each delay the speed is changed additionally. In order to calculate these speeds, Equation 4, Equation 5 and Equation 6 for the different phases must be extended for recovery. The total time is split in n intervals with the duration of an hour and is described by the tuple

$L := (L_1, L_2, L_3, ..., L_{n-1}, L_n)$ with the corresponding speed in the intervals $V := ((v_1, v_2, v_3, ..., v_\theta, ..., v_{n-1}, v_n)$.

To calculate the speed in phase I Equation 8 replaces Equations 4.

$$v_{IR_\theta} = \frac{(\frac{D}{T}\frac{(A+H)}{A}A) - D_\theta}{A - \theta} \tag{8}$$

For each point in time θ (in phase I, so $\theta < A$) it is possible to determine the speed v considering recovery by Equation 8. Hereby, the first term of the numerator $\frac{D}{T} \cdot \frac{(H+A)}{A}$ calculates the planned speed to built up a buffer of H hours until A. By multiplying the planned speed with A the planned distance is calculated in which the buffer H is built-up until A. By reducing the total distance by the already steamed distance D_θ the actual rest distance in phase I is calculated. In the denominator the difference between A and θ, equal to the rest of time, is calculated. Thereby, the speed is the ratio of rest distance and rest time in phase I.

To calculate the speed in phase II Equation 9 replaces Equations 5.

$$v_{IIR_\theta} = \frac{(\frac{D}{T}\frac{(A+H)}{A}A) + (\frac{D}{T} \cdot (B - A)) - D_\theta}{B - \theta} \tag{9}$$

To determine the speed the same procedure as in phase I is also used in phase II. In the numerator the rest distance is calculated and divided by the rest time of phase II in the denominator, done in Equation in 9.

$$v_{IIIR_\theta} = \frac{D - D_\theta}{T - \theta} \tag{10}$$

D_θ is the already steamed distance at time θ, given by D_θ= $\Sigma_{i=1}^{\theta} v_i \cdot t$, and t is the time of an interval. In phase III, the speed is also calculated by the ratio of the rest distance and rest time. In case the formulas exceed the maximum speed for the rest of the journey, the maximum speed will be steamed and the voyage takes longer.

3.4. Discrete simulation vs analytical solution

In order to evaluate the expected costs and reliability for any speed profile (A, B, H, R), the consequences (expected cost and reliability) of each delay setup on sea need to be evaluated. So, they are weighted with the probability w of the occurrence of the delay setup. As the used model is discrete, it is possible to plot the paths as illustrated in Figure 3.

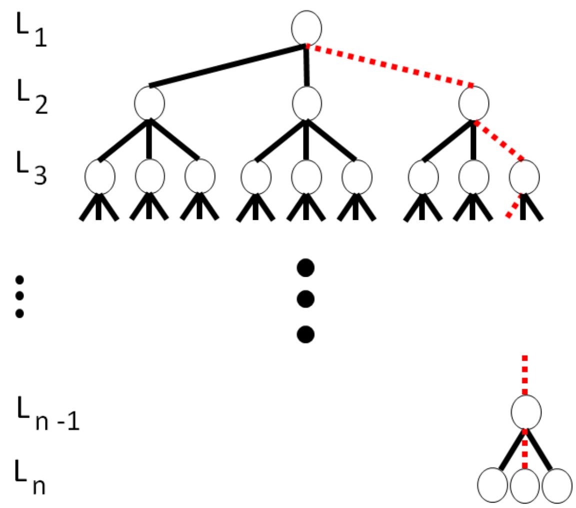

Figure 3: Sketch of the different paths of one speed profile. One path as an example is shown by the red dotted lines.

In order to find a good approximation for the expected average costs and reliability following this certain speed profile the values for the possibility for occurring events during a voyage, hereafter called *path*, need to be evaluated. Considering the results of Subsection 3.2.2 it is possible to evaluate the probability of each path, following the steps shown in Figure 4. Equation 11 calculates the expected costs for one speed profile.

$$\sum_{u=1}^{U} w_u \cdot p \cdot \sum_{i=1}^{T} \frac{a \cdot e^{b \cdot v_i}}{24} \tag{11}$$

This method is rather straight forward, however, demands much time and calculation effort as all possible case have to be calculated, the so-called exhaustive search. Approaches using Markov Chains or branch and bound algorithms are not expedient, as all paths including their ways need to be evaluated. Therefore, it is questionable whether an exact algorithm can lead to realistic results. Thus, heuristic solutions might be more useful. However, the database is rather poor, so many parameters must be estimated and any

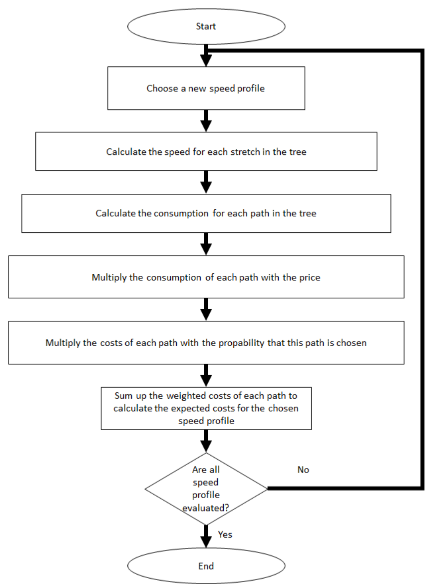

Figure 4: Flow chart of the evaluation of the speed profiles

solution basing on this will be uncertain. Therefore, the method of simulation is chosen, which uses appropriate chosen parameters, offers an exact solution and can be calculated many times until a satisfied solution is found. Lucas et al. (2015) discuss the merits of analytics and simulation. They point out that the advantage of simulation is not requiring overly restrictive modelling assumptions. According to Lucas et al. (2015), one goal of simulation models is to find robust policies for a complex problem. A problem suited for simulation is easy to understand and to model realistically, but difficult to solve analytically without simplifying it. The expected values of both bunker fuel consumption and reliability need to be calculated as a function of the decision variables. This calculation is highly complex for two reasons:

- The problem of finding good speed profiles is a trade-off between two objectives: bunker fuel consumption and reliability. Of course, there are different multi-objective approaches like goal programming, as introduced in Charnes and Cooper (1957) to solve this dilemma. However, as shown in Subsection 3.1, it is difficult to compare the financial effects of bunker fuel consumption and delay.

- A delay requires different reactions depending on the time of occurrence. At any time of the voyage a delay may occur and, thus, the need for a speed-up, which leads to different bunker fuel consumption and reliability. This creates a large number of possible scenarios and, additionally, delays usually have different lengths, which further increases the number of scenarios. The problem can be simplified by discretization of time, e.g. for a period of one hour. Nevertheless, the number of scenarios is still high. Assuming, a voyage consists of n discrete periods and the delay have the same length, the number of possible scenarios is 2^n. By consideration of m different lengths of delay, this number increases to $(m+1)^n$. For realistic values for n and m the effort for a calculation of all scenarios is extremely high.

Due to this complexity and following the argument by Lucas et al. (2015) simulation is a sensible method for this problem. It allows straight forward testing of many speed profiles without the need of making any oversimplifying assumptions. Therefore, it is used in this paper to evaluate good speed profiles.

4. Numerical Example

The idea is to design and simulate many different speed profiles in order to measure their performance with respect to bunker consumption and reliability. Thereby, each speed profile faces the same obstacles as all the others. In the end, an estimated average bunker consumption and an estimated average level of reliability of each speed profile for a voyage are calculated and compared for six cases which differ in their consumption and reliability constraints and objectives.

4.1. Simulation parameters

The simulation contains the following parameters:

- As stochastic methods are used a significant number of repetitions is needed to include all possible events and gain realistic results. So, the number of repetitions is set to 10,000.

- The distance and the total time are taken at a value of 3000 nm with 200 h respectively 1000 nm in 75 h and 50 h. These are typical values for voyages of ocean going vessels, e.g. about 3000 nm is a voyage from Le Havre (France) to Port Said (Egypt) and about 1000 nm is from Genoa (Italy) to Piraeus (Greece), taken from Seadistances (2020). It is also possible to use routes between individual continents, but this would increase the computational effort without providing new knowledge. The resulting speeds are also typical for liner shipping, shown e.g. in Cheaitou and Cariou (2019).

- The database for the probabilities for incidents is very poor and thus, they can only be estimated. This assumption is based on the data from Notteboom (2006).

- The parameters a and b which describe the bunker fuel consumption are calculated by regression, basing on real data taken from Alphaliner (2017). Therefore, the use of realistic bunker fuel consumption is secured.

- The duration of the incidents are taken as realistic values, described in Abioye et al. (2019).

- During the time of the incidents, it is assumed that the ship will not move until the incident time has elapsed, so no bunker fuel is consumed and the distance remains the same.

- The time A and B, the height of buffer after the built-up phase H and the buffer at the end of the voyage T are freely varied until the optimal solution is found, taking the constraints into account.

4.2. Voyage simulation set-up

In order to find good speed profiles, three vessels (called V1, V2 and V3), see Table 2, and four voyages (D1, D2, D3 and D4), shown in Table 3, are simulated. The simulation is conducted as follows: The random events are simulated in an array, and all speed profiles are evaluated against an array of random events. An event means that a delay of random length occurs at a distinct random point in time.

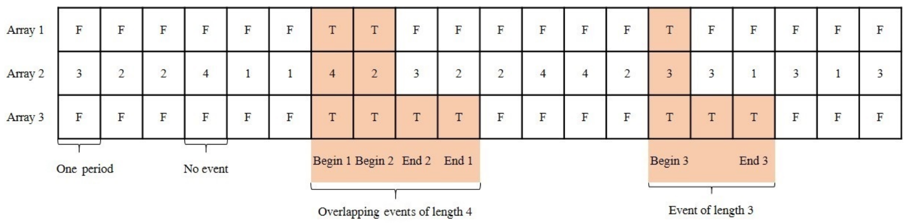

Figure 5: Discrete event simulation framework

Considering the events

The total voyage time is discretized into periods. Three arrays are used for the random event simulation. The length of the arrays correspond to the number of periods the voyage is expected to last, plus some additional periods for delayed vessels.

- The first array is used to determine the random occurrence of events and is of Boolean type (False or True)
- The second array is used to set the random length of an event following some discrete distribution.
- The third array is generated from array 1 and 2. It is of Boolean type and holds information whether there is an event in a certain period or not. If the lengths of two events overlap, then they are aggregated to one longer-lasting event, beginning with the earlier start and ending with the later end as demonstrated in Figure 5.

Only array 3 is relevant for the experimental simulation of speed profiles, since array 1 and 2 are generated and exploited only to generate array 3. One run has three phases:

1. Randomization of array 1 and array 2.
2. Calculation of array 3 using arrays 1 and 2.
3. Evaluation of all considered speed profiles with respect to the random events in array 3.

This simulation runs many times (e.g. 10,000 simulation runs), and every speed profile is evaluated against every other run.

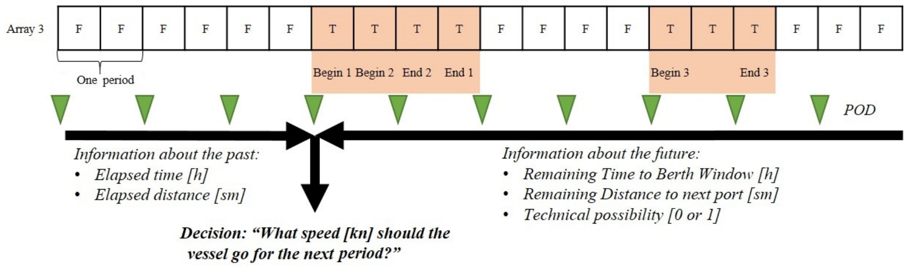

Figure 6: Discrete period decision framework

Adjusting speed in the simulation environment

The different speed profiles prescribe planned speed adjustments at A and B. Furthermore, in case of delay, unplanned adjustments are carried out in order to recover the delay. As a result, the simulation environment needs some structure to model the sequence of speed adjustments. Therefore, vessels steaming at different speeds may face events at the same time, but at different places. This is relevant for periods that are close to the destination. It is assumed that the overall expected hours of delay depend on the voyage time, but not on the voyage distance. Speed adjustments are possible at the end of every period.

Note that there is no actual decision making during the voyage, as all the decisions had been made, when the speed profile was created. The simulation environment merely executes the speed profile to transform information about the past and assumptions about the future into speed for the immediately upcoming period. This is illustrated in Figure 6.

For each run of randomization of events and speed profile evaluation, three results are saved:

- Bunker consumption [in tons]
- Reliability [0 or 1]
- Deviation from planned berthing time [in hours]

Following these three criteria the speed profiles are evaluated.

Evaluation of the simulation

In order to evaluate and compare the speed profiles, the performance of all runs is aggregated in the following way:

- The mean bunker consumption over all runs [in tons]
- The percentage of early or on-time arrivals (α reliability)
- The partial expectation of positive deviation from the planned berthing time (β deviation) [in hours]
- The partial expectation of negative deviation from the planned berthing time (γ deviation) [in hours]

The reliability measurements of speed profiles are inspired by inventory service levels (see, for example, Cachon and Terwiesch (2013)). In inventory management, decision makers use performance measures, such as the in-stock probability (this inspires the α reliability) and the fill rate (this inspires the β and γ deviation). While α reliability (from hereon "α") simply counts the number of runs during which a profile has not arrived late, it does not make any statements about the extent of delay or earliness. In fact, arriving early and just in time is evaluated as "true" and arriving late as "false". The β deviation (from hereon "β") makes a statement about the extent of earliness and the γ deviation (from hereon "γ") is the partial mean of the delay in hours and thus, a measurement of the extent of delay. While α is an empirical probability, β and γ are absolute values.

Only dominating speed profiles should be considered to be good speed profiles. A speed profile P1 is called dominating if there is no other speed profile P2 which is better than P1 with regard to bunker consumption, α, β, and γ simultaneously.. Thereafter, the speed profiles are compared regarding their dominance. The list of dominating speed profiles is then sorted, filtered, and browsed to identify the best speed profile using the criteria of reliability, deviation and bunker consumption.

Speed profiles in the simulation

For the simulation, many different variations of the generic speed profiles have been created. Fifty profiles perform no recovery or speed adjustment at all, but build up a buffer steadily. Therefore, $A = B = T$ and $H = R \geq 0$.

Fifty speed profiles have the same parameter settings but recover delays by speeding up. Furthermore, there are hundreds of speed profiles that adjust speed as planned. The parameter settings used here are summarized in Table 1. Recovery of delays was simulated in the third phase between B and the destination port D.

Table 1: Parameter settings of speed profiles in the simulation

Parameter [h]	Min	Max	Step size
H	10	70	10
R	0	H	H/6
A	T/10	T	T/10
B	A	A+T/2	T/10

4.3. Simulation results

Scenarios have been created and ran 10,000 times each in this simulation, so each speed profile is facing the same events. Each scenario is a combination of a distinct vessel V and a distinct voyage.

Table 2: Vessel parameters, the values for a and b are calculated by regression following formula 1

Type	ID	Cargo (TEU)	a	b
Panamax	V1	2,500	0.011118	2.8714
Post-Panamax	V2	5,000	0.0090264	3.0532
Neo Post-Panamax	V3	13,000	0.010706	3.182

In Table 3, in the calculation of $P_{stretch}$, it is assumed that the length of one period equals one hour. The parameters P_{total} and $P_{stretch}$ are Bernoulli coefficient and the simplified Bernoulli coefficient as defined in Equation 2 and Equation 3 in Subsection 3.2.2.

Table 3: Voyage settings

ID	Time [h]	Distance [nm]	P_{total} [%]	$P_{stretch}$ [%]
D1	200	3.000	70 %	0.6 %
D2	200	3,000	25 %	0.144 %
D3	75	1,000	33 %	0.533 %
D4	50	1,000	33 %	0.798 %

The parameters a and b of the bunker fuel consumption Function 1 are characteristic for the vessel type. The given values in Table 2 are the result of polynomial regression over the empirical results by Alphaliner (2017). Combining the three vessel types (Table 2) and the four voyage settings (Table 3), there are twelve different scenarios in the simulation. Figure 7 depicts the reliability and positive as well as negative deviations measure α, β, and γ of these twelve scenarios. Each column represents one voyage setting. Every graph includes the dominating speed profiles for the three given vessel types. The horizontal axis displays the bunker consumption in tons. As expected, α and β are approximately convex curves over bunker consumption. Due to this non-linearity the dependence of reliability on bunker fuel consumption is different at different levels of consumption. At low levels, a strong increase in reliability is achieved by a small increase in consumption, however, at high levels high rise of consumption just leads to minor increase of reliability. As γ is a concave function on bunker fuel consumption, the effect is the other way around.
In each scenario, many speed profiles are dominating. As a result, these profiles are not recommended for use. The curves of the three different vessels are of the same convex shape, but shifted, as expected. Larger vessels consume more bunker in order to reach the same level of reliability.

The PHSP without recovery is the only dominating speed profile with respect over all twelve scenarios. Keeping in mind that this profile calculates the speed by Equation 7 and never adjusts the speed even when the vessel is delayed. This is actually a trivial case, since no buffer and no recovery certainly leads to lower bunker consumption and thus PHSP is never dominated.

Which speed profiles are dominating in many scenarios? In the simulation, 262 of the 3,040 speed profiles are dominating in all twelve scenarios. Speed profiles that have no planned speed adaptation ($A = B = T$) perform well and are often dominating. However, some speed profiles having $A \leq B < T$ also dominate many scenarios. There are few speed profiles dominating in all scenarios, but there are many speed profiles that are dominated in every scenario.

To get some insight into the group of well-performing speed profiles, see Figure 8.

In Figure 8, only speed profiles that are dominating with respect to α and γ and with $\alpha \geq 90$ % and $\gamma \leq 1$ h are depicted. These constraints

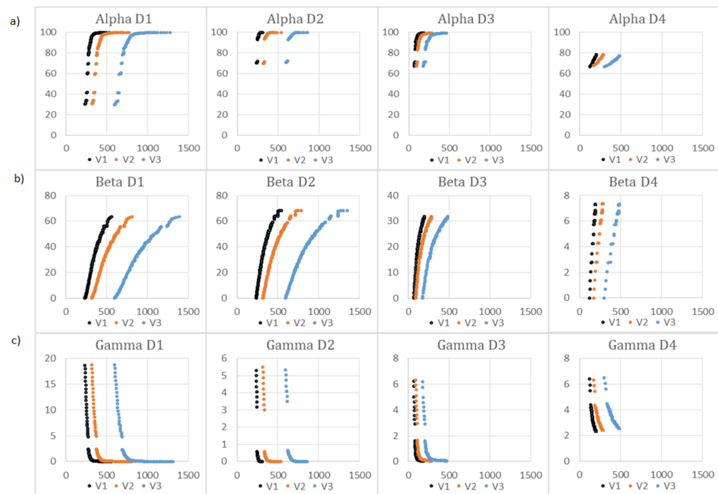

Figure 7: Simulation results of twelve scenarios. The bunker fuel consumption in tons is drawn on the horizontal axis. The vertical axis in the graphs above (Figure 6a) show the α-reliability in percent, in the middle ones (Figure 6b) the β-deviation in hours and in graphes below (Figure 6c) the γ-deviation in hours. Please note the different scales of the vertical axis.

reduce the number of speed profiles to 39. The notation is "A-B-H-R" and all parameters are a percentage of the voyage time T. From this example, some observations can be made:

- Low levels of H and R lead to lower consumption and to lower α. Vice versa, high levels of H and R lead to disproportionately higher levels of consumption and also to higher levels of α. γ is ordinal consistent with α, subject to the constraints. A speed profile having a higher α always has a lower γ.
- Most of these 39 speed profiles use medium levels for A and B between 40 and 60. Lower levels lead to extremely high consumption.
- All of these 39 speed profiles forgo the buffer-maintaining phase and set $A = B \geq T$.
- None of these 39 speed profiles depletes the complete buffer.

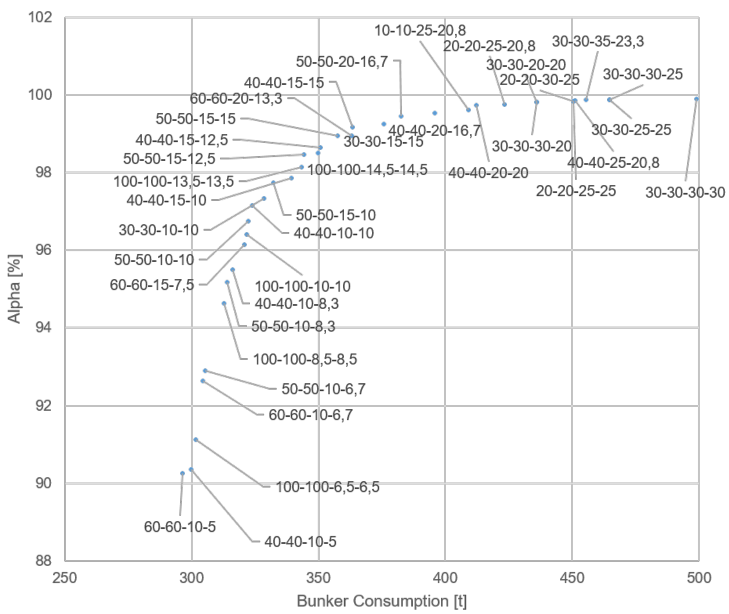

Figure 8: Dominating speed profiles for the scenario V1-D1 in the notation "A-B-H-R"

- Most of these 39 speed profiles use buffer heights H between 10 and 20. Note that the random event length has an expectation of 15. Using higher buffer levels leads to very good reliability and disproportional high consumption.

These results can be used in the planning of shipping services in order to find optimal solutions for specific routes and vessels. However, out of these solutions the shipping companies need to find out the most appropriate speed profiles which fit in the different planning strategies and aims. For a shipping company the amount of various speed profiles is confusing. Additionally, shipping companies have different planning strategies and aims in different services, e.g. services that primarily transport perishable goods must place a special focus on reliability. For other services, low costs are particularly vital or the service must be as reliable as possible without exceeding a specific limit on consumption. To cover these different needs six cases have been constructed, consisting of one objective and a set of constraints, i.e. consumption, reliability and deviation from the schedule. For planning a specific service the suitable case can now be selected and thus, the best speed profile can be determined through the simulation. The cases are described below:

1. The aim is the minimization of the bunker fuel consumption under consideration of the proportion of vessels which arrive in time is equal or above a limit of 99 % and the mean delay is equal or lower than 1 hour.
2. The objective is the maximization of the proportion of vessel arrive in time, where the bunker fuel consumption is equal or less than 10 % above the mean consumption and in-time vessels arrive at least 3 hours before schedule.
3. The delays of delayed vessels is minimized, where the bunker fuel consumption is equal or less than 50 % above the mean consumption and the proportion of vessels which arrive in time is equal or above a bigger than a limit of 95 %.
4. The aim is the maximization of the proportion of vessel arrive in time under consideration that vessels arrive in time at least 10 hours before schedule and the mean delay of delayed vessel is equal or less than 1 hour.
5. The delays of delayed vessels is minimized, where the bunker fuel consumption is equal or less than 5 % above the mean consumption.
6. The objective is the minimization of the bunker fuel consumption, where the proportion of vessels which arrive in time is equal or above a limit of 93 %, in time vessels arrive at least 5 hours before schedule and the mean delay is equal or lower than 0.25 hours.

Table 4 lists the six evaluated cases. Using these examples, a case can be chosen in which the personal boundary conditions are met.

Table 5 presents the best speed profiles to be used in the six cases for the twelve scenarios. The supplement “w/r” means “with recovery” and “n/r” means “no recovery”. For example, given a vessel of the Panamax class (V1) operating a liner voyage of 3,000 nm having 200 hours until the next berth window (D1), a good speed profile is searched that minimizes the bunker

Table 4: Six cases

Case	Objective	Constraint 1	Constraint 2	Constraint 3
1	Min Bunker	$\alpha \geq 99$ %	$\gamma \leq 1h$	
2	Max α	Bunker $\leq Min\{Consumption\} \cdot 1.1$	$\beta \geq 3h$	
3	Min γ	Bunker $\leq Min\{Consumption\} \cdot 1.5$	$\alpha \geq 95$ %	
4	Max α	$\beta \geq 10h$	$\gamma \leq 1h$	
5	Min γ	Bunker $\leq Min\{Consumption\} \cdot 1.05$		
6	Min Bunker	$\alpha \geq 93$ %	$\beta \geq 5h$	$\gamma \leq 0.25h$

Table 5: Best speed profiles for the six cases

Case	V1-D1	V1-D2	V1-D3	V1-D4	V2-D1	V2-D2	V2-D3	V2-D4	V3-D1	V3-D2	V3-D3	V3-D4
1	A=B= 80 H=R= 30	A=T w/r H= 36	A=T n/r H= 35		A=T w/r H= 35	A=T n/r H= 31	A=T n/r H= 33		A=T w/r H= 36	A=T w/r H= 16	A=T w/r H= 16	
2		A=B= 120 H= 10 R= 3.33				A=T n/r H=8				A=T n/r H=8		
3	A=B= 60 H=R= 20	A=T w/r H= 35			A=B= 80 H=20 R=16.67	A=B= 120 H=R= 30				A=B= 120 H= 30 R= 25		
4	A=B= 100 H=70 R=58.3	A=T n/r H= 15	A=T n/r H= 17		A=T n/r H= 40	A=T n/r H= 14	A=T n/r H= 17		A=T n/r H= 40	A=T n/r H= 15	A=T n/r H= 17	
5	A=T n/r H= 4	A=T n/r H= 4	A=T n/r H= 1	A=T n/r H= 1	A=T n/r H= 4	A=T n/r H= 4	A=T n/r H= 1	A=T n/r H= 1	A=T n/r H= 4	A=T n/r H= 4	A=T n/r H=1	A=T n/r H= 1
6	A=B= 80 H=R= 20	A=T w/r H= 6	A=T n/r H= 26		A=T w/r H=R= 22	A=T n/r H= 36	A=T n/r H= 27		A=T w/r H=R= 23	A=T n/r H= 34	A=T n/r H= 27	

consumption. Further, the operator wants the probability of meeting the berth window to be at least 99 percent and the expected delay not to exceed 1 hour (Case 1). The best speed profile for this case is:

Given a vessel of the neo post-Panamax class (V3) operating a liner voyage of 1,000 nm having 75 hours until the next berth window (D3), a speed profile that maximizes the probability to meet the berth window (α) is searched.

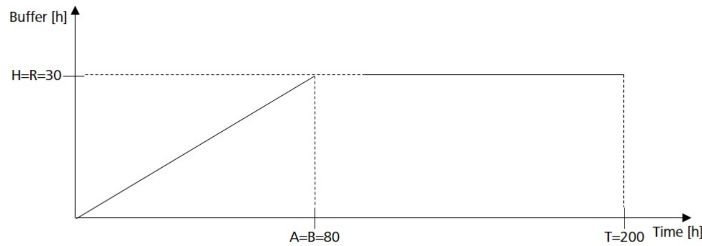

Figure 9: Case 1: V1-D1

Furthermore, the operator wants the expected earliness to be at least 10 hours and the expected delay not to exceed 1 hour (Case 4). The best speed profile for this case is depicted in Figure 10.

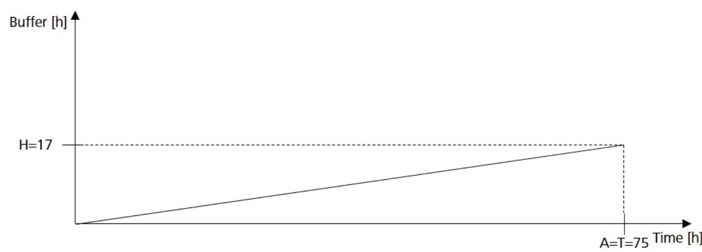

Figure 10: Case 4: V3-D3

4.4. Managerial insights

From the case evaluation (Table 5), some managerial insights can be deviated:

- A decision maker should set $A = B < T$ or $A = B = T$ but not $A < B$. This limits the recommended number of planned adjustments of speed to one.
- Good speed profiles have a positive rest buffer $R \geq 0$. This means the vessel is planned to arrive early if there is no unexpected delay.

- If the PHSP speed is already high (D4), there are fewer options to increase the reliability. As a result, many cases become infeasible.
- For different types of vessels on the same voyage the use of similar speed profiles is beneficial. Therefore, a homogeneous fleet can operate using the same speed profile on the same voyage.
- Most of the cases require constant speed and buffer built-up over the whole duration of the voyage. This is the best way to avoid peaks in bunker consumption. Especially if P_{total} is relatively low, constant speed and constant building up of buffer is recommended.
- Longer voyages can exploit the advantages of early buffer ramp-up and thus tolerate speed adjustments. As a result, more complex speed profiles setting $A < T$ are recommended for longer voyages. Also, recovery is recommended only for longer voyages.
- If there is a very tight maximum bunker consumption constraint (Cases 2 and 5), the decision maker must prohibit recovery of delay and accept a lower level of reliability.
- Although PHSP is dominating, it is not recommended in the tested cases. PHSP is used only if the bunker consumption is minimized without any constraints concerning the minimal level of reliability.

5. Conclusion

5.1. Contribution

In this paper, the problem of finding good operational rules for container liner ships was described when stochastic events causing delay. The generic description of buffering speed profiles to deal with uncertainties at sea is a contribution to maritime freight transportation research. From a practitioner's point of view, this is a worthwhile consideration to develop a neat operational rule concerning how fast to steam. Therefore, a set of parameters describing each speed profile has been introduced. Furthermore, measures of reliability and deviation of container liner services, which are used to find dominating speed profiles and select the fittest speed profile in distinct cases, have been presented. Ways to create an analytical solution are shown, however, the complexity of different types of vessel, different settings of the voyage, and uncertainty makes calculations basing on an analytical solution quite hard. Therefore, a discrete event simulation is suitable (see Lucas et al. (2015)). Within this discrete simulation, dominating speed profiles have been identified for three typical types of vessels on different voyages. The simulation approach allows decision makers to compare thousands of speed profiles and filter them by their individual requirements with respect to bunker fuel consumption, respectively deviations.

Different reactions to events

In this paper, many parameter settings (see Section 4.2) are derived from the generic speed profile (see Figure 1). However, the complexity and variety of speed profiles can be amplified by different reactions to events:

- Do not adapt speed.
- Adapt the speed proportionally to the delay.
- Adapt the speed in exaggeration (e.g. technically maximal speed).
- Vary the reaction in different phases of the voyage.
- Rebuild the used buffer partially.

5.2. Further research

Round trips

Qi and Song (2012) have argued that it is important to review not only voyages but also round trips. On round trips, delay may have a cascading effect of cumulative uncertainties on sequential legs. Therefore, the probability of delay will be higher on this leg. Since delayed ships need to speed up in order to maintain the timetable, there is less room for buffering and delay recovery and, furthermore, they consume more bunker. As a result, the β may be more important on round trips than on single voyages as it describes the expected extent of earliness. On round trips, earliness may be the key to avoid this cascading effect.

Non-linear buffer reduction

Although the linear depleting of buffer is the most efficient way, a convex decreasing function of speed may be more reliable. Owing to the exponentially increasing bunker function, it is efficient to limit the adaptations of speed to a minimum. This means continuously slowing down the ship, but not at once. Hence, a convex buffer reduction leads to higher bunker consumption and higher levels of reliability. A convex function may exist which has the same bunker consumption as the linear function but a better level of reliability.

Real world data

In this research paper, numerical examples have been extensively used in the simulation. This required assumptions regarding the probability P_{total}, the distribution of event length, the objectives, and the constraints (cases). In order to make the presented approach more applicable, one would need to conduct extensive case studies to obtain real world data as input for the presented simulation approach. In this paper, it is assumed that the probability of events depends solely on the voyage. However, the vessel type may be a factor in determining a more realistic probability, owing to different technological levels of robustness, different stages in the life cycle of a vessel, and different capabilities to deal with distinct factors of uncertainty.
As mentioned before the database for delays at sea is rather poor, so one important issue is the improvement of data by studies focussing on this topic. Basing on the better database the results of the model can be compared with realistic conditions and events to prove, validate and enhance the model.

Fuel-consumption curve

The exact formula as described in the fuel consumption curve is not important for the model. But in order to keep the result realistic, it is necessary to follow further discussion in the literature to implement more factors, with a special focus on payload.

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5. Conclusion

5.1. Summary and discussion

In this thesis current problems of the container liner shipping industry and their background were described. In this context, three specific findings can be formulated:

- Firstly, it is described that the decisions about cargo flow are largely dependent on the contribution margin of laden container. With regard to empty repositioning as a consequence of the transport of the full containers, the combination of determination of empty and full containers in the decision-making processes from the beginning achieves advantageous results in medium-term and long-term.

- Secondly, it is described that the costs for bunker fuel consumption make up a large amount of the total costs of a liner shipping service. It is evaluated that these costs depend on uncertainties such as fluctuations and random events and on the required level of reliability. Therefore, optimization of the bunker costs by risk prevention strategies is proposed.

- Thirdly, it is described that the rating of vessels with regard to their use in a service largely depends on the time charter costs. It is shown that by taking bunker fuel costs into account and including reliability, more differentiated and long-term profitable decisions can be made.

For all of these results, it is necessary to create a general speed-consumption-curve, which is also valid at low as well as at high speeds and is presented here.
All models developed in the articles Westarp, A. Graf von and Schinas (2016), Westarp, A. Graf von (2020), Westarp, A. Graf von and Brabänder (2021) and their enhancements in Subchapter 1.3.1 and Subchapter 1.3.2 are basic models which successfully tackle the current problems of liner services as described in Subchapter 1.1. However, the results have to be reviewed critically on the level of content as well as on the used methodology.

Some of the findings of this dissertation are especially surprising for the practitioner because they openly contradict common practice:

- In the short term, the method of always prioritizing full containers over empty containers in the transport, as is customary in practice, maximizes revenues, but in the long term you forego profits.

- Although the polynomial speed bunker fuel consumption function is used in all of the practical and academic calculations and considerations shown, exponential speed bunker consumption functions at least sometimes provide better estimations, especially for very slow and very fast speeds.

- Although the likelihood of delays on the high seas is very small, the consequences of such incidences are so dramatic that ignoring these possibilities, as it is currently the norm, can lead to a dramatic deterioration in the operating result. By implementing speed policies, practitioners can adjust and achieve their strategic goals in terms of punctuality and bunker fuel consumption costs.

For articles Westarp, A. Graf von and Schinas (2016) and Westarp, A. Graf von and Brabänder (2021) it was not possible to receive real data due to restrictive information policies of several contacted liner shipping companies. Additionally, some of the liner shipping companies do not have these data themselves and are dependent from the vessel owning companies. Although, when data was available there was some resistance of the liner shipping company to cooperation. This problem is regrettable and not uncommon in the relationship between academics and liner shipping companies. This can been seen in the example of Wang and Meng (2012a), who derivate their regression curve based on only twenty bunker fuel consumption points of vessels of the same size. Exclusively due to the willingness and the excellent cooperation with the consulting firm *Comtide* was it possible to use real data for statistical analysis in Westarp, A. Graf von (2020). However, the complete data were not allowed to be published and the amount of data already published was limited in order to ensure that it is impossible to conclude the name or type of vessel. In Westarp, A. Graf von (2020) between 300 and 500 data points per vessel are used. However, the data for only three different vessels of four sequenced years do not suffice for generalization of the consumption for other vessel types. Additionally, all three vessels were of different vessel types, but had a similar capacity of between 16,000 and 18,500 Gross Tonnages as stated in Westarp, A. Graf von and Brabänder (2021). As for example the vessel *HMM Algeciras* already mentioned in Subchapter 1.1 has about 230,000 Gross Tonnage (Marine Traffic (2020)). Lim (1994) notes that it is dangerous to generalize the orders of magnitude that result from larger vessels. This shows the demanding need for more real data and more testing for examination of the general validity of the speed-consumption-curve.

However not only the speed bunker fuel consumption data have to be reviewed carefully. Because it is difficult to get information about speed bunker fuel consumption data it almost impossible to obtain market data, because the liner shipping companies are at risk of violating antitrust regulations and the data can be used by any competitor.

Due to these limits no real case could be evaluated, so real data was combined with a fictitious scenario in Subchapter 1.3.1. In the other Subchapter 1.3.2 the focus was set on methodology instead of the concrete results, so the lack of real data poses no problems.

Westarp, A. Graf von and Brabänder (2021) present only possibilities to evaluate port-port relations. The negligence of cascading effects and delays in ports is a simplification for the calculations in Subchapter 1.3.1 and Subchapter 1.3.2. For Qi and Song (2012) is important to review not only voyages but round voyages, but assessments of the procedures and their circumstances in ports are complex. So, it is not reasonable to assume the financial and operational effects of delays.

The problem hereby is that any assumptions about what will happen in a port are difficult to defend. However β and γ reliabilities which are already introduced in Westarp, A. Graf von and Brabänder (2021) will be important to support any doing in the port.

As the quality and quantity of data is unpleasant an evaluation study of real data of these effects and costs is needed in order the evaluate the situation and the introduced algorithms. Such a new study should give a new overview over the delays, the circumstances which lead to the delay and the relationships and realistic parameters to get more realistic results. With these data the wish of Wang and Meng (2012a) to consider networks could be fulfilled by enhancing the models. Hereby the hardest problem will be to include the costs related to the delay in ports.

As already mentioned the results of the algorithms depend on the quality of data. Regarding speed and bunker fuel consumption some data were avail-

able for this thesis, but some other data are more difficult to get due to regulations. Other data such as bunker fuel price fluctuate and are hard to implement in strategy planning. However, for example Stefanakos and Schinas (2014) found approaches to forecast the development of bunker fuel price.
Westarp, A. Graf von and Brabänder (2021) provides a new approach for the bunker fuel consumption. However, due to a lack of data only three vessels of about the same size could be examined. It would be beneficial to generalize this approach to more vessel types, e.g. with different size.
As shown in Westarp, A. Graf von (2020) and Westarp, A. Graf von and Brabänder (2021) liner shipping vessels create and reduce buffer most effectively by steaming with constant speed. However, following the concept of Westarp, A. Graf von and Brabänder (2021) a convex function is more expensive but provides more reliability in the third phase. Further research is needed to investigate if a convex function exists that has the same bunker consumption as the linear function, but has a higher level of reliability.

5.2. Current forecasts and future prospects for container shipping

As shown, container shipping is dominated by an abundance of rapidly changing constraints and uncertainties, so that forecasts are difficult to make. Currently, the most regarded two studies dealing which the future of container shipping industry, Fenton et al. (2018) and Saxon and Stone, are published with a prediction of the future for 25 respectively 50 years. Although both studies have the same approaches they also differ in several points. Both studies identify politics, automation, digitalization, and technical progress such as robotics, self-driving cars and vessels as determining factors of the future development of the container market. Saxon and Stone assume that transported containers without vessels, i.e. self-propelled and floating containers, are likely to be used, while Fenton et al. (2018) is convinced that vessels will still be vital for transportation. They agree that the factors are waning that have actuated globalization, e. g. most of the goods that are transportable in containers are already containerised. Fenton et al. (2018) claims that containerization still possesses some potential such as increased speed of trade and those countries that currently still lacking of the needed infrastructure. However, in comparison to the already containerised amounts this is vanishingly small. Both studies expect a continuous growth in transportation volume, which depends on five points:

1. The influence of technical progress e.g. robotics and 3D-printing depend on the level of acceptance and progress in the market. It can be assumed that through 3D-printing and automation, the production will be moved closer to the consumer.
2. Changing habits of the people.
3. Developing countries of South America, Africa and Southeast Asia, especially India, spawn a new middle-class society that consume less material goods and more services, so-called dematerialisation, which need less volumes of transportation.
4. Technical progress needs less resources, such as recycling or manufacturing processes that requires less material. Again, this reduces the global volumes of transportation.
5. Political decisions that promote certain technologies and materials, suppressing others, have a strong impact on transportation.

Again, both studies agree that the impacts of all these factors are hard to predict.
Saxon and Stone summarize that three large alliances have grown within the last three years. However, the members of an alliance still remain competitors, so clear strategies are missing. Additionally, small market participants can also generate economies of scale and thus, are kept in the market by the alliances. Eliminating the smaller ones would not solve the problem of overcapacity because the tonnage would remain in the market. Greater cooperation between shipping companies or alliances could reduce overcapacity, but is prevented by regulations to promote competition for the benefit of the costumers.
It is foreseen that digitalization will be disruptive, but on the other hand will create additional values (e.g. communication, price transparency, digitalization products in transportation). This carries the risk that digital giants will take over logistics and shipping companies, as they are ahead in terms of digitalization and thus the crucial technologies required for improved efficiency in production, transport and coordination.

Fenton et al. (2018) indentify the following sources of value creation in the future:

1. Greater economies of scale
   Whether even larger container vessels will be built is debatable, as the advantages of the economies of scale are only usable in case of a high utilization. Additionally, the infrastructures of the called ports need extrem costly improvement to prepare the ports for bigger vessels. The approach of reducing overcapacities with slow steaming has largely been exhausted, so high utlilization is unreachable.
2. Flexibility
   It will be necessary to increase the flexibility of the container lines in order to respond quickly to customer requests. Some coustomers might be willing to pay extra fees for premium services. However, flexibility is only possible with smaller vessels, e.g. 10,000 TEU vessels.
3. Supply chain reliability and predictability
   Customer needs and desires are increasing and transport companies should react to this, by increasing the speed of procedures and add services e.g. supporting the customers to track their own containers or offering predictive analysis. This requires reliability which is much easier with smaller vessels. Served friendliness, simplicity and access at all times are important for customers. digitalization plays the central role here.
4. Consolidation and integration
   Since years the companies have had limited options to deal with the effects of overcapacity. Even in case of bankruptcies or of merger and acquisitions the vessel capacity is still in the market. Alliances offer limited support. The container industry is described less concentrated than other transport branches, e.g. the US Domestic aviation industry or international express parcels services. So, in the container shipping industry is still room for consolidation.
5. Automation and productivity
   One highlighted factor is the autonomous driving on land and at sea. Today, there are already automatic terminals like HHLA Container Terminal Altenwerder (CTA) in Hamburg (see Hamburger Hafen und Logistik AG (HHLA) (2020)), but it is expected, that only autonomous vessels generate big improvements in productivity. In addition to speed, it is primarily about the susceptibility to errors and a more efficient hinterland connection.
6. Environmental performance
   About 7% of all global carbon emissions results from cross-border trans-

Table 6: The recommendations of the two studies for preparing for the future

Fenton et al. (2018)	Saxon and Stone
Focus on the end customer	Invest in digitalization to improve the value chains to reduce costs significantly and to focus on the customer.
Monitor the trigger points. Recognize trends. Make plans for the future.	Consolidate, i.e. buying out competitors and partners.
Promote digitalization with a focus on creating added value.	Promote vertical cooperation between shipping companies and terminal operators and increase data exchange.
Drive automation and innovation.	Be visionary, be bold, be persistent and be a leader.

port of goods. More regulations from the states are expected, however many technologies are being developed to aid compilation with the new regulations. It is not clear which technologies will be accepted, e.g. various options are being discussed for propulsion alongside liquid gas oil, inclusing nuclear propulsion systems.

Table 6 shows the suggestions of the two studies.

As already shown, the question of whether even larger container vessels will be built and operate are controversially discussed. Ulrich (2017) states that larger vessels have few advantages and demand high investment costs for companies and port and terminal operators.g Saxon and Stone also describe the disadvantages of bigger vessel and carries out the problems of port operators such as depth of the fairways and the size of the ports. Although, it is technically possible to overcome these obsticals, these investments in infrastructures are very costly. Additionally, bigger vessels stay longer in the ports, that decreases the economies of scale. From a purly technical point a vessel size of 50,000 TEU is considered realistic. For the next 20 years vessels of the size of 30,000 TEU are expected in case the demand for bigger vessels increase. This depends heavily on the bunker fuel price, as the possible economies of scale increase with a higher bunker fuel price. However, the study predicts, that 50,000 TEU vessels would only become real in 2067 if automatisation increased productivity. Therefore, large flows of goods and an efficient organization are necessary, which can only be achieved by a powerful analysis of data through digitalization. Additionaly, coordination with the ports is vital, as almost 50 % of the vessels are currently more than 12 hours late and catching up is too expensive and makes planning a lot more difficult. So, by changing data of the ports and vessels the organization will be improved leading to benefits for the customers as they could lower their warehouse capacity and could increase the productivity (use of so-called *smart logistics*). An increase in productivity can also be achieved by researching new technologies, e.g. concept of the box-of-boxes, common loading and discharge of 20 containers at once or self-driving containers in hyperloops.

In study Fenton et al. (2018) 30 experts were interviewed to generate four possible scenarios. Then they evaluated the probability that one particular scenario will come true. One important key figure is the ratio between the growth of the transportation volume and the growth of the global economy in percent. This figure will be called *growth ratio* hereafter.

1. Scenario: *Digital Reinvention* (estimated probability about 60 %)
   Moderate growth ratio 1-1.5. The economic growth rates of China and India are moderate. Flexibility is more important than economies of scale. The current hub-and-spoke system is replaced by a system providing port-to-port connections. digitalization supports the organization with analysis and optimisation. Less human resources are needed, as automation is determining all transport processes. Only three or four large shipping companies are existing and alliances do not longer play a major role. Freight forwarders are completely digitalized and shipping is only part of the supply chain.

2. Scenario: *Digital Disruption* (estimated probability about 40 %)
   High growth ratio 1.5 - 2. China and India are growing moderately. The current hub-and-spoke system is being replaced by a system that provides port-to-port connections. Recognizable value comes from digitalization alone. Automation is a very important factor. Digital giants are taking over control of shipping industry. Alliances and shipping

companies do not play a significant role. Freight forwarders are fully digitized.

3. Scenario: *Third wave of globalization* (estimated probability 0 %)
   Huge growth ratio > 2. India is growing very fast und is becoming the motor of global economy. China is growing moderately, container shipping is determined by 30,000 TEU vessels. Large ports are called by these huge container vessels and small ports are connected with the bigger ports by feeders (hub-and-spoke sytem). digitalization is very important. Automation driving of all land vehicles and vessels. Alliances are very important. There are still many market participants. Vertical integration has only limited value.

4. Scenario: *Peak of container and consolidation* (estimated probability 0 %)
   Growth ratio < 1. Slow down of the transport sector. The containerization limit has been exceeded. China and India have low economical growth. Flexibility is more important than economies of scale. Vessels have become much smaller because large vessels cannot be filled. digitalization is only growing slowly. Hub-and-spoke systems connect the ports. Three or four large shipping companies have remained in the market. Digital giants are not interested in the market as other markets promise higher profits and growth. Automatization is mostly focused on landoperations. Vertical integration do not promise convincing benefits. Alliances are no longer of great value either.

Saxon and Stone describe developments assuming a *growth ratio* between 0.9 and 1.5, leading to a volume of the transport of 2 to 5 times as large as it is today. Africa and Southeast Asia will be more important for shipping. Further market consolidation is assumed due to vicious circles of overcapacity and consolidation, so by 2067 there will only be three or four major shipping companies left. Alliances will be of minor importance. Technical progress will lead to autonomous vessels with a tonnage of 50,000 TEU dominating the container shipping and to self-propelled containers on land as on sea. digitalization makes it possible to concentrate on customer needs, which will make freight forwarder unnecessary. In addition, processes are carried out automatically, digitally and computer-monitored and enable punctual and transparent arrival. It will be possible to create additional premium services with special, individual benefits for customers. There will be a merger of physical and digital giants.

In conclusion, the two studies agree that the container market will change dramatically in the future. Both anticipate growth in transportation, with an emphasis on the future importance of China and especially India. In addition, they assume that alliances will loose importance, and concentration on individual companies will continue. Both expect digital giants breaking into classic industry due to their strength in technology and digitalisation. Technical progress in propulsion, autonomous control, data exchange and analysis is given a decisive importance. Other new technologies such as recycling, 3D printing and robotization will lead to the relocation of production closer to the customer and less material usage, which requires less global transport capacity. The extent of this influence is difficult to assess. While Saxon and Stone assume larger ships of up to 50,000 TEU, study Fenton et al. (2018) think that smaller and flexible vessels will be necessary. In preparation for the future, both studies recommend investing in digitalization in order to improve the value chain and meet customer requirements such as reliability. Both studies agree, that the future of container shipping will continue to be very dynamic and change rapidly.

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