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Jorin Dornemann, Nicolas Rückert, Kathrin Fischer, and Anusch Taraz

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Artificial Intelligence and Operations Research in Maritime Logistics

Jorin Dornemann [1], Nicolas Rückert [2], Kathrin Fischer [2] and Anusch Taraz [1]

1 – Hamburg University of Technology, Institute of Mathematics

2 – Hamburg University of Technology, Institute for Operations Research and Information Systems

Purpose: The application of artificial intelligence (AI) has the potential to lead to huge progress in combination with Operations Research methods. In our study, we explore current approaches for the usage of AI methods in solving optimization problems. The aim is to give an overview of recent advances and to investigate how they are adapted to maritime logistics.
Methodology: A structured literature review is conducted and presented. The identified papers and contributions are categorized and classified, and the content and results of some especially relevant contributions are summarized. Moreover, an evaluation, identifying existing research gaps and giving an outlook on future research directions, is given.
Findings: Besides an inflationary use of AI keywords in the area of optimization, there has been growing interest in using machine learning to automatically learn heuristics for optimization problems. Our research shows that those approaches mostly have not yet been adapted to maritime logistics problems. The gaps identified provide the basis for developing learning models for maritime logistics in future research.
Originality: Using methods of machine learning in the area of operations research is a promising and active research field with a wide range of applications. To review these recent advances from a maritime logistics' point of view is a novel approach which could lead to advantages in developing solutions for large-scale optimization problems in maritime logistics in future research and practice.

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1 Introduction

Artificial Intelligence (AI) is currently one of the major topics in research as well as in practice. It can be used to gain information from analyzing huge datasets, for example for anomaly detection or picture recognition. Simultaneously, Operations Research (OR) is a well-known field and its methods are commonly applied to use given information for developing optimal decisions, e.g. regarding production or scheduling. Especially the Logistics sector uses OR regularly for optimizing their processes, e.g. for optimizing the routing of trucks (Hillier and Lieberman, 2010, p. 4).

In the Logistics sector, Maritime Logistics is of particular importance. More than 11 million tons of containers and dry bulk were shipped across the oceans in 2018. Consequently, maritime transport is described as “the backbone of globalized trade” (UNCTAD, 2019). As a result, fast, efficient, and reliable transportation is necessary. Meanwhile, the advancing digitalization of the sector and the ever-increasing amount of available data are opening up new opportunities. Data collected on ships can be made usable by intelligent methods to extract information. A combination with well-known OR methods offers the possibility to use synergies and advantages of both methods.

In this work, we examine how the combination of OR and AI is discussed, evaluated, and applied in the scientific community. The objective of this paper is to identify opportunities for the combined application of OR and AI in Maritime Logistics, to generate an overview as well as to detect research gaps. This includes questions regarding application areas which are (probably) most suitable for utilizing OR and AI, as well as the discussion where the two methods overlap.

The paper is structured as follows: In Section 2 we give some theoretical background on OR and AI/Machine Learning, respectively. This is followed in Section 3 by describing our methodical approach to the literature review. After this we will present our findings and highlight some important publications in Section 4. In Section 5 we then identify some research gaps before we conclude and give an outlook on future research perspectives.

2 Theoretical Background

2.1 Planning problems in maritime logistics

There are many different planning problems in Maritime Logistics, which can be categorized by their area of application.

Planning problems at sea are, for example, the strategic design of a container liner network, i.e. on the selection of ports and routes as well as the operative decision about the vessel speed (e.g. Meng, et al., 2014).

Various planning problems exist with regard to terminals and ports, since this is where Logistics at sea and Logistics on land meet. The planning of the positioning and the scheduling of a vessel at the berth, called Berth Allocating Problem (BAP), is a relevant planning problem. At the terminal, several planning problems regarding intralogistics and storage yard optimization have to be addressed (Anwar, Henesey and Casalicchio, 2019). In particular, the routing of trucks, straddle carriers or AGVs (automated guided vehicles) and the efficient storage of containers to reduce movements of cranes and reshuffling are analyzed in research (Stahlbock and Voß, 2007; Speer and Fischer, 2017; Böse, 2020).

The connection of ports and terminals with the so-called Hinterland can be enabled through different modes of transport like truck, rail or inland vessel. For all modes of transport different planning problems exist, like the decision which mode of transport to use or the routing of the vehicle. Furthermore, repositioning of empty containers is an important aspect of planning problems in practice as well research (Braekers, Caris and Janssens, 2013, e.g.). Also, methods of revenue management can be applied to Maritime Logistics, for example for container shipping companies (Zurheide and Fischer, 2012).

Generally speaking, all these problems are optimization problems and hence can be tackled with OR methods, while to use AI a large amount of data is necessary. These data can be supplied by public organizations or can be obtained from and stored by private organizations. For research, open data platforms are necessary to utilize AI. Automated identification systems (AIS), which record and store vessel positions and details like ships' headings, is a popular data source for the scientific community (e.g. Nguyen, et al., 2018). Furthermore, weather data can be used as well for routing optimization. In practice, most companies can theoretically utilize their own data, e.g. regarding customer inquiries.

The use of AI is suitable for forecasting travel times (for vessels and trucks) and ship arrivals (Hill and Böse, 2017). Image recognition for identifying of number plates or container numbers can also be applied (e.g. LeCun, Bengio and Hinton, 2015).

2.2 Operations Research

OR is used to coordinate operations, processes, and activities in organizations, such as companies and military institutions (Hillier and Lieberman, 2010, pp. 3–4). It can be defined as the development and application of quantitative models and methods for decision support (Kandiller, 2007; Eiselt and Sandblom, 2010). The aim is to find the optimal solution for a planning problem. These problems come, for example, from the field of transport planning or personnel deployment planning (Hillier and Lieberman, 2010, p. 4).

Mathematical models in OR can be distinguished into (amongst others) linear programming (LP), mixed integer programming (MIP) and non-linear programs (NLP) (Suhl and Mellouli, 2013, p. 12). Furthermore, also simulations, Markov chains and game theory are methods and concepts of OR amongst others (Hillier and Lieberman, 2010).

There are two categories of solution procedures. On the one hand, a model can be solved to optimality. This involves algorithms such as the Simplex procedure or the Branch and Bound method. These methods in most cases require a lot of time to compute the optimal solution for large realistic problems (Rothlauf, 2011, p. 68). On the other hand, there are heuristics. Their goal is not to find the optimal solution, but to achieve a good solution fast. However, it usually cannot be guaranteed that a heuristic solution is close to the optimal one (Rothlauf, 2011, p. 85). Often heuristics are developed specifically for a given problem. As a consequence, a wide range of different heuristics for different problems exists, e.g. the savings procedure for the VRP. Heuristics that can be applied to different problems are called metaheuristics. Examples are Tabu Search or Simulated Annealing (Suhl and Mellouli, 2013, p. 13).

2.3 Artificial intelligence

AI is concerned with making computers capable of emulating intelligent behavior (Holsapple and Jacob, 1994, p. 3). The overall goal is to make machines mimic “cognitive“ functions, such as “learning“ and “problem solving“ (Russell and Norvig, 2009, p. 2). Approaches include statistical methods, computational intelligence, and traditional symbolic AI. Many different tools are used in AI, and besides versions of search and mathematical optimization there are also methods based on logic, probability, and economics.

AI also includes evolutionary techniques, which use biologically inspired mechanisms leading to the evolution of new solutions, thus solving global optimization problems. Common approaches are the “Ant Colony Optimization” (Dorigo, 1992) or the “Particle Swarm Optimization” (Kennedy and Eberhart, 1995), where swarm intelligence is mimicked in a setting where different agents interact with one another while moving through the solution space based on simple mathematical formulae over the particle’s position and velocity to find local and global optima.

Another approach are genetic algorithms, which use biologically inspired operators to generate high-quality solutions (Mitchell, 1997, p. 249). These algorithms are probabilistic methods based on a population-based process which relies on operators such as mutation, crossover and selection used to vary the individuals of that population. These individuals represent encoded solutions to the problem (Homberger, Bauer and Preissler, 2019, p. 143). Genetic algorithms have been successfully applied to solve learning and optimization problems.

While there is no clear cut between AI and heuristic approaches from the field of OR, genetic algorithms as well as evolutionary algorithms use techniques to emulate AI and are therefore regarded as a subfield of AI (Homberger, Bauer and Preissler, 2019, p. 136).

As a theoretical concept, AI has been around for some time, but just recently AI has broken away from being just a theoretical concept to being applied to business problems. This is because of the wide availability of GPUs (graphics processing units), which allow to use parallel processing in a faster, cheaper and more powerful way. Their highly parallel structure makes them more efficient than general-purpose CPUs for algorithms where the processing of large blocks of data is done in parallel. Furthermore, the ascent of AI has to do with a deluge of any kind of data such as videos, images and geospatial data combined with practically infinite storage available (Ongsulee, 2017).
According to Arthur Samuel in 1959, Machine Learning (ML) as a subset of AI is the subfield of computer science that gives “computers the ability to learn without being explicitly programmed” (Muñoz Medina, 2014). It is particularly interesting in the area of optimization, as it addresses the study of algorithms that improve automatically through experience (Mitchell, 1997, p. 2). Machine learning is employed in a range of computing tasks where designing and programming explicit algorithms with good performance is difficult or infeasible. ML focuses on performing a task given some finite (and usually noisy) data, called „training data“ (Bengio, Lodi and Prouvost, 2018, p. 2). It applies algorithms that analyze data, learn from it and make informed decisions based on the learned insights. ML can serve two purposes. Firstly, instead of using extensive computations to find a solution, the expert uses ML to achieve a fast approximation. In this case, learning is used to build such approximations in a generic way, i.e. without deriving explicit algorithms. This method assumes expert knowledge of the problem. For the second purpose, this expert knowledge might not be sufficient

and known methods and algorithms may be dissatisfying. In that case ML is applied to learn from the decisions algorithms made and to learn out of this experience to find the best performing behavior (Bengio, Lodi and Prouvost, 2018, p. 3).

In machine learning, one differentiates between different learning methods. In supervised learning, training data consisting of input and target pairs is used to find a function that for every input has an output which is as close to the target as possible. Finding such a function is called learning and is solved via optimization problems, where the measure of discrepancy between the output and the target can be chosen depending on the task (Bengio, Lodi and Prouvost, 2018, p. 6). The case where only the input is provided is called unsupervised learning. For example, the aim is to discover groups of similar examples in the data, called clusters, or to determine the distribution of the data within the input space, called density estimation (Bishop, 2006, p. 3). Another learning method is reinforcement learning, in which case an agent interacts with an environment through a Markov decision process. The problem is to find suitable actions to take in a given situation in order to maximize a reward, but, in contrast to supervised learning, here the learning algorithm is not given examples of optimal outputs. Instead it must find them through trial and error (Bishop, 2006, p. 3). A popular tool in ML is the decision tree, which is a decision support tool that uses a tree-like structure to create a model for decisions and their possible consequences. A decision tree consists of nodes and branches. The crucial part in building a decision tree is deciding which features to choose and what conditions to use for splitting (branching). ML can be used to learn these features from data by recursively partitioning the source set into subsets

(Quinlan, 1987), which constitute the successor children of that node, following splitting rules based on classification features (Shalev-Shwartz and Ben-David, 2014, p. 255).

One particularly interesting subfield of ML is Deep Learning (DL) (LeCun, Bengio and Hinton, 2015), a very young field of AI based on artificial neural networks. DL focuses on building large parametric approximators using deep neural networks (DNN), which are neural networks with a high number of layers. With these high dimensional networks one can achieve an unprecedented flexibility to model highly complex, non-linear relationships between variables (Kraus, Feuerriegel and Oztekin, 2020, p. 628). It has only recently started to gather more attention, as the methods are dependent on the availability of both computational power as well as large datasets. But since nowadays large datasets are common in most businesses, Deep Learning is on the way to becoming the industry standard for predictive analytics in OR (Kraus, Feuerriegel and Oztekin, 2020). Figure 1 illustrates the embedding of the discussed subfields of AI and the relation to OR.

In summary, in a broader sense AI does not only include algorithms from machine learning and deep learning, but one can also include intelligent algorithms and heuristics such as genetic algorithms or evolutionary algorithms such as particle swarm optimization.

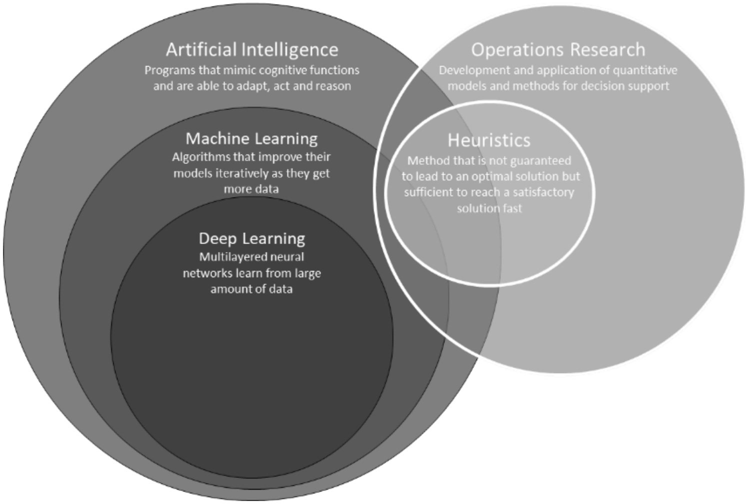

Figure 1: Subfields of AI and OR

2.4 Differentiation

To understand how AI, and ML in particular, can be used to complement OR techniques to tackle optimization problems, one has to understand the differences, but also the similarities between OR and ML.
Machine Learning and OR both use iterative methods to solve problems of a practical nature. Optimization problems in OR can be formulated as a constrained maximization or minimization program, where the objective

function defines the measure of solution quality (Bengio, Lodi and Prouvost, 2018, p. 4). Many learning problems are also formulated as minimization of a loss function, which generally is the measure of discrepancy between the output, meaning the predictions of the model being trained, and the target (Le Roux, Bengio and Fitzgibbon, 2011, p. 404).

But even though they are closely related, especially through optimization, there are also aspects which separate these two areas, namely the methods used to tackle these problems. In general, while AI is used to extract information out of a (big) dataset to gain knowledge, OR is used to support decision making by using this knowledge. OR mainly focuses on solving optimization problems through knowledge of the structure of the problem. It requires some insight into solving that kind of problem, which is then passed to the machine, but it is not based on a model obtained by training on a data set and does not adapt itself iteratively over time. An ML algorithm on the other hand is an algorithm which adapts itself to data (Bishop, 2006, p. 2). The core objective is to generalize from its experience, which means the ability to perform accurately on new examples after having experienced a training data set (Mohri, Rostamizadeh and Talwalkar, 2012, p. 7).

While optimization algorithms can minimize the loss on a training set, machine learning is concerned with minimizing the loss on unseen samples, called test data. Because of this, alternative techniques have to be used in order to prevent the model from overfitting on the training data (Le Roux, Bengio and Fitzgibbon, 2011, p. 403). This is not to say that an OR solution method is in general worse than an ML method. In fact, OR methods might be faster than an ML method, because they are perfectly suited for this exact problem. But an ML method can be more flexible and generalize to a wider range of problems without the need for expert knowledge of structural properties.

There are different possibilities to connect OR and AI methods to exploit their synergies. For example, Bengio, Lodi and Prouvost (2018) differentiate between three possible algorithmic structures and categorize approaches accordingly. In the category end-to-end learning, an AI is trained to develop a solution directly from the problem input. In our work, also heuristic solution methods like Genetic Algorithms are counted towards this category. The category Learning meaningful properties of optimization problems includes methods where AI is used to generate further information for the parametrization before the actual optimization. The third category Machine learning alongside optimization algorithms uses a structure in which the OR method repeatedly requests machine learning methods for further optimization. So, the two methods alternate in an iterative process, and this process ends when a good solution is found (Le Roux, Bengio and Fitzgibbon, 2011, p. 422).

As seen above, because of the similarities of both areas as well as the differences in the methods applied, both areas can profit from each other by combining their knowledge to learn how to solve problems in an efficient way.

3 Methodology of Literature Review

The structure of this literature review is based on the methodology of Tranfield, Denyer and Smart (2003).

For the selection of the studies it is necessary to define the time horizon, keywords and to select databases. Considering the objective of the paper and the currentness of the topic, the time horizon is set from 2010 to today (March 2020). To find also most recent research results, the database arxiv (with not yet reviewed papers) was included in the search. Furthermore, the databases Scopus, Web of Science and IEEE are used, aiming at finding all relevant publications from different disciplines like management, Logistics and engineering.

The following table describes the structure of the search strings used consisting of four 'and' pillars with each of them having different terms combined with 'or'.

Table 1: Search terms

	AND	AND	AND	AND
OR	Operations research	Artificial intelligence	Logistics	Maritime
OR	Optimization	Deep learning	Transport	Port
OR		Machine learning	Traffic	Container
OR			Routing	Ship
OR			Scheduling	Hinterland

The combinations of these terms in the query are searched in title, abstract and keywords of publications in the databases. In the next step, the publications were screened by analyzing title and abstract. It turned out that when using this precise search string, many articles were listed that focus on other topics. These papers either do not fit because of the method (not AI and OR) or of the research field (not Maritime Logistics). For example, some papers utilize AI and OR for software engineering using containers in the programming language Java, which is not related to containers in the maritime definition. Furthermore, many papers list AI in their keywords, but do not make clear what AI is used for.

In total, more than 200 publications were found in the four databases (199 Scopus + 55 IEEE + 49 Web of Science + 15 Arxiv). The above-mentioned screening and selection results in 40 publications, excluding duplicates (22 Scopus + 5 IEEE + 15 Web of Science + 3 Arxiv). Furthermore, some snowballing was done to find additional publications. In the snowballing procedure, the reference list of already found and selected papers is analyzed with regard to suitable further papers (backward snowballing). Furthermore, the papers citing a paper can also be analyzed (forward snowballing). These further papers are then evaluated and, if appropriate, are added to the literature review (Wohlin, 2014) Ten new publications were found through snowballing techniques.

4 Results of Literature Review

4.1 Overview

Most of the publications were published in the second half of the decade, which shows that the relevance of the topic has recently been increasing. Figure 2 shows the number of relevant publications.

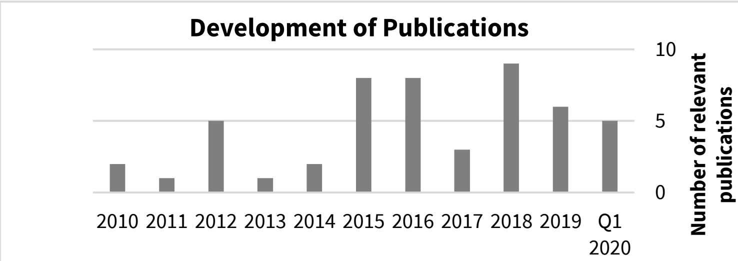

Figure 2: Development of Publications

The application areas range across all fields of Maritime Logistics. Many publications use AI and/or OR for oversea routing. Authors utilize, for example, Automatic Identification System (AIS) data for trajectory predictions to avoid ship collision or weather data to avoid heavy storms (e.g. Lee, et al., 2018; Li, Liu and Yang, 2018; Virjonen, et al., 2018). Furthermore, some papers deal with Berth Allocation Problems (BAP) and related issues like quay crane scheduling or BAP for bulk terminals (Pratap, et al., 2015; e.g. Castilla Rodríguez, et al., 2020). The distribution of the application areas is shown in Figure 3.

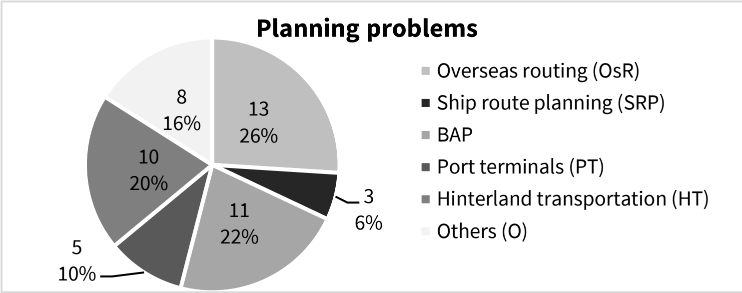

Figure 3: Planning problems (plan. prob.) of AI in Maritime Logistics

As described in Section 2, there are different possibilities to combine the strengths of OR and AI. Following our categorization based on Bengio, Lodi and Prouvost (2018), there are three categories. For a better overview, end-to-end learning is split into those papers using heuristics like genetic algorithms or ant colony algorithms, and those that do not use evolutionary methods. End-to-end learning is used in most papers as can be seen in Figure 4.

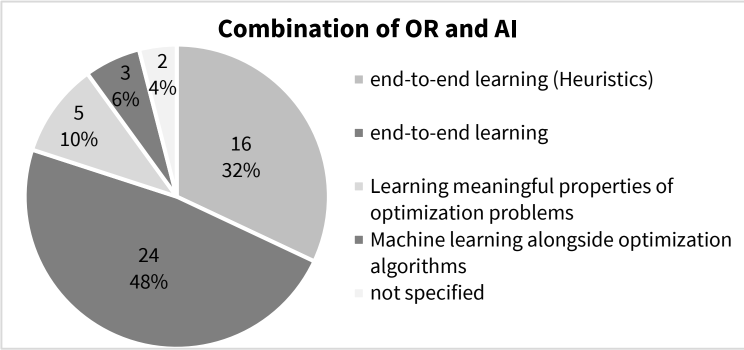

Figure 4: Combination of OR and AI in Maritime Logistics

Regarding the different AI methods and algorithms, ant colony algorithms and genetic algorithms make up a large part of the methods used for problems in Maritime Logistics (see Figure 5). Deep learning is used in twelve publications. In the papers, different approaches of machine learning like k-nearest-neighbor or support vector machines are used (Zhang, et al., 2016; e.g. Virjonen, et al., 2018). In addition, in some of the papers several methods are applied simultaneously or are compared. In this case, the dominant method is considered only once in Figure 5. All in all, it can be stated that intelligent heuristics dominate the usage of AI. For this reason, most publications use unsupervised algorithms.

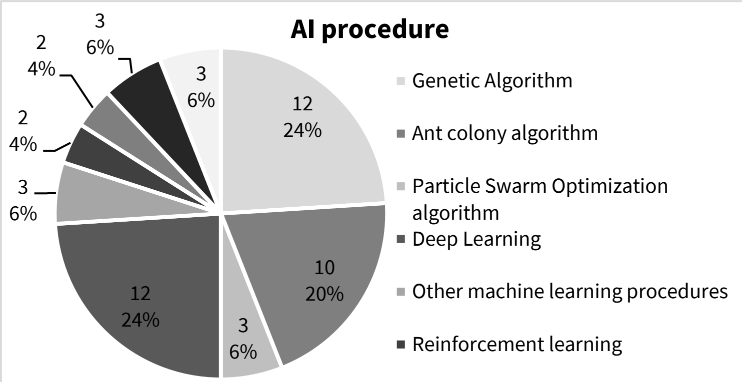

Figure 5: AI procedure

The following table gives an overview of the 50 papers that we analyzed. Moreover, it describes the categories Combination of AI & OR, AI methods used and the respective planning problem in more detail.

Table 2: Papers analyzed

Author	Year	Combination of AI & OR	AI procedure	Application area (Abbr. of plan. prob.)
Tsou, et al.	2010a	end-to-end learning	Ant Colony Algorithm	Collision Avoidance Path Planning (OsR)
Tsou, et al.	2010b	end-to-end learning	Genetic Algo-rithm	Collision Avoidance Path Planning (OsR)
Xu, et al.	2011	end-to-end learning	Back Propa-gation Neu-ral Network	Vessel Trajectory Predictor (OsR)

Author	Year	Combination of AI & OR	AI procedure	Application area (Abbr. of plan. prob.)
Escario, et al.	2012	end-to-end learning	Ant Colony Algorithm	Optimal Trajectories of Autonomous Surface Vessels (OsR)
Kaveshgar, et al.	2012	end-to-end learning	Genetic Algorithm	Quay Crane Scheduling Problem (BAP)
Lalla-Ruiz, et al.	2012	Machine learning alongside optimization algorithms	Path Relinking	Berth Allcoation Problem (BAP)
Rodriguez-Molins, et al.	2012	end-to-end learning	Genetic Algorithm	Berth Allcoation Problem (BAP)
Wojtusiak, et al.	2012	Machine learning alongside optimization algorithms	Learnable Evolution Model (LEM)	Variant of Vehicle Routing Problem (HT)
Expósito-Izquierdo, et al.	2013	end-to-end learning	Estimation of Distribution Algorithm	Quay Crane Scheduling Problem (BAP)
Lajjam, et al.	2014	end-to-end learning	Ant Colony Algorithm	Quay Crane Scheduling Problem (BAP)
Ting, et al.	2014	end-to-end learning	Particle Swarm Optimization	Berth Allcoation Problem (BAP)

Author	Year	Combination of AI & OR	AI procedure	Application area (Abbr. of plan. prob.)
Dobrkovic, et al.	2015	end-to-end learning	DBSCAN, Genetic Algorithm, Ant Colony Algorithm	Estimating Ship Arrival with AIS (O)
Gue, et al.	2015	end-to-end learning	Ant Colony Algorithm	Ship Routing (SRP)
Kambey, et al.	2015	end-to-end learning	Ant Colony Algorithm	Container Truck Hinterland (HT)
Lazarowska	2015	end-to-end learning	Ant Colony Algorithm	Oversea Routing (OsR)
Orgaz, et al.	2015	end-to-end learning	Genetic Algorithm, Data Mining Case Based Reasoning	Route Planning (HT)
Pratap, et al.	2015	end-to-end learning	Genetic Algorithm	Robust Berth Allocation for Bulk Terminals (BAP)
Supeno, et al.	2015	end-to-end learning	Genetic Algorithm	Container Terminal Truck Scheduling (PT)

Author	Year	Combination of AI & OR	AI procedure	Application area (Abbr. of plan. prob.)
Xue, et al.	2015	end-to-end learning	Ant Colony Algorithm	Container Drayage with Truck (HT)
Daranda	2016	end-to-end learning	Neural Network	Maritime Traffic Prediction (O)
Gómez, et al.	2016	end-to-end learning	Neural Network	Operational Parameter Forecasts in Automated Container Terminals (PT)
Hottung, et al.	2016	end-to-end learning	Biased Random-Key Genetic Algorithm	Container Pre Marshalling Problem (HT)
Lisowski	2016	end-to-end learning	Neural Network	Ship Trajectory Optimisation (OsR)
Liu, et al.	2016	end-to-end learning	Particle Swarm Optimization, Artificial Fish Swarm Algorithm	Quay Crane Scheduling Problem (BAP)

Author	Year	Combination of AI & OR	AI procedure	Application area (Abbr. of plan. prob.)
van Riessen, et al.	2016	Machine learning alongside optimization algorithms	Decision Tree	Hinterland Transport Mode Decision (HT)
Yan, et al.	2016	end-to-end learning	Unsupervised Data Mining	Vessel Movement Analysis and Pattern Discovery (O)
Zhang, et al.	2016	Learning meaningful properties of optimization problems	Neural Network, Support Vector Machine	Service Maintenance, Short-term-traffic Forecast Ferry Terminal (PT)
Garcia-Flores, et al.	2017	Learning meaningful properties of optimization problems	Not specified	Demand Forecasting Rail Scheduling at Container Port (HT)

Author	Year	Combination of AI & OR	AI procedure	Application area (Abbr. of plan. prob.)
Margain, et al.	2017	end-to-end learning	Ant Colony Algorithm	Capacitated Vehicle Routing Problem (HT)
Protopapadakis, et al.	2017	end-to-end learning	Deep Learning, Deep Stacked Autoencoders	Anomaly Detection (O)
Gao, et al.	2018	end-to-end learning	Recurrent Neural Network, Deep Learning	Vessel Trajectory Predictor (OsR)
Hoseini, et al.	2018	end-to-end learning	Hybrid Imperialist Competitive and Genetic Algorithm	Berth Allcoation problem (BAP)
Lee, et al.	2018	Learning meaningful properties of optimization problems	Data Mining Techniques	Vessel Speed Decision with Wind Data (OsR)
Li, et al.	2018	end-to-end learning	Ant Colony Algorithm	Ship Weather Routing (Oversea) (OsR)
Li, et al.	2018	end-to-end learning	Ant Colony Algorithm	Ship Weather Routing (Oversea) (OsR)

Author	Year	Combination of AI & OR	AI procedure	Application area (Abbr. of plan. prob.)
Liu	2018	end-to-end learning	Genetic Algorithm, Particle Swarm Optimization	Shipping Route Planning (SRP)
Müller	2018	end-to-end learning	Biased Random-Key Genetic Algorithm	Liner Ship Fleet Repositioning Problem (SRP)
Nguyen, et al.	2018	end-to-end learning	Deep Learning, Recurrent Neural Network	Trajectory Reconstruction, Anomaly Detection and Vessel Type Identification (O)
Virjonen, et al.	2018	end-to-end learning	K-Nearest Neighbour Algorithm	Ship Trajectory Prediction (OsR)
Kanović, et al.	2019	end-to-end learning	Particle Swarm Optimization, Genetic Algorithm	Ship Lock Zone Controlling (O)

Author	Year	Combination of AI & OR	AI procedure	Application area (Abbr. of plan. prob.)
Larsen, et al.	2019	end-to-end learning	Feedforward Neural Network, Deep Learning	Load Planning Problem (O)
Nguyen, et al.	2019	end-to-end learning	Deep Learning, Recurrent Neural Network	Anomaly Detection (O)
Tang	2019	Not specified	Bee Colony Evolutionary Algorithm	Scheduling of Transport Paths (PT)
Verma, et al.	2019	end-to-end learning	Reinforcement Learning	Ship Load Sequencing in Ports (PT)
Zhao and Shi	2019	end-to-end learning	Recurrent Neural Network, Deep Learning	Vessel Trajectory Predictor (OsR)
Castilla Rodríguez, et al.	2020	Learning meaningful properties of optimization problems	Estimation of Distribution Algorithm	Quay Crane Scheduling Problem, Decision Support (BAP)

Author	Year	Combination of AI & OR	AI procedure	Application area (Abbr. of plan. prob.)
Ham-mouti, et al.	2020	end-to-end learning	Genetic Algo-rithm	Berth Allcoation problem (BAP)
Gkerekos, et al.	2020	Not specified	Not specified	Oversea Routing (OsR)
Hottung, et al.	2020	Learning meaningful properties of optimization problems	Deep Neural Network	Container Pre-Mar-shalling Problem (HT)
Iran-nezhad, et al.	2020	end-to-end learning	Reinforcement Learning	Container Hinter-land Transport (HT)

4.2 In depth-analysis of selected papers

In the following, we highlight some approaches where Machine Learning is used in combination with OR to solve optimization problems in Maritime Logistics. We follow the distinction in Bengio, Lodi and Prouvost (2018) to survey how these techniques are applied. Note that the different sections are not necessarily disjoint.

4.2.1 End-to-End Learning

The first and most obvious approach is to tackle a given combinatorial optimization problem solely with ML techniques. The ML model acts alone and is trained to find solutions to the problem directly from the input.
This is done in Nguyen, et al. (2018). The huge amount of AIS data, namely hundreds of millions of messages every day, provides a huge potential to extract, detect and analyze relevant information. The authors develop a deep learning model to provide an automatic system which can process and extract useful information in an unsupervised way. They train a variational recurrent neural network (RNN), which converts the noisy, irregular-sampled AIS data to consistent and regularly-sampled hidden states that may correspond to specific activities such as “under way using engine”, “at anchor” or “fishing”. Higher levels, meaning task-specific layers of the RNN, correspond to task-specific layers, which are able to address different tasks such as trajectory reconstruction, anomaly detection or vessel type identification. In contrast to state-of-the-art methods, the model is able to jointly address multi-tasking issues (Nguyen, et al., 2018).

Another example is Müller (2018), where AI methods are applied to solve the liner shipping fleet repositioning problem (LSFRP). Liner shipping companies have large networks of connected ports to transport containers by operating several services. These services are modified on a regular basis due to economic and seasonal trends. In that context, vessels are reassigned to other services and have to be repositioned. Repositioning vessels considering the costs for moving the vessels is defined as the LSFRP. For this problem, a biased random-key genetic algorithm (BRKGA) is developed. In contrast to other genetic algorithms, the random-key genetic algorithm aims at encoding the chromosomes with floating point values in the range of [0,1] instead of using integers to eliminate the offspring feasibility problem. This concept was extended to the BRKGA [Gonçalves et al, 2011] by applying a different crossover strategy to generate the new population. While the proposed method is able to find good solutions for smaller instances, it is not able to compete with the current state-of-the-art heuristic for larger instances of the LSFRP. Note that in an attempt to improve the algorithm, the author combines BRKGA with a local search heuristic, which improved the performance. This attempt therefore also fits in the section „Machine Learning alongside OR“, which highlights the fact that these categories should not be seen as mutually exclusive (Müller, 2018).
Larsen, et al. (2019) believe that ML is useful to solve combinatorial optimization problems with incomplete information, because the application has to be able to make decisions on a tactical level, and the ML model is able to use the stochasticity of the problem to quickly predict tactical solutions under uncertainty. They tackle the load planning problem (LPP). The problem is to decide how many of a given set of containers of different types can be

loaded on a given set of railcars of different types and how many of the railcars of each type are needed. The decisions must be made without knowledge of the container weights since this information is not available at the time of assigning the containers. Furthermore, the problem requires solutions in real time, which cannot be generated for the stochastic nor the deterministic version of the problem using commercial solvers. In the training stage, the authors use solutions to the deterministic version of the problem, which can be formulated as a MILP, to train a neural network to predict the solution of the stochastic LPP. It is shown that the ML model is able to quickly find accurate solutions online, because some of the complexity of the problem is outsourced to the training stage (Larsen, et al., 2019).

4.2.2 Learning meaningful properties of Optimization Problems & Machine Learning alongside OR

In many applications, using only ML to find solutions is not the most suitable approach. Rather, ML can be used to provide the optimization algorithm with valuable information to help solve the problem. This can be done in different ways. ML can either be applied to provide additional information to the optimization algorithm, which can be called „Learning meaningful properties of OR problems", or ML is used alongside optimization algorithms. The difference to the previous approach is that the same ML method is frequently called from a master algorithm to support lower level decisions (Bengio, Lodi and Prouvost, 2018).
The first approach is chosen in Lee, et al. (2018), where a speed optimization problem is considered. The aim is to find a Pareto optimal solution by

considering the trade-off between minimizing fuel cost and maximizing service level. Instead of using theoretical fuel consumption functions, data mining techniques are applied to weather archive data to estimate the real fuel consumption considering the variabilities in weather conditions. A Particle Swarm Optimization technique based solver which uses the weather impact data is applied to generate Pareto optimal solutions. A decision support system is developed for Liner operators to decide about sailing speeds of vessels for each leg considering customer requirements, showing the trade-off analysis between fuel consumption and service level. Numerical experiments then show that especially for long voyage legs where weather conditions are highly variable the improvement on fuel estimation is significant, which offers considerable cost improvements (Lee, et al., 2018).
An example for the second approach is Hottung, Tanaka and Tierney (2020). They adopt the method of frequently calling an ML model for solving the Container Pre-marshalling Problem (CPMP). This problem is concerned with the re-ordering of containers in container terminals during off-peak times so that containers can be quickly retrieved when the port is busy. The goal is to find a minimal sequence of container movements that sort a set of container stacks according to the time each container is expected to exit the yard. While there are a number of exact methods to solve this problem, their computation time is too long to be used in a decision support system. This is why there is a large number of heuristics, which are highly specialized, costly and time-intensive to design. Hottung, Tanaka and Tierney therefore develop a so called Deep Learning Heuristic Tree Search (DLTS), which merges the heuristic approach of a tree search with DNNs for the CPMP to generate heuristics for branching and bounding in the search tree

without a deep understanding of the structures of the CPMP. The DNNs are trained offline via supervised learning on existing (near-)optimal solutions for the CPMP to learn solution strategies and lower bounds to the CPMP. In the tree search procedure the DNNs are then integrated to decide which branch to choose next and to prune the search tree. While DLTS does this with extraordinarily little expertise input from the user regarding the problem, it is able to outperform state-of-the-art heuristic solutions to the CPMP. This shows the huge potential in solving optimization problems with the help of ML (Hottung, Tanaka and Tierney, 2020).

A similar approach is chosen in van Riessen, Negenborn and Dekker (2016). Their motivation is to derive real-time decision rules for suitable allocations of containers to inland services. To obtain this, first optimal solutions to problem instances are generated by an exact solving method, which is not suitable for real-time decisions because of the computation time as well as incomplete information. Then a decision tree is created using a supervised learning method, which learns decision rules for the allocation of a container to a suitable service based on the container and order properties, such as the time of availability, the transportation lead time, and container mass. This set of rules can be used in real-time as a decision tool to provide a set of suitable services to a human planner. A case study shows that the developed decision support system is able to reduce inefficiency and therefore transportation costs without extensive IT development (van Riessen, Negenborn and Dekker, 2016).

Another application of ML alongside optimization algorithms is done in Expósito-Izquierdo, et al. (2013). They apply an evolutionary algorithm, the

Estimation of Distribution (EDA) algorithm, to solve the Quay Crane Scheduling Problem (QCSP), where the goal is to minimize the handling times when performing the tasks of loading and unloading containers onto/from a container vessel. While EDAs are well suited for exploring the solution space and locating promising regions, they have certain shortcomings in finding local optimal solutions. To overcome these limitations, the authors combine their EDA with a local search algorithm, which is used to carry out the intensification of the schedules found. But since local search is a time-consuming algorithm, it is only applied to a subset of solutions with the best objective function value. Their computational results show that this is a promising method to obtain high quality solutions in a competitive time frame (Expósito-Izquierdo, et al., 2013).

This approach is continued in Castilla Rodríguez, et al. (2020). Their motivation is to overcome the limitations of the previously developed algorithm, namely the limitation to deterministic data and the assumption that there are no constraints with respect to internal delivery vehicles. They combine the previously developed intelligent evolutionary algorithm, which generates high quality schedules for the cranes, with a simulation model that incorporates uncertainty and the impact of internal delivery vehicles. The proposed method allows to combine the strengths of mathematical optimization algorithms which implement ML with real scenarios where non-deterministic scenarios may rule out highest quality solutions in theory, as these theoretically optimal solutions may be limited by other factors such as the availability of internal delivery vehicles. This again shows that applying ML techniques to operational research problems provides more flexibility in real life scenarios, where decisions have to be made in real time and under uncertainty (Castilla Rodríguez, et al., 2020).

5 Conclusion and outlook

A literature review of reports and journal papers on the combination of AI and OR in Maritime Logistics of the last ten years was conducted. The findings are categorized by the different applications of AI in Maritime Logistics as well as the different techniques, and an overview on the current state of research is provided. This section recaps and presents future research directions.

The problems that occur when searching for new developments in the usage of Machine Learning for optimization problems are two-fold. On the one hand there is an inflationary use of AI keywords in the area of optimization publications as this area gains more and more attention. On the other hand, even if AI methods are used, the descriptions of these methods are often condensed in a way that makes it difficult to understand the chosen models.

Besides, it was shown that ML can be applied in different ways to tackle optimization problems. On the one hand, there is the setting of end-to-end learning, where ML models are trained to find solutions directly from the input. On the other hand, ML is also used alongside OR methods. AI methods are used to help with the branching and bounding decisions as well as with modelling uncertainty in decision making in a better way than standalone OR models are able to. There are many publications in the area of OR which are concerned with modelling uncertainty, but which do not use ML methods. To adapt these models and apply ML techniques to better model uncertainty is a promising research gap for future research.

Standard ML methods, especially evolutionary algorithms, are still the most common approach. But there is a rising interest in using deep learning methods as a new technique to tackle optimization problems, which is due to the new possibilities that the wide availability of GPUs offers in terms of computation power. It is noteworthy that most of the approaches which use ML methods to tackle optimization problems in Logistics choose end-to-end methods to get the solution directly from the input, rather than implementing ML techniques in existing OR algorithms. But with the increasing interest in deep learning, new approaches of combining these two areas become popular. Especially the approach chosen by e.g. Hottung et al. (2020) to implement deep neural networks into search trees appears to be promising. These deep learning techniques which allow to model highly complex non-linear relationships between variables offer a great perspective to support existing OR solution methods and will be an important factor in future research.

Most of the applications of ML in Maritime Logistics rely on AIS data as their main input, which is due to the broad availability of these large datasets. This is also the reason why applications in other areas of Maritime Logistics apart from routing vessels are underrepresented. To use ML also at the intersection of Logistics at sea and Logistics on land (terminals and hinterland), more data needs to be provided in order to create more possibilities for the application of models which rely on large datasets. There has also been a growing interest in combining ML and OR to let programs automatically learn heuristics for optimization problems to avoid the costly and time-intensive development of highly specialized heuristics by humans. But our research also has shown that there are only a few attempts to transfer these methods to problems in Maritime Logistics. This research gap may be due to the lack of IT infrastructure compared to other areas of Logistics, but it also offers a great perspective for future research to apply these new ML approaches with the help of the ever-increasing amount of data available to problems of Maritime Logistics.

Although most of the approaches presented in this literature review are just the first steps in trying to apply ML to enhance the performance of solution methods for optimization problems, it has a huge potential to produce efficient solution strategies for optimization problems in the future. Hence, there are many opportunities for future research to exploit the possibilities of applying AI to optimization problems in Maritime Logistics.

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