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Invited Review

The synergistic effect of operational research and big data analytics in greening container terminal operations: A review and future directions

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A B S T R A C T

Container Terminals (CTs) are continuously presented with highly interrelated, complex, and uncertain planning tasks. The ever-increasing intensity of operations at CTs in recent years has also resulted in increasing environmental concerns, and they are experiencing an unprecedented pressure to lower their emissions. Operational Research (OR), as a key player in the optimisation of the complex decision problems that arise from the quay and land side operations at CTs, has been therefore presented with new challenges and opportunities to incorporate environmental considerations into decision making and better utilise the 'big data' that is continuously generated from the never-stopping operations at CTs. The state-of-the-art literature on OR's incorporation of environmental considerations and its interplay with Big Data Analytics (BDA) is, however, still very much underdeveloped, fragmented, and divergent, and a guiding framework is completely missing. This paper presents a review of the most relevant developments in the field and sheds light on promising research opportunities for the better exploitation of the synergistic effect of the two disciplines in addressing CT operational problems, while incorporating uncertainty and environmental concerns efficiently. The paper finds that while OR has thus far contributed to improving the environmental performance of CTs (rather implicitly), this can be much further stepped up with more explicit incorporation of environmental considerations and better exploitation of BDA predictive modelling capabilities. New interdisciplinary research at the intersection of conventional CT optimisation problems, energy management and sizing, and net-zero technology and energy vectors adoption is also presented as a prominent line of future research.

1. Introduction

Maritime transport is by far the most cost-effective mode to move high volume goods and raw materials around the globe, carrying over 90% of the world's trade (ICS, 2019). Seaborne container trade, in particular, accounts for approximately 60% of all world seaborne trade, which was valued at around 12 trillion U.S. dollars in 2017 (Statista, 2020). The quantity of goods carried by containers has risen from around 102 million metric tons in 1980 to about 1.83 billion metric tons in 2017 (Statista, 2020), and likewise vessels and Container Terminals (CTs)[1] have increased significantly in size and capacity. Existing ultra large container vessels have a carrying capacity of around 24,000 Twenty-foot Equivalent Unit (TEU) (MarineInsight, 2021), and container ports can handle over 40 million TEU a year (World Shipping Council, 2020).

CTs, as the forefront of the intermodal transhipment between sea and land, have been therefore presented with an unprecedented increase in intensive workload imposed simultaneously from the sea and the land sides. They are responsible for handling a wide range of interrelated operations and activities, and thus a series of planning and scheduling tasks with a significant level of uncertainty, complexity, and interdependence. At the same time, CTs are facing with an ever-increasing pressure to monitor and reduce their environmental externalities. They are most often located in proximity to residential areas and emissions from the vessels mooring at their quay sides and their handling equipment, as well as emissions from the movement of internal and external trailer trucks within their remit are increasingly highlighted. Shipping-related particulate matter emissions are known responsible for approximately 60,000 deaths annually, with most deaths occurring

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[1] A full list of acronyms used within the paper is available in Appendix A

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near coastlines in Europe, East Asia and South Asia (Corbett et al., 2007), and vessels are becoming the largest polluters of mega port cities, such as Los Angeles (Barboza, 2020). Greenhouse gas emissions are also quite substantial in port cities, and in 2011 only shipping emissions in ports accounted for 18 million tonnes of CO_2 emissions, and the largest proportion of these emissions came from containerships (Merk, 2014). Incorporating pollution-related concerns into decision-making has, therefore, become an important challenge for container terminal operators.

Operational Research (OR) has long played a prevailing part as a key contributing science in the optimisation of CTs' decision problems. Berth allocation, stowage planning, quay crane allocation and scheduling, stacking optimisation, storage and space allocation, quay side and land side transport planning are all examples of well-studied OR problems that arise in the context of CTs. A key challenge in the face of the OR of the 2020s in general, and in the context of CT operations in particular, pertains to its capability in: (i) incorporating the emergent sustainability concerns and (ii) embracing the 'big data' movement. Multiple review papers and editorial notes have been published in leading OR journals to reflect both challenges and set these as future agendas for OR in its various domains of application (Agarwal & Dhar, 2014; Barbosa-Póvoa, da Silva, & Carvalho, 2018; Bektaş, Ehmke, Psaraftis, & Puchinger, 2019; Choi, Wallace, & Wang, 2018; Gunasekaran, Irani, & Papadopoulos, 2014; Hazen, Skipper, Boone, & Hill, 2018; Mortenson, Doherty, & Robinson, 2015; Tang & Zhou, 2012; White & Lee, 2009). The synergy between OR and different Big Data Analytics (BDA), machine learning and data mining tools for addressing challenges and opportunities that are created by the availability of big data and major advancements in machine intelligence (Agarwal & Dhar, 2014) has been particularly highlighted (Corne, Dhaenens, & Jourdan, 2012; Hindle, Kunc, Mortensen, Oztekin, & Vidgen, 2020; Kraus, Feuerriegel, & Oztekin, 2020; Meisel & Mattfeld, 2010), and research on the two-way interplay between OR and BDA has been intensified. Within the context of CT operations, OR incorporation of sustainability and environmental requirements, and exploitation of the 'voluminous' and 'velocious' data that is generated and stored by CT operators from their round-the-clock operations is significantly lagging behind, and a clear agenda for future research in the area is rather absent from the state-of-the-art literature. While environmental considerations have been scantily incorporated into different CT decision problems such as berth allocation (De, Pratap, Kumar, & Tiwari, 2020), quay crane scheduling (Yu, Wang, & Zhen, 2016), yard crane deployment (Yu, Li, Sha, & Zhang, 2019), and yard crane scheduling (Sha et al., 2017), and the collective effect of OR and BDA has been rarely exploited in areas such as the container reshuffling and relocating problem (Maldonado, González-Ramírez, Quijada, & Ramírez-Nafarrate, 2019; Zhang, Guan, Yuan, Chen, & Wu, 2020b), integrated berth allocation and quay crane assignment (Yu et al., 2018) and optimal assignment of external trucks to time slots (Caballini, Gracia, Mar-Ortiz, & Sacone, 2020), the pertinent literature in both areas is still very fragmented and divergent and there is a significant need for a guiding framework. In this paper, we review the literature on the application of OR and BDA, and the incorporation of environmental considerations into CT decision problems, and shed light on multiple prominent and untapped research opportunities with significant real-life applications and scientific contributions at the intersection of OR, BDA and environmental considerations incorporation into CT operational planning. The paper will, therefore, seek to answer three research questions that we pose as follows:

1. What is the role of OR/BDA in improving different CT operations?
2. How could environmental considerations be incorporated into decision making when addressing CT operational problems?
3. If there is a synergistic effect in the co-application of OR and BDA, then how is this contributing to decarbonising CT operations?

To answer these questions, we first establish our adopted review framework, and then we present an overview of the literature pertinent to each of the areas of OR, BDA and environmental considerations in relation with CT decision problems independently and collectively.

2. The classification scheme and the scope of analysis

This review paper is particularly interested in the interplay of OR and BDA in addressing key operations and processes of container terminals, with a particular focus on the synergistic effect from the two disciplines in addressing environmental concerns. The adopted scope of analysis and classification scheme pertaining to each of the three broad areas of OR, BDA and environmental considerations in CT operations is briefly discussed next, and the review structure is further described at the end of this section.

2.1. Container terminal operations and the key optimisation problems

A typical container terminal can be viewed as an open system of import and export containers flow in opposite directions from the quay and the land interfaces. From the quay side, upon the arrival of a container vessel at the port, a berthing area must be allocated to the vessel along the quay of the terminal. Given the limited availability of the quay side of the terminal and the required handling resources, this gives rise to the optimisation problem of the *Berth Allocation Problem*[2]. Once the vessel is moored at the allocated berthing area, it must be served; that is, import containers must be discharged from the vessel and export containers must be charged onto the vessel using one or several Quay Cranes (QCs). The allocation of QCs to the moored vessels and sequencing the corresponding discharging and charging operations of the specified export and import containers calls for the optimisation of the *QC Scheduling Problem*. Each import container discharged by a QC is loaded onto an Internal Movement Vehicle (IMV) which must transfer it to a pre-determined location in the terminal yard. IMVs are also responsible for taking specific export containers from the yard to the QCs for the charging operations onto the vessel. Operational problems that pertain to the allocation of sufficient number of IMVs to each QC and routing them can be considered as the *Transport Operations Problems*. From the land side, external trucks bring in export containers or take out import containers from the container terminal yard. Once external trucks are at the terminal, they are directed to the unloading/loading locations in the storage yard, where Yard Cranes (YCs) unload the export container from them and place it on top of a stack in a pre-determined location in the yard, and/or (retrieve and) load an import container from a certain stack in the yard onto the truck. Import and export containers that enter the terminal yard from the sea and land sides by the vessels and external trucks, respectively, are directed to a pre-determined storage space. Towards the improvement of the storage space assignment results, terminal operators usually perform a series of pre-marshalling activities involving a number of stacking, loading, unloading, and reshuffling moves. Here, for ease of categorisation and for consistency with classification used in Carlo, Vis, and Roodbergen (2014a), all these operations along with the storage space assignment problem, and the problems associated with the allocation and sequencing tasks for the available YCs, are collectively considered under the *Storage Yard Operations Problems* category.

[2] A detailed exposition and classification scheme of the optimisation problems presented in this section will be provided in section 3 of the paper.

Note that, as CTs differ in terms of layout and the handling equipment used for ship-to-yard transportation and the interface between the yard and the hinterland, unless differentiation is necessary, hereafter we use the term Material Handling Equipment (MHE) as a generic term to refer to different handling equipment such as QCs, YCs, IMVs, Rail-Mounted Gantry Cranes (RMGCs), Rubber-Tired Gantry Cranes (RTGCs), straddle carriers, reach stackers, chassis-based transporters, multi-trailer systems with manned trucks, Automated Guided Vehicles (AGVs), and Automated Lifting Vehicles (ALVs) (Stahlbock & Voß, 2007).

In sum, while there are other processes and optimisation problems that arise in the context of CTs, and recognising that there are different ways to classify corresponding problems, for the purpose of consistency with the extant literature, we focus our review on the following four categories of CT optimisation problems:

- Berth Allocation Problem (BAP)
- QC Scheduling Problem (QCSP)
- Storage Yard Operations Problems (SYOP)
- Transport Operations Problems (TOP)

The conscious choice of this categorisation enables this survey paper to adopt existing classification schemes in previously published key review papers in this journal (Bierwirth & Meisel, 2015; Carlo et al., 2014a; Carlo, Vis, & Roodbergen, 2014b), and present an update on the most relevant developments based on these established frameworks. It is worth adding that within this categorisation of OR problems, 'operational' problems that are often dealt with centrally by the 'container terminal operator' are of interest. Therefore, optimisation problems that are of a higher level strategic or tactical nature, such as the yard template planning (Zhen, 2016; Zhen, Xu, Wang, & Ding, 2016a), container terminal layout design (Gharehgozli, Zaerpour, & de Koster, 2020), and in-terminal handling equipment, technology, and operating system selection (Vis, 2006), or problems that are not centrally decided by the terminal operator, such as the container stowage planning (Avriel, Penn, Shpirer, & Witteboon, 1998; Imai, Sasaki, Nishimura, & Papadimitriou, 2006; Kang & Kim, 2002) are excluded from consideration. For further details on these problems, and other container terminals processes, operations, equipment, key performance indicators, and external stakeholders, we may refer to the studies of Vis and de Koster (2003), Vo, Stahlbock, and Steenken (2004) and Stahlbock and Voß (2007).

2.2. Big data analytics

With the rapid development of networking, data storage, and data collection capabilities, 'big data' has become an omnipresent term to describe large-volume, complex, and constantly growing datasets with multiple, heterogeneous, and autonomous sources (Xindong, Xingquan, Gong-Qing, & Wei, 2014). BDA refers to the overall process of applying advanced analytic techniques of data mining, statistical analysis, and predictive analysis (Jin & Kim, 2018; Russom, 2011; Tiwari, Wee, & Daryanto, 2018) on these high-volume, high-velocity and high-variety information assets to identify patterns, correlations and trends, and enable enhanced insight, decision-making, and process automation (Hazen et al., 2018). BDA approaches are capable of coping with 'big data' that is "massive, high dimensional, heterogeneous, complex, unstructured, incomplete, noisy, and erroneous" (Ma, Zhang, & Wang, 2014) and are created from handheld devices, the web, social media, ERP systems, cloud platforms, Internet of Things (IoT), multimedia, and many other new applications that all have the characteristics of volume, velocity, and variety (Choi et al., 2018; Tsai, Lai, Chao, & Vasilakos, 2015).

In this paper, our take on BDA is that of a business analyst who is mainly concerned with the practice of advanced analytical techniques on big data (no matter on what platform and how these big data sets are generated, collected and stored) for deriving insights, decisions, and actions. More specifically, we are mainly interested in machine learning and data mining methods used for BDA (mainly for predictive analytics) and their interplay with prescriptive analytics tools of OR in CT operations. Therefore, we are mostly interested in exploring the application of methods such as (supervised) classification techniques (e.g., k-nearest-neighbour, decision tree-based algorithms, Naïve Bayesian classification, neural networks, deep learning algorithms, support vector machine, and linear/logistics regression), unsupervised classification or clustering techniques (e.g., partition based methods, hierarchical methods, and biclustering), dimension-reduction techniques (e.g. singular value decomposition, principal component analysis, and kernel-based methods), association rule mining techniques, and feature selection, and other data mining methods such as rough set approaches, random forests, parallel support vector machines, fast learning, distributed machine leaning, and ontology learning in CT operations. In this paper, we are interested in reviewing how these techniques have so far complemented OR methodologies in addressing CT operational problems and tackling environmental considerations, and what can be further achieved.

2.3. Environmental considerations

Around 85% of all emissions in port cities come from containerships and tankers (Merk, 2014). Container vessels have relatively short stays in ports but high emissions during these stays. It is estimated that most shipping emissions in ports (CH_4, CO, CO_2 and NO_x) will grow fourfold up to 2050 to bring CO_2 emissions from vessels in ports to approximately 70 million tonnes in 2050, and NO_x emissions to up to 1.3 million tonnes (Merk, 2014).

Enhancing the sustainability of operations at container terminals and incorporating environmental considerations into decision making is a broad area of study and research that can be approached differently from strategic, tactical or operational planning levels. Reinforcing energy efficiency, electrification of equipment, adopting alternative fuels and renewable energy sources, improving methods to measure and estimate in-port energy consumption, exploiting advanced energy storage systems, and other approaches such as cold ironing, peak shaving, and designing intelligent power distribution systems in reefer areas (Iris & Lam, 2019b) are all examples of measures directed towards greening container port operations.

In this paper, we are mostly interested in reviewing the explicit and implicit incorporation of environmental considerations into the key optimisation problems that arise within the CT ecosystem. Development of a classification scheme for papers that explicitly incorporate environmental concerns into decision making is of utmost interest, and a review of papers that focus on various optimisation problems that implicitly (yet significantly) contribute to the improvement of CT operational sustainability will be presented to shed light on various ways OR can expand its role within this remit. We are also interested in finding out whether BDA has been at all applied in reinforcing environmental considerations in CT operations, and thus identify existing approaches and opportunities for the synergy of OR and BDA.

It is worth mentioning that while we fully acknowledge the fact that greening ports relies to the largest extent on the CT resources transformation into net-zero options, and the development of other relevant decarbonisation technological and infrastructural innovations such as vessels electrification, micro grid and smart grid establishment, and shore power supply, this review paper focuses particularly on the operational interventions possible through the traditional relevant OR decision problems, as well as new optimisation problems that arise in association with these

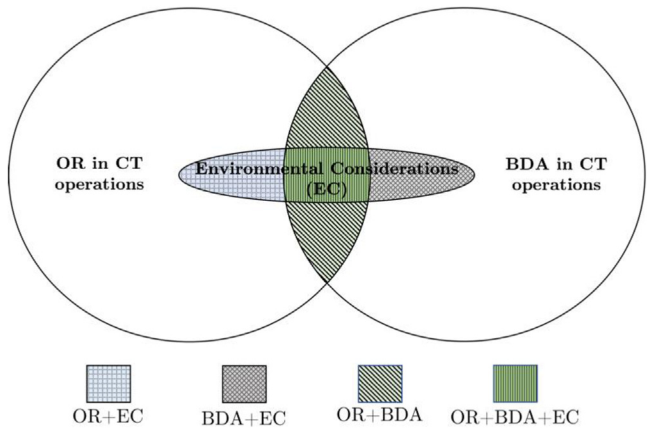

Fig. 1. The proposed classification scheme and the overlapping areas of OR, BDA and environmental considerations in CT operations.

new initiatives. We are also interested in finding out new ways in which the predictive leverage of BDA can contribute to more efficient and environmentally friendly operation of port legacy and new resources. Therefore, technological, infrastructural and engineering aspects of zero-emission ports are not within the scope of this survey paper. It may be also worth adding that the OR's biggest contribution when it comes to decarbonising port operations is mostly along the lines that 'the cleanest energy is that which is never used' and as such is within the remit of 'demand management' and cannot be overlooked. This can in cases be even a more preferred solution to very cost-intensive infrastructural developments; for example, while shore connection and cold ironing can minimise vessels emissions during mooring at the port, if the provided electricity is not from renewable and clean sources, the effectiveness of the technology is quite limited compared with an emissions-aware BAP that reduces port stay significantly.

2.4. Review structure and methodology

Given the above discussions, an intuitive structure for this review paper would be to survey most relevant papers in the areas of OR and BDA in relation with CT operations independently, and then zoom in on the overlapping areas of these mutually dependent research disciplines, while also highlighting all the pertinent literature with environmental considerations (Fig. 1). However, the extant literature pertaining to the OR in CT decision problems is too broad, and an exhaustive review is neither possible, nor an intention of the current review paper. Therefore, as will be shortly discussed in the description of the review methodology below, a limiting mechanism is applied to our review of OR in CT operations; such scope restrictions are not required in the areas with a scarce body of literature, including *BDA*, *OR+EC*, *OR+BDA*, and *OR+BDA+EC* areas in Fig. 1.

As regards the methodology of the review, starting with the OR in CT operations literature, we have followed a step-by-step search and screening methodology in Scopus to ensure most relevant and high-quality papers are included. In the first step, several rounds of trial and error with different search terms and keywords combinations were carried out within resources' titles, abstracts and keywords. The returned results were then scrutinised to determine a final inclusive Boolean search term to collect OR in CT operations papers as follows: *"container AND (terminal OR port) AND (operation* OR decision OR optimisation OR optimization OR schedul* OR assign* OR rout* OR (berth AND (alloc* OR assign*)) OR (storage AND space) OR problem OR (quay AND crane) OR RTG OR handl* OR reshuffl* OR housekeep* OR rehandl* OR charg* OR discharg* OR stack* OR dispatch*)"* . This resulted in 9,550 titles that cover all available resources up until the end of October 2022. Following this, the resulting titles were filtered to cover the period of 2013 onward only. This reduced the total number of papers to 4,729. The main reason for selecting 2013 as the starting year is that the oldest of the four key review papers (Bierwirth & Meisel, 2015; Carlo et al., 2014a; Carlo et al., 2014b) used as benchmark classification schemes for OR sub categories, i.e., that of Carlo et al. (2014b), covers papers published up to the end of 2012. Any repetitive entry from the previous reviews could then be identified and discarded in later stages. This step was then followed by selecting a set of 20 top and mainstream OR and transportation journals[3] and limiting the results to the selected set only, which reduced the total number of resources to 289 titles. Following this step, two of the authors read through the titles, abstracts and keywords and discarded irrelevant papers, and results were compared to address any inconsistencies. Finally, all remaining papers were carefully reviewed and missing papers that had skipped our search procedure were identified through snowball sampling and screening the references of the identified papers, as well as by looking into the papers that had cited our identified references. As a result, we ended up with a total of 103 papers in the OR in CT operations area that were selected for this review.

While the same stepwise approach of Boolean search term identification, initial screening, and snowball sampling were used for collecting BDA in CT operations papers, no date range limitation or journal title exclusion were applied, and other academic search engines such as Google Scholar and Web of Science were also searched in addition to Scopus. The main reason for this was the scarcity of relevant papers in the area. The Boolean search term "*container AND (terminal OR port) AND (operation* OR problem* OR decision* OR process* OR procedure* OR job) AND (analy* OR (big AND data) OR (data AND min*) OR artifi* OR (artificial AND intelligence) OR machine OR (deep AND learning) OR (data AND science))*" was used to collect an initial set of BDA in CT operations papers. All BDA in CT operations papers with explicit incorporation of environmental considerations were expected to appear as a subset of this generic search. Similarly, OR papers with explicit environmental concerns were returned as the subset of the generic search described above for OR in CT operations; but to collect any other relevant paper with an "optimisation" element as well as an environmental angle within the CT operations environment, another layer of search using the Boolean search term "*container AND (port OR terminal) AND (emission* OR (emission AND reduction) OR (greenhouse AND gases) OR GHGs OR energy OR (energy AND efficiency) OR CO2 OR Carbon OR electrification) AND optim**" was conducted.

All in all, a total of 226 papers were selected for this review paper which are distributed in the 6 areas of review (see Fig. 1) as illustrated in Fig. 2.

Fig. 3 illustrates the total number of papers in each category published in each year. We remind that the first column indicating '2013 and before' in Fig. 3, does not include any OR paper before 2013 and these are due to the other categories indicated in the figure. It is observed that the majority of BDA and synergistic papers (i.e., *OR+EC, OR+BDA, BDA+EC and OR+BDA+EC*) have been published after 2016 (around 70% of the total papers), indicating the recency of these subject categories.

[3] Annals of OR; Computers & Operations Research; Decision Sciences; Decision Support Systems; European Journal of Operational Research; Interfaces; International Journal of Production Economics; Journal of the Operational Research Society; Management Science; Mathematical Programming; Mathematics of Operations Research; Naval Research Logistics; Omega; Operations Research; OR Letters; OR Spectrum; SIAM Journal on Optimization; Transportation Research Part B: Methodological; Transportation Research Part C: Emerging Technologies; Transportation Science.

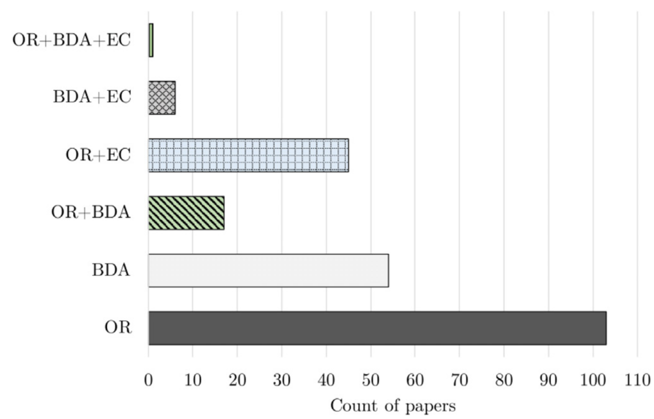

Fig. 2. Distribution of the selected papers within each of the six areas of review.

In order to grasp an idea of the OR community's recognition of the subject matter, distribution of the identified papers within 10 mainstream OR and transportation journals is illustrated in Fig. 4.

Fig. 4 shows that only around 50% of all papers reviewed in this survey are published in the presented journals; with 96% of them belonging to the OR in CT operations area. All other 5 categories (i.e., *BDA, OR+EC, OR+BDA, BDA+EC and OR+BDA+EC*) constitute just around 4% of all publications in the 20 journals we identified as mainstream OR and transportation journals, and to our surprise only one of the BDA papers (Ruiz-Aguilar, Turias, & Jiménez-Come, 2015) has been published in one of these journals. This is well in line with the situation reported in Mortenson et al. (2015) who argue that despite the connection between OR and analytics, the amount of research into analytics published in journals associated with OR is surprisingly limited. Most of these papers are published in either journals that are out of our selected set (e.g., Expert Systems with Applications, Applied Soft Computing Journal, Journal of Cleaner Production, etc.) or other OR and information management journals and conferences. It may be also worth noting that around 44% of all papers in OR outlets have been published in EJOR.

3. OR in container terminal operations

In Section 2, four major categories of optimisation problems pertaining to container terminal operations were introduced. As stated earlier, this categorisation is consistent with, and builds upon previous literature review papers of Bierwirth and Meisel (2015), Carlo et al. (2014a); Carlo et al. (2014b) and allows a concise presentation of the most recent and relevant developments using the dedicated classification scheme that is developed within each of these papers. These classification schemes are based on different groups of mutually exclusive attributes to help characterise and position research developments. The adopted classification schemes for BAP (Bierwirth & Meisel, 2015), QCSP (Bierwirth & Meisel, 2015), SYOP (Carlo et al., 2014a) and TOP (Carlo et al., 2014b) are presented in Appendix B in Tables B.1-B.4, respectively. For brevity, a detailed exposition of each classification scheme is avoided here, and the reader is referred to the original review papers for that purpose.

It is worth mentioning that we add an additional generic attribute group corresponding to "*method attribute*" to all classification schemes in Appendix B to capture and present a high-level indication of the solution methodology used in the reviewed papers. Without delving into much detail, this attribute set is comprised of: (i) exact methods (*exact*) which encompass all approaches involving the development of a dedicated exact algorithm (e.g., branch-and-bound, branch-and-cut, branch-and-price, dynamic programming, cutting plane algorithm, Bender's cuts algorithm, etc.), (ii) approximate methods (*approx*) which cover all algorithms that compute a solution that is guaranteed to be within a certain factor of the optimal solution (e.g., primal-dual method, Lagrangian relaxation, etc.), (iii) stochastic optimisation methods (*stoch*), (iv) robust optimisation approaches (*robust*), (v) (meta)heuristic approaches (*heur*), (vi) hybrid approaches such as matheuristics that combine exact and heuristic solution algorithms (*hybrid*), (vii) simulation (*simul*), and (viii) off-the-shelf solvers such as CPLEX, Gurobi, etc. (*solver*).

On top of the 4 categories of decision problems, i.e., BAP, QCSP, SYOP and TOP, an additional category corresponding to "integrated problems" will be also reviewed at the end of this section. This category includes papers that integrate problems relating to more than one of the identified problem classes into a unified modelling and/or solution framework (e.g., integration of seaside problems of BAP and QCSP). We start each section with a general introduction into the concerned problem class and encode papers identified in each category within its dedicated classification scheme. A classification of the papers based on the optimisation problem category considered is presented in Fig. 5. As indicated, most of the papers are either SYOP focused or integrate more than one of the problem classes. The rising proportion of integrated papers indicate a significant development from previous review papers (e.g., Bierwirth and Meisel (2015); Carlo et al. (2014a)) that identified underdevelopment of integrated OR problems in CT operations as a prominent gap and a direction for further research.

As far as solution methodologies are concerned, Fig. 6 illustrates more than 40% of the reviewed papers use (meta)heuristic approaches and this is followed by exact methods at around 25%.

Another important area identified as underdeveloped in previous review papers corresponds to the incorporation of uncertainty. We observe that only less than 15% of the papers in our selected set consider one or several uncertain problem inputs, and incorporate them into optimisation mainly through stochastic and robust optimisation approaches. It is important to reiterate that our review on OR in CT operations is not meant to be an exhaustive and inclusive review of all research outputs within this broad field,

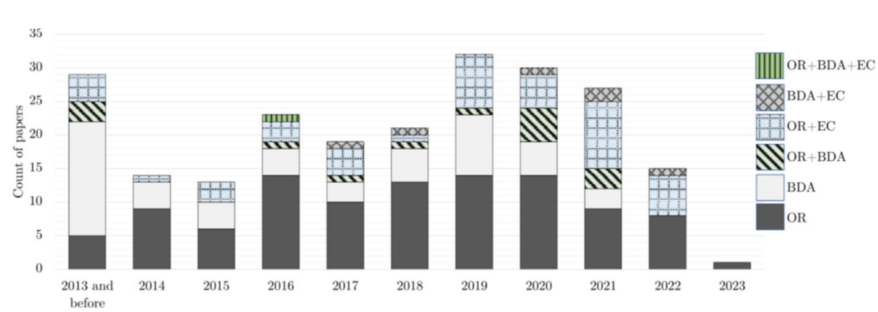

Fig. 3. Yearly count of papers in each of the six areas of the review.

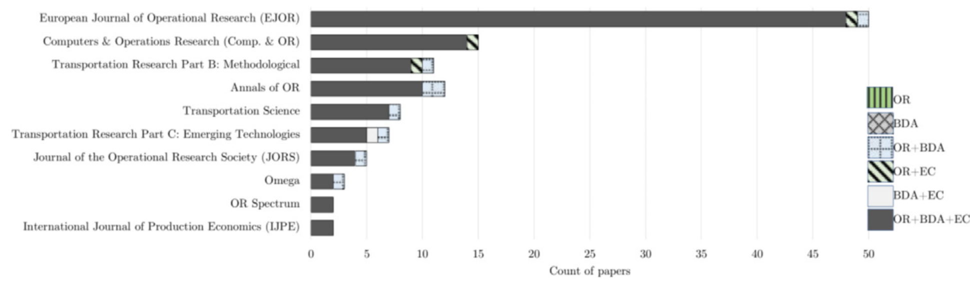

Fig. 4. Number of papers within each category published in mainstream OR and transportation outlets.

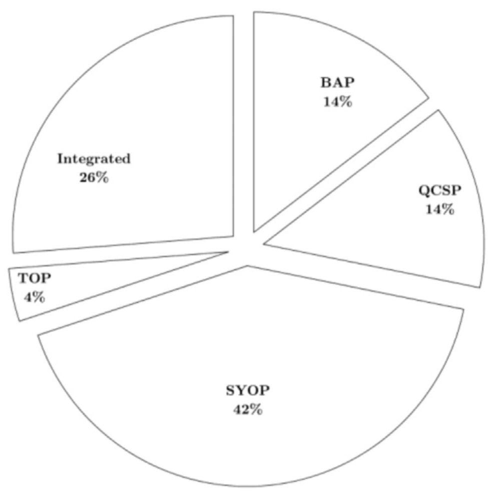

Fig. 5. Percentage of papers focusing on each of the optimisation problem classes considered.

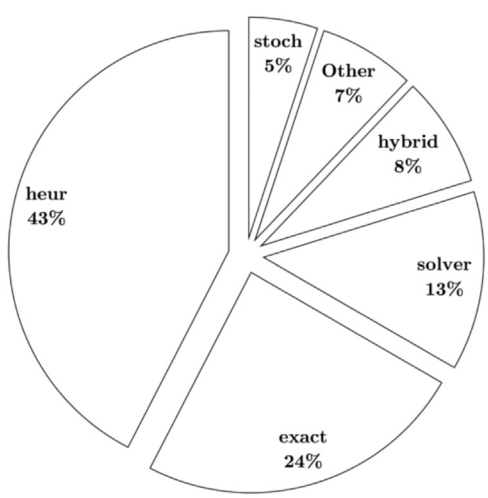

Fig. 6. Distribution of different solution methodologies employed in the reviewed papers.

and all the analyses presented, and conclusions made in this paper are limited to the selected resources qualifying the filtering criteria applied (e.g., publication type, year, and the selected OR and transport journals). It is, therefore, needless to mention that there are a number of papers published within journals that are out of our list, e.g., (Cahyono, Flonk, & Jayawardhana, 2020; Legato, Mazza, & Gullì, 2014; Liu, Zheng, & Zhang, 2016a; Niu, Xie, Tan, Bi, & Wang, 2016; Shang, Cao, & Ren, 2016; Umang, Bierlaire, & Erera, 2017; Xiang, Liu, & Miao, 2018; Yu, Ning, Wang, He, & Tan, 2021; Zehendner, Rodriguez-Verjan, Absi, Dauzère-Pérès, & Feillet, 2015), that consider several of the areas considered here.

3.1. Berth allocation problem

The BAP is the problem of deciding when and where in the port vessels should be moored. Different variants of the BAP are identified based on the continuous or discrete layout of the berthing area, and the static or dynamic nature of vessel arrivals. In the continuous BAP, which is more common, vessels can be berthed anywhere along the terminal quay; however, in the discrete case the quay is partitioned into a number of sections called 'berths'. The static BAP assumes that all vessels are already in the port, while in the case of the dynamic BAP vessels arrive continuously during container operations. The main objective of the BAP is often to allocate each vessel to a berthing time and a berthing position such that the total vessel turnaround time comprising its waiting time and handling time is minimised. Various constraints pertaining to the length of the vessels, the depth of the berth water, time windows, priorities assigned to the vessels and their desired berthing positions are usually considered. The key input parameters to a typical BAP (i.e., the static BAP with a continuous wharf) include the length of the berthing quay, the estimated arrival time, estimated handling time, length, and desired berthing position of each vessel. The outputs from the optimisation of the BAP determine the berthing start time and the berthing position of each vessel.

As stated before, the classification scheme developed by Bierwirth and Meisel (2010, 2015) has been used to encode recent relevant developments. A schematic diagram of their proposed classification framework (extended by our methods attribute group) is illustrated in Fig. 7, and the description of attribute values is given in Table B.1 in Appendix B.

All identified BAP papers have been encoded based on this classification scheme in Table 1. Following the approach in Bierwirth and Meisel (2015), each paper has been classified using an ordered coding approach of "*att1* | *att2* | *att3* | *att4* | *att5*", where *att1*, *att2*, *att3*, *att4*, and *att5* respectively refer to the value of spatial, temporal, handling time, performance measure, and method attributes

Table 1
Classification of BAP papers.

Reference	Problem classification
Ursavas (2022)	*disc* | *stoch* | *fix* | *compl* | *simul*
Al-Refaie and Abedalqader (2020)	*disc* | *dyn* | *fix* | *misc* | *solver*
Xiang and Liu (2021b)	*hybr* | *stoch* | *QCAP* | *wait* | *exact+robust*
Zhang et al. (2020a)	*disc* | *dyn* | *fix* | *compl* | *solver*
Wawrzyniak et al. (2020)	*disc* | *dyn* | *fix* | *misc* | *heur*
Nishi et al. (2017)	*disc* | *dyn* | *pos* | *hand* | *hybrid*
Kramer et al. (2019)	*disc* | *dyn* | *pos* | *compl+wait* | *solver*
Correcher et al. (2019b)	*disc+draft* | *dyn* | *pos* | *wait+tard* | *heur*
Emde and Boysen (2017)	*hybr* | *dyn* | *fix* | *wait* | *heur*
Ursavas and Zhu (2016)	*disc* | *stoch* | *stoch* | *misc* | *stoch*
Mauri et al. (2016)	*hybr* | *dyn* | *fix* | *wait+hand* | *heur*
LLalla-Ruiz et al. (2016)	*disc* | *dyn* | *fix* | *wait+hand* | *solver*
Zhen (2015)	*disc* | *stoch* | *fix* | *misc* | *stoch+robust*
Du et al. (2015)	*cont* | *dyn* | *fix* | *tard* | *solver*
Golias et al. (2014)	*disc* | *stoch* | *fix* | *hand* | *heur*

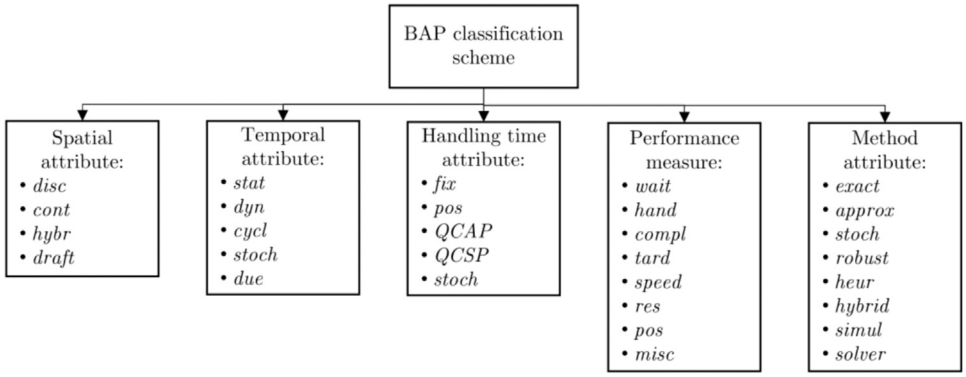

Fig. 7. The BAP classification scheme (Bierwirth & Meisel, 2010, 2015).

for the given publication. Whenever more than one value for an attribute is associated with a paper (e.g., when multiple performance measures are used in the objective function(s), or more than one solution method is used) "+" has been used between the attribute values of the attribute section in the coding. Also, when the value of an attribute is not explicitly specified in the paper and cannot be conjectured from the model, a "-" is used. This approach has been followed for all other problem categories discussed next.

In their review paper of the literature on BAP, Bierwirth and Meisel (2015) argue that despite existing developments, planning methods for the handling of uncertain problem data such as the vessel's arrival time and the estimated vessel's service time are of significant importance. However, Table 1 shows that in only five of the papers cited, uncertainty has been considered and addressed. Ursavas (2022) capture the uncertainty in vessels' Estimated Time of Arrival (ETA) and handling times using a dynamic discrete-event simulation optimisation tool used within a decision support system for determining the priority controls for the berth allocation to the calling vessels. Zhen (2015) considers the uncertainty in the vessel's operation time and proposes both a stochastic programming and a robust formulation to cope with situations where limited information about probability distributions is available. Ursavas and Zhu (2016) consider uncertainty in vessels' ETA and handling times and propose a stochastic dynamic programming framework for characterising optimal policies of berth allocation under uncertainty. Al-Refaie and Abedalqader (2020) consider the berth scheduling problem under emergent ship arrivals, and propose a three-step approach to maximise the number of served emergent ships at minimal disturbance to service schedule of regular ships. Finally, Golias, Portal, Konur, Kaisar, and Kolomvos (2014) consider the vessel arrival and handling times as uncertain problem inputs.

As regards other developments within the BAP literature, Lalla-Ruiz, Expósito-Izquierdo, Melián-Batista, and Moreno-Vega (2016) consider time-dependent water depth and tidal constraints in BAP, Correcher, Van den Bossche, Alvarez-Valdes, and Berghe (2019b) study the BAP in terminals with irregular layouts, Emde and Boysen (2017) focus on BAP for CTs that service feeder ships and deep-sea vessels, and Du, Chen, Lam, Xu, and Cao (2015) incorporate the impacts of tides and the virtual arrival policy into the BAP. Several papers have also focused on the formulation and algorithmic enhancements of different variants of the BAP (Kramer, Lalla-Ruiz, Iori, & Voß, 2019; Mauri, Ribeiro, Lorena, & Laporte, 2016; Nishi, Okura, Lalla-Ruiz, & Voß, 2017; Wawrzyniak, Drozdowski, & Sanlaville, 2020; Zhang, Qi, & Li, 2020a).

3.2. Quay crane scheduling problem

The QCSP seeks to allocate the optimum number of QCs to a vessel and determine the optimum sequence in which the vessel is loaded/unloaded (Alsoufi, Yang, & Salhi, 2018). The berthing positions for vessels are assumed given to the QCSP and an identical estimated container handling rate is often used for all QCs. The key input pertaining to the charging and discharging information of the containers is also usually available from the vessel stowage plan in advance of the vessel arrival. The prevailing objective function used in typical QCSPs corresponds to the minimisation of the completion times of the tasks or cranes; however, other performance indicators such as QC utilisation rate and traveling times have been also scarcely used within the literature as the objective function.

A schematic diagram of the classification scheme developed by Bierwirth and Meisel (2010, 2015) is illustrated in Fig. 8, and the description of attribute values is given in Table B.2 in Appendix B.

A QCSP can be modelled and solved differently depending on the interpretation of the notion of a 'task', the existence of precedence relationships, and the potential limitations imposed from practical constraints and restrictions such as movement limitations, interferences with other QCs, and the safety distances required between QCs. All identified QCSP papers have been encoded on the basis of these characteristics and in accordance with the classification scheme of Bierwirth and Meisel (2010, 2015) in Table 2.

As regards the inclusion of uncertainty, only one of the cited papers, i.e., Chen and Bierlaire (2017), incorporates uncertainty in task processing times into the adopted modelling approach. This is rather striking, especially given that the review paper of Bierwirth and Meisel (2015) also concluded that stochastic approaches are missing from the QCSP literature. Bierwirth and Meisel (2015) argue that given the uncertainty in processing times of containers, this is rather surprising, and there is a crucial need to put forth more reliable crane schedules that can deal with uncertain parameters such as container cycle times, waiting times for transport vehicles, and stochastic events like breakdowns of handling equipment. Our update here indicates that this is still a widely open research gap.

Recent developments since the previous review by Bierwirth and Meisel (2015) have been mostly concerned with the modelling of the QCSP with respect to new QC technologies such as the ship to shore multi-trolley portal gantry container cranes (Abou Kasm & Diabat, 2020) and QCs in frame bridges based automated container terminals (Zhen, Hu, Wang, Shi, & Ma, 2018), as well as the modelling of more complex operations such as dual-spreader operations (Lashkari, Wu, & Petering, 2017), double cycling (Ku & Arthanari, 2014) and operations in indented berths (Beens & Ursavas, 2016). A group of papers have also focused on the development of new exact and approximate algorithms for the problem (Abou Kasm & Diabat, 2019; Al-Dhaheri & Diabat, 2016; Msakni, Diabat, Rabadi, Al-Salem, & Kotachi, 2018; Sun, Tang, & Baldacci, 2019a; Sun, Tang, Baldacci, & Lim, 2021; Zhang, Zhang, Chen, Chen, & Chen, 2017).

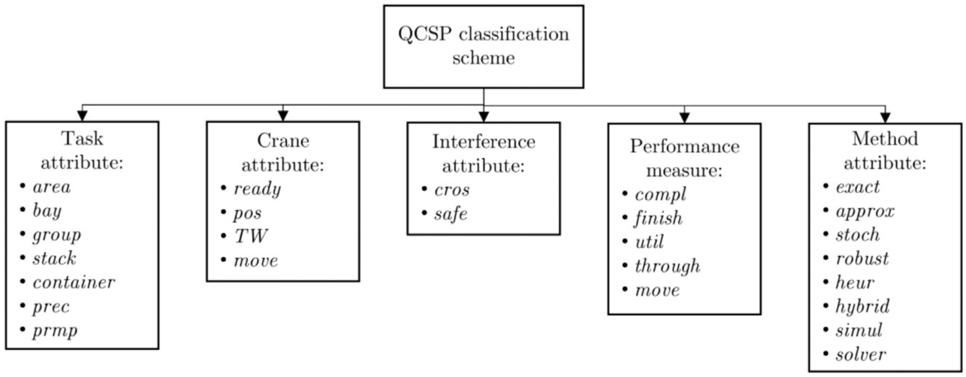

Fig. 8. The QCSP classification scheme (Bierwirth & Meisel, 2010, 2015).

Table 2
Classification of QCSP papers.

Reference	Problem classification
Sun et al. (2021)	*group+prec* | *ready+pos+move* | *cross+safe* | *compl* | *exact+heur*
Abou Kasm and Diabat (2020)	*stack+prmp* | *pos* | *cross+safe* | *compl* | *heur+exact*
Sun et al. (2019a)	*bay* | *move* | *cross* | *compl* | *exact*
Abou Kasm and Diabat (2019)	*prmp* | *pos* | *cross+safe* | *finish* | *exact*
Zhen et al. (2018)	*group+prec* | *move* | - | *finish* | *heur*
Msakni et al. (2018)	*bay* | *pos+move* | *cross+safe* | *compl* | *heur*
Alsoufi et al. (2018)	*bay+prec* | *move* | *safe+cross* | *compl* | *exact+heur*
Zhang et al. (2017)	*bay* | - | *cross* | *compl* | *approx*
Lashkari et al. (2017)	*container* | - | - | *compl* | *heur*
Chen and Bierlaire (2017)	*group+prec* | *pos+move* | *safe+cross* | *compl* | *solver*
Al-Dhaheri and Diabat (2016)	*container+prmp* | *move* | *cross+safe* | *compl* | *solver*
Beens and Ursavas (2016)	*container* | *pos* | *cross+safe* | *move* | *exact*
Ku and Arthanari (2014)	*Bay+prec* | *move* | *cross+safe* | *finish* | -
Chen, Lee, and Goh (2014)	*Group+prec* | *move+TW* | *cross+safe* | *compl* | *solver*

3.3. Storage yard operations problems

A CT yard serves as a temporary storage space for import, export and transhipment containers. Based on the categorisation proposed by Zhang, Liu, Wan, Murty, and Linn (2003), containers to be handled in the yard can be classified into four types, namely: (i) import containers to be discharged from the vessel, (ii) import containers already discharged, (iii) export containers that are yet to arrive, and (iv) export and transit containers in the yard. The arrivals of type (i) and the departures of type (iv) containers are often assumed known in advance as they are directly triggered by vessel schedules; however, the time epochs to handle type (ii) and type (iii) containers are often unknown (Zhang et al., 2003) and are at best determined through the use of a Truck Appointment System (TAS) (if one is operated by the CT) or through the analysis of historical data. This uncertainty complicates SYOPs which are in essence concerned with finding the 'best' allocation for containers in the yard such that the yard's operational time for housekeeping (aka., pre-marshalling and re-marshalling) of containers, storing, retrieving, and reshuffling is minimised (Carlo et al., 2014a) and optimal schedules for YCs are determined.

A schematic diagram of the classification scheme for SYOP developed by Carlo et al. (2014a) is illustrated in Fig. 9, and the description of attribute values is given in Table B.3 in Appendix B. All identified SYOP papers have been encoded on the basis of this classification scheme in Table 3.

Since, accessing middle slots in a stack of containers require reshuffling, which is a non-productive and costly operation (Bacci, Mattia, & Ventura, 2020), in most of the cited SYOP studies in Table 3, reshuffling moves have been the main focus (Azab & Morita, 2022; Bacci et al., 2020; Boge & Knust, 2020; Parreño-Torres, Alvarez-Valdes, & Ruiz, 2019; Tanaka & Voß, 2019). As regards uncertainty, Table 3 shows that few of the studies have considered a stochastic optimisation setting (Feng, He, & Kim, 2022a; Feng, Song, Li, & Zeng, 2020; Ku & Arthanari, 2016a; Zweers, Bhulai, & van der Mei, 2020a). These papers incorporate uncertainty in the number of relocations required (Zweers et al., 2020a), external truck arrivals (Feng et al., 2020), retrieval sequence of containers (Boge, Goerigk, & Knust, 2020; Zehendner, Feillet, & Jaillet, 2017), and containers' departure time windows (Ku & Arthanari, 2016a). To address the uncertainty of external trucks arrival, Feng et al. (2020) capture the randomness of retrieval time through the use of appointed time windows and stochastic programming. Similarly, Ku and Arthanari (2016a) consider the blocks relocation problem with departure time windows for containers, induced by the TAS, and propose a stochastic dynamic programming model for the problem to minimise the expected number of reshuffles for a stack of containers. Zweers et al. (2020a) propose a two-phase approach for container relocations in which a rule-based method is used to estimate the number of relocation moves in a bay. Boge et al. (2020) consider the pre-marshalling problem with uncertain priority values for the retrieval sequence of items. They develop a robust optimisation approach and show that the level of robustness can be improved by using just a few additional relocations. To address a similar kind of uncertainty, Zehendner et al. (2017) introduce and solve the online container relocation problem.

Uncertainties associated with YC scheduling are missing from the relevant problems cited in Table 3 (Abou Kasm & Diabat, 2019; Galle, Barnhart, & Jaillet, 2018; Gharehgozli, Yu, De Koster, & Udding, 2014; Hu, Sheu, & Luo, 2016; Speer & Fischer, 2017). In a typical YC scheduling, a YC must be scheduled to handle all jobs with different ready times within its movement zone, in a given planning period. The time required by the YC to handle a job in turn is a key input to the problem that can be well subject to uncertainty.

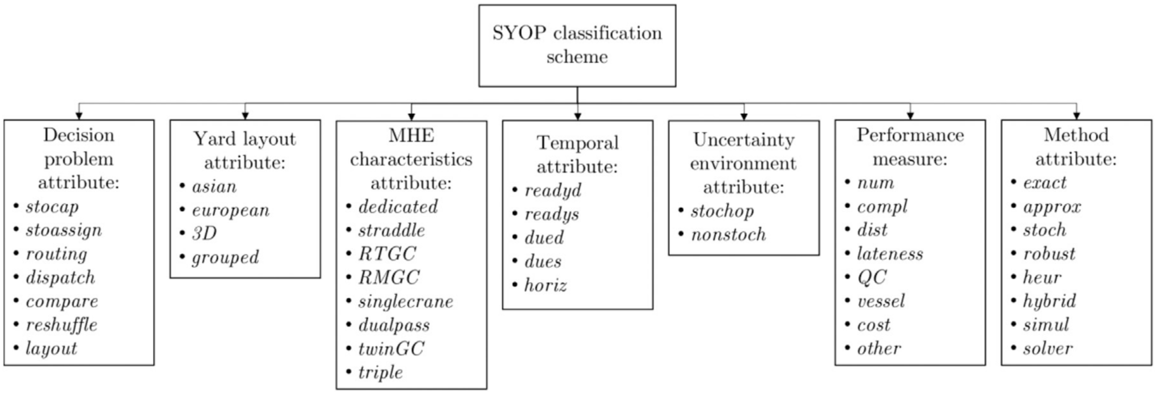

Fig. 9. The SYOP classification scheme (Carlo et al., 2014a).

Table 3
Classification of SYOP papers.

Reference	Problem classification
Jin and Tanaka (2023)	*stoassign | Asian | RTGC+RMGC | unspecified | nonstoch | num | heur*
Wang et al. (2022)	*stoassign | 3D | unspecified | readyd | nonstoch | other | hybrid*
He, Xiao, Yu, and Zhang (2022)	*stoassign | european | twinGC | readyd | nonstoch | GC util | -*
Feng, Song, and Li (2022b)	*dispatch | - | RMGC | - | nonstoch | compl | heur*
Feng et al. (2022a)	*stoassign | - | dedicated | dues | stochop | compl | heur*
Oelschlägel and Knust (2021)	*stoassign | - | - | readyd | nonstoch | space util+due | heur*
Azab and Morita (2022)	*reshuffle | - | RMGC | readyd | nonstoch | num | heur*
Zweers et al. (2020a)	*reshuffle | asian | dedicated | dues | stochop | num | hybrid*
Zweers et al. (2020b)	*reshuffle | - | dedicated | readyd | - | num | -*
Feng et al. (2020)	*reshuffle | - | dedicated | dues | stochop | num+other | exact*
Boge and Knust (2020)	*reshuffle | - | dedicated | dued | nonstoch | num | heur*
Boge et al. (2020)	*reshuffle | - | dedicated | dues | nonstoch | space util | robust*
Bacci et al. (2020)	*reshuffle | - | dedicated | dued | nonstoch | num | exact*
Tanaka and Voß (2019)	*reshuffle | - | dedicated | readyd | nonstoch | num | exact*
Tanaka, Tierney, Parreño-Torres, Alvarez-Valdes, and Ruiz (2019)	*reshuffle | - | dedicated | readyd | nonstoch | num | exact*
Parreño-Torres et al. (2019)	*reshuffle | - | dedicated | readyd | nonstoch | num | exact*
Feillet, Parragh, and Tricoire (2019)	*reshuffle | - | dedicated | readyd | nonstoch | num | exact*
Zhou, Chew, and Lee (2018)	*stoassign | - | - | readys | nonstoch | dist | hybrid*
Tanaka and Tierney (2018)	*reshuffle | - | dedicated | readyd | nonstoch | num | exact*
Silva et al. (2018)	*reshuffle | - | dedicated | readyd | nonstoch | num | heur*
Gharehgozli and Zaerpour (2018)	*stoassign | - | dedicated | readyd | nonstoch | compl | heur*
Galle et al. (2018)	*stoassign+routing | - | dedicated | readyd | nonstoch | dist+num | heur*
De Melo da Silva, Toulouse, and Wolfler Calvo (2018)	*reshuffle | - | dedicated | readyd | nonstoch | num | exact*
Zehendner et al. (2017)	*reshuffle | - | dedicated | readys+dues | nonstoch | num | heur*
Speer and Fischer (2017)	*routing | - | triple | dued | nonstoch | GC util | exact*
Gharehgozli, Vernooij, and Zaerpour (2017)	*routing+stoassign | - | twinGC | - | nonstoch | compl+GC util | simul+heur*
Ku and Arthanari (2016b)	*reshuffle | - | dedicated | readyd | nonstoch | num | -*
Ku and Arthanari (2016a)	*reshuffle | - | dedicated | dued | stochop | num | stoch*
Hu et al. (2016)	*routing | european | twinGC | - | nonstoch | compl | hybrid*
Hottung and Tierney (2016)	*reshuffle | - | RMGC | dued | nonstoch | num | heur*
Ehleiter and Jaehn (2016)	*routing | - | twinGC | horiz | nonstoch | num | hybrid*
Wu, Li, Petering, Goh, and De Souza (2015)	*routing | - | triple | - | nonstoch | dist | -*
Wang, Jin, and Lim (2015)	*reshuffle | - | dedicated | dued | nonstoch | num | heur*
Cordeau, Legato, Mazza, and Trunfio (2015)	*reshuffle+routing | - | - | horiz+readyd | nonstoch | dist+GC util | hybrid*
Zhang, Wu, Kim, and Miao (2014)	*stoassign | - | dedicated | readyd | nonstoch | space util | hybrid*
Jin, Zhu, and Lim (2014)	*routing | - | dedicated | readyd | nonstoch | num | heur*
Jiang, Chew, Lee, and Tan (2014)	*stoassign | - | dedicated | readyd | nonstoch | num | solver*
Gharehgozli et al. (2014)	*routing | european | RMGC | - | nonstoch | dist | exact*
Dayama, Krishnamoorthy, Ernst, Narayanan, and Rangaraj (2014)	*routing | - | dedicated | readyd | nonstoch | compl | heur*
Rei and Pedroso (2013)	*stoassign | - | dedicated | readyd | nonstoch | compl | stoch*
Petering and Hussein (2013)	*reshuffle | - | straddle+RTGC | readyd | nonstoch | num | heur*
Jiang, Chew, Lee, and Tan (2013)	*stoassign | asian | RTGC | dued | nonstoch | space util | heur*

Similarly, the time required for the YC to travel from one location to another may be uncertain due to road traffic.

The recent SYOP literature has otherwise concentrated on the development of new formulations and solution algorithms for different variants of the block relocation problem and container premarshalling. Jin and Tanaka (2023) develop an iterative deepening branch-and-bound algorithm to address the unrestricted container relocation problem with duplicate priorities. Wang, Ma, Xu, and Xia (2022) consider the 3D yard allocation problem with time dimension to minimise the occupied two-dimensional area of the storage block, and develop a simulated annealing-based algorithm with a dynamic programming procedure for the problem. Oelschlägel and Knust (2021) consider storage loading problems with limited height of stacks and propose a variable neighbourhood search heuristic for the problem. Azab and Morita (2022) study the block relocation problem with appointment scheduling. Zweers, Bhulai, and van der Mei (2020b) propose a model for container premarshalling and develop a heuristic and an optimal branch-and-

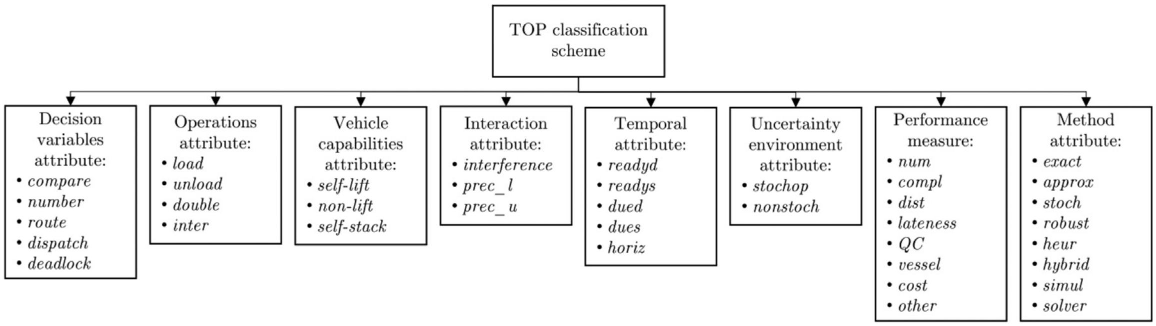

Fig. 10. The TOP classification scheme (Carlo et al., 2014b).

Table 4
Classification of TOP papers.

<table>
<tr><th>Reference</th><th>Problem classification</th></tr>
<tr><td>Zhuang et al. (2022)</td><td>route | double | non-lift | Interference | readyd | nonstoch | compl | heur</td></tr>
<tr><td>Kress et al. (2019)</td><td>route | load | self-lift | prec_l | readyd | nonstoch | vessel | heur</td></tr>
<tr><td>Jiang et al. (2018)</td><td>route | double | self-lift | Interference | readyd | nonstoch | compl | hybrid</td></tr>
<tr><td>Gelareh et al. (2013)</td><td>route | unload | non-lift | prec_l | readyd | nonstoch | compl | approx</td></tr>
</table>

bound algorithm for the problem. Boge and Knust (2020) focus on the parallel stack loading problem and propose a simulated annealing algorithm. Bacci et al. (2020) consider the block relocation problem and propose an exact algorithm for the restricted version of the problem. Tanaka and Voß (2019) develop a branch-and-bound algorithm with iterative deepening for the block relocation problem with a stowage plan. Parreño-Torres et al. (2019) address the pre-marshalling problem by developing two alternative families of models and an iterative solution procedure. Silva, Erdoğan, Battarra, and Strusevich (2018) consider the block retrieval problem and propose a branch-and-bound algorithm and a linear time heuristic for the problem.

3.4. Transport operations problems

In CT's, equipment is typically utilised for three sets of operations corresponding to: (i) vessel (un)loading, (ii) containers transportation within the CT, and (iii) storage yard's operations (i.e., stacking, retrieving, and reshuffling of containers). The first and third type operations were discussed in Sections 3.2 and 3.3 under the QCSP and the SYOP categories, respectively; TOP category decision problems discussed in this section, however, emerge from the second type operations in CTs. These operations take place at the intersection of the seaside and landside areas and are crucial for streamlining operations in both sides and avoiding bottlenecks (Carlo et al., 2014b). TOPs are typically concerned with selecting the vehicle type (self-lifting such as straddle carriers and ALVs, or non-lifting such as yard trucks and AGVs), optimising the number of vehicles required, and vehicle routing and dispatching (Carlo et al., 2014b).

A schematic diagram of the classification scheme for TOP developed by Carlo et al. (2014b) is illustrated in Fig. 10, and the description of attribute values is given in Table B.4 in Appendix B. Classification of a total of 4 papers under TOP category is given in Table 4.

The main source of uncertainty in TOPs relate to the containers' ready/due times, travel times, and waiting times, but none of these have been incorporated into the models developed in the provided updates in Table 4. Instead, the focus of the presented studies has been mostly on the incorporation of new transportation technology developments within automated CTs. Gelareh, Merzouki, McGinley, and Murray (2013) focus on the optimal deployment of Intelligent and Autonomous Vehicles (IAVs) by extending an existing formulation for AGV scheduling to minimise the makespan of operations for transporting containers between QCs and YCs, and develop a Lagrangian relaxation-based decomposition approach for the problem. Zhuang, Zhang, Teng, Qin, and Fang (2022) formulate the integrated scheduling of intelligent handling equipment at automated CTs as a blocking hybrid flow shop scheduling problem with bidirectional flows and limited buffers, and develop an adaptive large neighbourhood search algorithm to address the problem. Jiang, Xu, Zhou, Chew, and Lee (2018) study the dispatching of frame trolleys in a frame bridge based automated container terminal to minimise the makespan of all jobs, considering frame trolleys conflicts and handshakes. Kress, Meiswinkel, and Pesch (2019) consider the routing of straddle carriers with the objective of minimising the turnaround times of the vessels.

3.5. Integrated problems

In practice, the CT operational problems are highly dependent on the outcome of individual problems that can have a significant impact on one another. What makes the situation yet more compound is indeed the 'chicken and egg situation' that exists between different CT decision problems. While it is very difficult, if not impossible, to integrate all CT optimisation problems, there is much value in integrating some aspects of the problem, such as the quay side problems of BAP and QCSP. This has been variously identified as an important agenda for OR research in CT operations (Bierwirth & Meisel, 2015; Carlo et al., 2014a; Carlo et al., 2014b).

Bierwirth and Meisel (2010) discuss three different integration mechanisms corresponding to: (i) deep integration, (ii) functional integration by pre-processing, and (iii) functional integration with a feedback loop. In deep integration a monolithic model is solved where the interdependencies of the involved problem-individual decisions are considered in the background of the merged set of constraints. While promising the best overall solution, solving the corresponding monolithic model can be extremely difficult due to the huge complexity of the merged problems (Bierwirth & Meisel, 2010, 2015). In functional integration by pre-processing, one of the problems is solved under particular circumstances in order to tune the input data for the other problem. Finally, in functional integration with a feedback loop, problems are solved alternately such that the outcome of one problem is fed back to the other problem, restricting its decision space (Bierwirth & Meisel, 2010, 2015).

Table 5
Integrated problems.

Reference	Problems integrated	Method
Zhen, Zhuge, Wang, and Wang (2022b)	BAP and storage space allocation	*stoch*
Tan and He (2021)	BAP and QCSP	*heur*
Rodrigues and Agra (2021)	BAP and QCSP	*hybrid*
Liu, Li, Sheng, and Wang (2021)	BAP and vessel sequencing problem	*heur*
Kong, Ji, and Gao (2021)	QCSP and IMV scheduling	*heur*
Bouzekri, Alpan, and Giard (2021)	Laycan allocation, BAP and QCSP	*solver*
Qin, Du, Chen, and Sha (2020)	QCSP, IMV and YC scheduling	*solver*
Kizilay, Hentenryck, and Eliiyi (2020)	QCSP, IMV and YC scheduling, and storage space allocation	*solver*
Chen et al. (2020)	AGV and YC scheduling	*heur*
Abou Kasm, Diabat, and Cheng (2019)	BAP and QCSP	*solver*
Zhen, Yu, Wang, and Sun (2016b)	QCSP and IMV scheduling	*heur*
Correcher, Alvarez-Valdes, and Tamarit (2019a)	BAP and QCSP	*exact*
Iris and Lam (2019a)	BAP and QCSP	*heur*
Ma, Chung, Chan, and Cui (2017)	BAP, QCSP and storage space allocation	*heur*
Xie, Wu, and Zhang (2019)	BAP and QCSP	*exact*
Iris, Christensen, Pacino, and Ropke (2018)	QCSP and IMV scheduling	*heur*
Wang, Zhen, Wang, and Laporte (2018a)	BAP, QCSP and storage space allocation	*exact*
Agra and Oliveira (2018)	BAP and QCSP	*exact*
Zhen, Liang, Zhuge, Lee, and Chew (2017)	BAP and QCSP	*exact*
Jiang and Jin (2017)	YC deployment and storage space allocation	*exact*
Jin, Lee, and Cao (2016)	YC deployment and storage space allocation	*heur*
Dkhil, Yassine, and Chabchoub (2018)	Storage space allocation and straddle carrier scheduling	*heur*
Kaveshgar and Huynh (2015)	QCSP and IMV scheduling	*heur*
Türkoğulları, Taşkın, Aras, and Altınel (2016)	BAP and QCSP	*exact*
Liu, Lee, Zhang, and Chu (2016b)	BAP and tactical yard allocation	*heur*
Tang, Zhao, and Liu (2014)	QCSP and IMV scheduling	*heur*
Robenek, Umang, Bierlaire, and Ropke (2014)	BAP and storage space allocation	*exact*
Chen, Langevin, and Lu (2013)	QCSP and IMV scheduling	*heur*

An overview of recent publications integrating problems that belong to more than one of the presented categories of CT decision problems with a description of the integrated subproblems and the method is given in Table 5. The table indicates that as expected the seaside problems of BAP and QCSP have been more often integrated than other problem categories.

Uncertainty (particularly specific to vessel ETAs, container loading/unloading volumes and QC rates) has been only scantily considered in the integrated models presented in Table 5. This might be partially due to the added complexity arising from the integration itself, which in turn makes it more difficult to incorporate uncertainty. Iris and Lam (2019a) develop a recoverable robust optimisation approach for the weekly BAP and QCSP with uncertain vessel arrivals and container handling rate of QCs. Tan and He (2021) integrate the BAP and QCSP with uncertain vessel arrival times and fluctuation of loading and unloading volumes and propose a proactive strategy considering minimum recovery cost under uncertainty using a reactive strategy. Rodrigues and Agra (2021) consider an integrated BAP and QCSP with uncertain vessel arrival times, and model the problem as a two-stage robust mixed integer program where the BAP decisions are taken before the exact arrival times are known, and the QCSP decisions are adjusted according to the arrival times.

4. Big data analytics in container terminal operations

CTs are open systems of continual import and export containers flow, and operational data that is continuously generated from the terminal operating system, sensors and mobile technologies, and other IoT devices is significantly huge and dynamic; however, much under-analysed by CT operators to add real value (Heilig, Stahlbock, & Voß, 2020). This is mainly due to the yet very limited practical penetration of BDA, data mining and machine learning tools into the CT operational environment which is per se partially a result of the very fragmented and divergent literature in the field and lack of a guiding framework for the potentials of BDA independently and in collaboration with other disciplines such as OR in operational enhancement of ports.

Recognising this gap, only recently few review papers focusing on the application of data mining and machine learning in support of CT operations have emerged in the literature. Filom, Amiri, and Razavi (2022) carry out a systematic literature review on the applications of machine learning methods in port operations. They divide all applications into five areas of demand prediction, landside operations, seaside operations, safety, and other applications, and find that the most prevalent use case of machine learning methods is to predict different port characteristics. Heilig et al. (2020) review data mining applications in CTs and particularly highlight the role of data mining in achieving more accurate forecasts regarding factors such as vessel arrival times, container dwell times, and drayage truck delays, waiting times and turnaround times. Mekkaoui and Benabbou (2020) conduct a systematic literature review of machine learning applications for port operations and identify improved forecasting of cargo throughput, traffic flow, vessel arrival times, container dwell times, and drayage trucks turnaround times as the key research focus of existing machine learning studies.

As it was presented in Section 2.4 of the paper, we have been able to identify a total of 54 papers in the area of BDA in CT operations. In Fig. 11, the result of our review is presented in the provided framework, and in Table 6, we link the corresponding literature to each of the BDA application categories and sub-categories presented in the figure.

As indicated in Fig. 11, BDA contributes to CT operations mainly through parameter prediction, anomaly detection, operations automation and other applications such as IoT analytics and predictive maintenance. As reported in Table 6, the majority of the papers identified are categorised under the ‘parameter prediction’ category (over 80% of the papers). This is not unexpected, as the predictive arm of BDA is its most valuable asset that is widely exploited. Table 6 also indicates that while few application areas within each sub-category have received a good deal of attention,

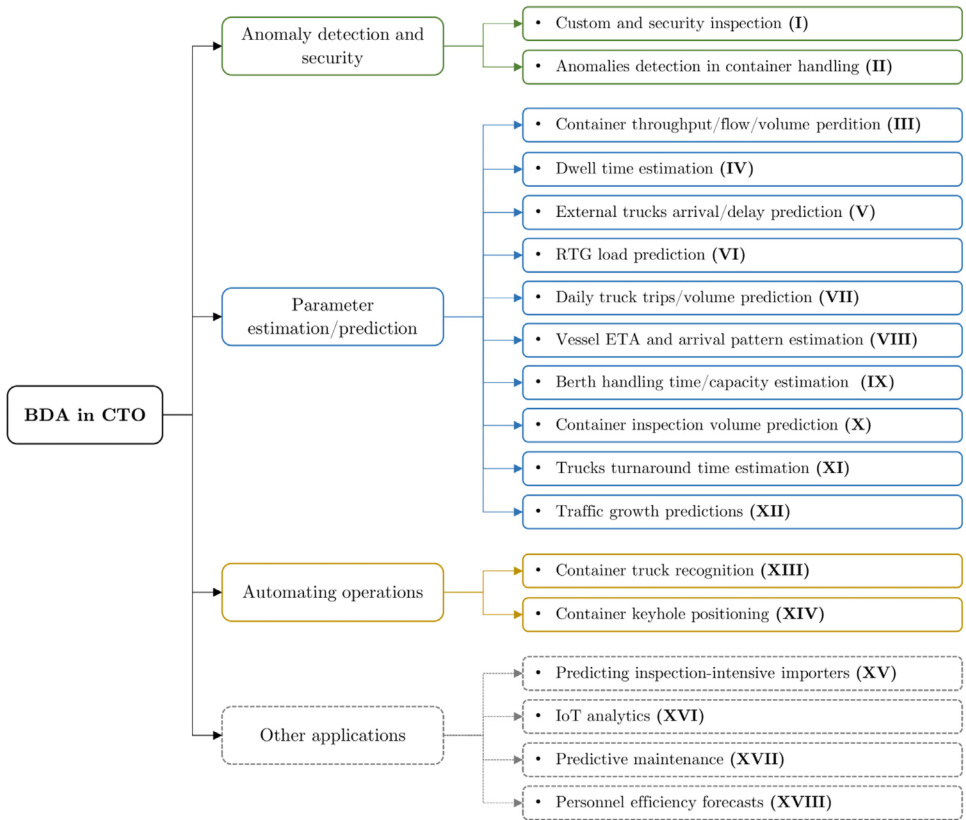

Fig. 11. Overview of applications of BDA in supporting CT operations.

Table 6
Studies on different applications of BDA in CT operations.

Main application category	Application sub-category	References
Anomaly detection and security	I*	(Chang, He, & Nguyen, 2010; Che et al., 2018; Hoshino, Oldford, & Zhu, 2010; Jaccard & Rogers, 2017; Jaccard et al., 2015; Jaccard et al., 2016; Liang et al., 2019)
	II	(Rahmawati & Sarno, 2021)
Parameter estimation or prediction	III	(Chan, Xu, & Qi, 2019; Gao, Chang, Fang, & Fan, 2019; Gao, Chen, Chang, & Fang, 2018; Geng, Li, Dong, & Liao, 2015; Gosasang et al., 2010; Jansen, 2014; Mak & Yang, 2007; Milenković et al., 2019; Peng & Chu, 2009; Rashed, 2016; Rashed, Meersman, Sys, Van de Voorde, & Vanelslander, 2018; Van Dorsser et al., 2011; Xie, Wang, Zhao, & Lai, 2013; Xie, Zhang, & Wang, 2017)
	IV	(Jokonowo et al., 2019; Kourounioti & Polydoropoulou, 2017; Moini et al., 2012; Mola, 2010; Zuhri, Sentia, Lubis, & Permai, 2019)
	V	(Huynh & Hutson, 2008; Wang & Zeng, 2018)
	VI	(Alasali et al., 2019)
	VII	(Al-Deek, 2001; Xie & Huynh, 2010)
	VIII	(Cannas, Fadda, Fancello, Frigau, & Mola, 2013; Du, Wang, Tang, & Guo, 2013; Flapper, 2020; Pani et al., 2014; Pani et al., 2015; Parolas, 2016; Sideris, 1999; Viellechner & Spinler, 2020; Wang et al., 2020a; Yu et al., 2018)
	IX	(Atak et al., 2021; Li & He, 2020; Linn et al., 2013; Nishimura et al., 2003; Wang et al., 2020a)
	X	(Ruiz-Aguilar et al., 2014, 2015; Ruiz-Aguilar et al., 2017; Urda Muñoz et al., 2019)
	XI	(Van der Spoel et al., 2016)
	XII	(García et al., 2014)
Automating operations	XIII	(Mi et al., 2019)
	XIV	(Li et al., 2020)
Other potential applications	XV, XVI, XVII, XVIII	Null

* Read in conjunction with Fig. 11.

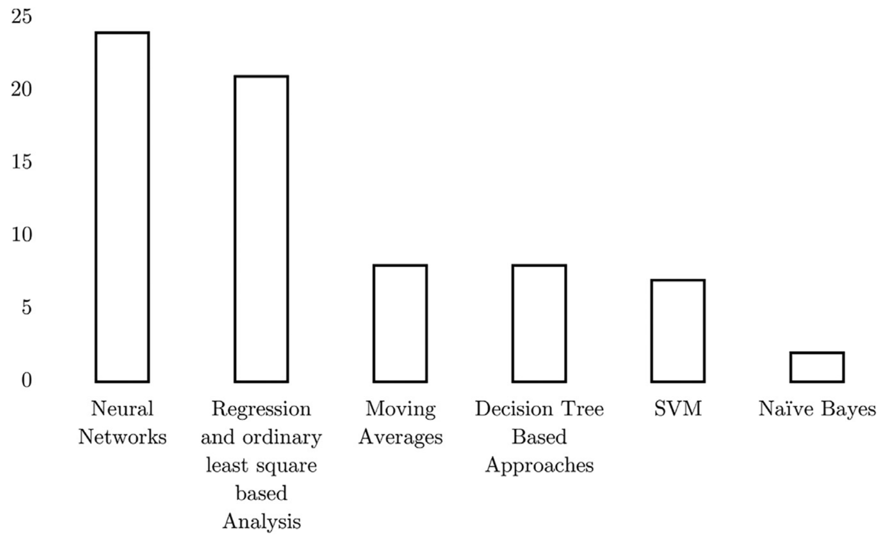

Fig. 12. Distribution of BDA methodologies employed by the reviewed papers.

others are much less researched and are lagging significantly behind.

Concerning the BDA methodology and algorithms employed by the reviewed paper, we realise that the applied methodologies could be broadly categorised into 6 different method groups of: (i) neural networks, (ii) regression and ordinary least square based analysis, (iii) moving average based approaches, (iv) decision tree based approaches, (v) support vector machine, and (vi) Naïve Bayes, with the first two categories, i.e., neural networks and regression based methods dominating the field (see Fig. 12).

Within each method category different variations and extensions were observed. Table 7 presents a general description for each method category and different variations observed, and also cites all references that use a relevant BDA algorithm. Note that some references appear in more than one category in Table 7 as they either use multiple methods, or compare their proposed method with a method from another category, and have been hence cited in front of more than one method group.

Next, we elaborate on the four main areas of BDA applications in CT operations illustrated in Fig. 11.

4.1. Parameter estimation or prediction

One of the best-perceived applications of BDA in CT operations is its predictive analytics use for estimating and forecasting key operational variables in CTs, such as container throughput, dwell time, and vessel arrival times, and this is where most of the existing literature is focused.

The first application area of BDA for parameter estimation shown in Fig. 11 is forecasting container throughput and container volume at sea ports. Not only is container throughput forecasting essential for efficient management of CT operations and the development of long-term investment plans for CTs (Mak & Yang, 2007), but also it helps greatly in reducing the omnipresent uncertainty that pertains to the associated decision problems (Milenković, Milosavljevic, & Bojović, 2019). At the same time, making precise forecasting of container throughput is a significantly complex task, as it is highly affected by many varying factors, such as seasons, the amount of imports and exports, and general economic conditions (Mak & Yang, 2007). Van Dorsser, Wolters, and Van Wee (2011) develop a method based on the combination of system dynamic modelling, judgement, and causal relations to forecast the throughput volumes at the Le Havre – Hamburg region. Gosasang, Chandraprakaikul, and Kiattisin (2010) use NN for predicting future container throughput at the Bangkok Port. Milenković et al. (2019) propose a fuzzy NN prediction approach based on metaheuristics for container flow forecasting at the Port of Barcelona and compare their results with traditional parametric ARIMA techniques. Mak and Yang (2007) use a modified version of SVM, called the least squares SVM to forecast the monthly container throughput in Hong Kong.

Another predictive application of BDA is to estimate the amount of time a container spends at a CT which is referred to as the Container Dwell Time (CDT). CDT has a direct impact on most of the CT operations and the CT productivity, and its reliable estimation is of high importance for CT operators (Jokonowo, Sarno, Rochimah, & Priambodo, 2019; Kourounioti & Polydoropoulou, 2017; Kourounioti, Polydoropoulou, & Tsiklidis, 2016; Moini, Boile, Theofanis, & Laventhal, 2012; Mola, 2010). Moini et al. (2012) identify determinant factors of CDT and compare the performance of three data mining algorithms to estimate CDT (i.e., Naïve Bayes, decision tree and a Naïve Bayes-decision tree hybrid). Kourounioti et al. (2016) apply ANN to identify the determinants of dwell time and find that the most important factors affecting significantly the model's accuracy are the container's size and type, the day and month of the container's discharge, the vessel's port of origin and the commodities transported.

External trucks arrival or delay prediction has been investigated in Huynh and Hutson (2008) and Wang and Zeng (2018). Huynh and Hutson (2008) use a decision tree technique to examine the sources of delay for dray trucks at the port of Houston, Texas and find that import transactions that require chassis tend to have high truck turnaround time because truckers need to find a matching chassis. To predict external truck arrivals, Wang and Zeng (2018) develop a prediction model based on the combination of deep belief net and SVM, where the deep belief net is used to obtain data characteristics, and SVM to obtain the predicted arrivals.

Alasali, Haben, and Holderbaum (2019) use an ensemble forecast model comprising ARIMAX and Monte Carlo simulation to estimate the expected day-ahead RTGCs electrical demand for use within an optimal management system that controls the energy storage systems at the Port of Felixstowe, UK. Al-Deek (2001) compares the performance of regression analysis and back-propagation NN in predicting the levels of cargo truck traffic moving inbound and outbound at seaports and finds that the NN model results are significantly accurate for both Florida ports considered. Xie and Huynh (2010) propose two kernel-based supervised machine learn-

Table 7
Classification of BDA in CT operations papers based on the BDA methodology applied.

Method	Description	Variations observed	References
Neural Networks (NN)	Methods central to deep learning and particularly useful for classification, clustering, forecasting, and pattern recognition. They are composed of basic units, mimicking biological neurons, that are linked to one another by connections whose strengths are modified over a learning process.	Artificial NN (ANN), Fuzzy NN, Deep NN, Recurrent NN, Back-propagation NN, Dynamic Bayesian network, Deep belief net, Convolutional NN, Self-Organising Maps (SOM)	(Al-Deek, 2001; Chan et al., 2019; Flapper, 2020; Gao et al., 2019; Gao et al., 2018; García et al., 2014; Gosasang et al., 2010; Jaccard et al., 2015; Jaccard et al., 2016; Li & He, 2020; Liang et al., 2019; Linn et al., 2013; Milenković et al., 2019; Ruiz-Aguilar et al., 2014, 2015; Ruiz-Aguilar et al., 2017; Urda Muñoz et al., 2019; Viellechner & Spinler, 2020; Wang & Zeng, 2018; Wang et al., 2020a; Yu et al., 2018)
Regression and ordinary least square based Analysis	Statistical methods that estimate the relationship between one or more exploratory variables and a target variable.	Fuzzy regression, logistic regression, multivariate adaptive regression splines, Poisson regression, Support Vector Regression, Gaussian Processes (GP), trigonometric regression	(Al-Deek, 2001; Atak et al., 2021; Chan et al., 2019; Du et al., 2013; Flapper, 2020; Geng et al., 2015; Hoshino et al., 2010; Kourounioti & Polydoropoulou, 2017; Mola, 2010; Nishimura et al., 2003; Pani et al., 2015; Peng & Chu, 2009; Rahmawati & Sarno, 2021; Rashed et al., 2018; Ruiz-Aguilar et al., 2017; Urda Muñoz et al., 2019; Van Dorsser et al., 2011; Xie & Huynh, 2010; Xie et al., 2013; Xie et al., 2017; Zuhri et al., 2019)
Moving average based approaches	A group of forecasting methods used to identify trend direction and mitigate the impacts of random and short-term fluctuations.	ARIMA, ARIMAX, SARIMA, SARIM	(Alasali et al., 2019; Al-Refaie & Abedalqader, 2020; Chan et al., 2019; Milenković et al., 2019; Rashed, 2016; Ruiz-Aguilar et al., 2014, 2015; Ruiz-Aguilar et al., 2017; Xie et al., 2017)
Decision tree based approaches	Nonparametric data mining methods used for classification and forecasting. Decision trees work on a training set to derive an inverted tree structure with root, internal and leaf nodes that can be used to determine objects classes.	Classification And Regression Tree (CART), Random Forest (RF), Gradient boosting	(Cannas et al., 2013; Huynh & Hutson, 2008; Moini et al., 2012; Pani et al., 2014; Pani et al., 2015; Van der Spoel et al., 2016; Viellechner & Spinler, 2020; Yu et al., 2018)
Support Vector Machine (SVM)	Supervised classification algorithms that find a separating hyperplane between classes by mapping the labelled data to a high-dimensional feature space	Least square SVM, ε-SVMs	(Chan et al., 2019; Mak & Yang, 2007; Mi et al., 2019; Parolas, 2016; Viellechner & Spinler, 2020; Wang & Zeng, 2018; Xie & Huynh, 2010)
Naïve Bayes	Supervised probabilistic classification methods based on Bayes theorem that assume independence between feature pairs	-	(Cannas et al., 2013; Moini et al., 2012)

ing methods corresponding to GP and ε-SVMs for predicting the daily truck traffic at seaport terminals using the data from two CTs at the Port of Houston. They compare their methods against the multilayer feed-forward NN model, and find that for all test datasets considered, while requiring less effort in model fitting, the GP and ε-SVMs models perform equally well, and their prediction performance compares favourably.

Vessel ETA and arrival pattern prediction is one of the key applications of BDA in CT operations that has been variously studied. While vessel operators typically have to notify their ETAs 24 hours before arrival, these are frequently updated due to unforeseen circumstances such as weather conditions, and delay in a previous port (Pani, Fadda, Fancello, Frigau, & Mola, 2014), which in turn cause a series of inconveniences impacting on the efficiency of CT operations (Pani, Vanelslander, Fancello, & Cannas, 2015). Flapper (2020) compares the performance of three machine learning algorithms corresponding to support vector regression, gradient boosting and k-Nearest Neighbours (kNN) in ETA prediction. To improve predictions, in addition to the time and vessel details features, Flapper (2020) uses a three way-points representation to include the current location of the vessel (i.e., when the prediction is made), its previous location (i.e., the location the vessel visited before the current location), and the target location to which the travel time will be predicted. Results of experiments conducted indicate that the gradient boosting method performs the best with the lowest root mean squared error while maintaining a reasonable computational time.

Another key role played by the predictive analytics capability of BDA in CT operations corresponds to its application in the accurate forecasting of berth handling time (Atak, Kaya, & Arslanoğlu, 2021; Li & He, 2020; Linn, Liu, Wan, & Zhang, 2013; Nishimura, Imai, Zhao, & Kaneko, 2003; Wang, Shen, Cao, Ding, & Xiao, 2020a). This is a measure that is central to the successful optimisation of several of the CT decision problems such as BAP and QCSP, and feeds important insight into task scheduling and resources allocation across CTs (Li & He, 2020). Li and He (2020) design a deep learning model and use it to predict berthing time at a typical container terminal in China based on relevant data of four years. Nishimura et al. (2003) develop a multiple regression model as well as an NN approach to estimate the vessel handling time. Within their multiple regression model, the handling time is assumed dependant on the number of containers handled, the number of IMVs assigned, and the distance between the berthing position and the dedicated container storage area in the yard. Wang et al. (2020a) propose a system to predict CT operations which consists of a module for predicting the number of vessels based on a kNN algorithm, and a module to predict vessel time (waiting and service) at the port using a regression model. Linn et al. (2013) develop ANN models to predict the QC rates, where data collected from CTs in Hong Kong are used to train and test their models.

While the most widely studied land side operational problems in CTs are perceived to be triggered by external trucks gate-in/gate-out events, a rather underestimated area of intensive operations within CTs correspond to container inspection. Just as external trucks cause container rehandling and reshuffling operations within the CT yard, containers intended for inspection must be retrieved, inspected and re-stored in the yard until they are charged onto the vessel or taken out by external trucks. The intensity of the retrieval and storage operations associated with inspection containers is in turn largely dependent on grasping a good estimate of the container inspection volume (Ruiz-Aguilar, Turias, & Jiménez-Come, 2014, 2015; Ruiz-Aguilar, Turias, Moscoso-López, Jiménez-Come, & Cerbán-Jiménez, 2017; Urda Muñoz, Ruiz-Aguilar, González-Enrique, & Turias Domínguez, 2019). Ruiz-Aguilar et al. (2015) propose a three-step procedure to better predict the number of inspections at border inspection posts, where in the first step the SARIMA is used to predict the data, in the second step SOM is used to decompose the time series into smaller regions with similar statistical properties, and in the third step ANN is used in each homogeneous region to forecast the inspections volume. Urda Muñoz et al. (2019) propose a deep ensemble NN approach to improve predictions of container inspection volume using time series database of the number of inspections carried out in the Port of Algeciras Bay between 2010 and 2018.

Finally, trucks turnaround time estimation (Van der Spoel, Amrit, & Van Hillegersberg, 2016) and traffic growth predictions (García, Cancelas, & Soler-Flores, 2014) are important decision making parameters that are scarcely predicted to improve the related optimisation processes. Van der Spoel et al. (2016) develop predictive models for truck turnaround time using both regression and classification methods. The authors use data generated in a simulated terminal and show that congestion, start time and route through the terminal together are good predictors of turnaround time. García et al. (2014) use ANN to predict the possible traffic growth at CTs, and analyse data from 33 ports in 16 different countries.

4.2. Anomaly detection and security

In 2019, 811 million TEUs of containers were handled globally in ports (UNCTAD, 2020). This ever-increasing cargo container volume at CTs increases significantly security risks as any container may be potentially used for malicious acts of smuggling prohibited items across borders (Jaccard, Rogers, Morton, & Griffin, 2016). At the same time, the physical inspection of all or even a fraction of port containers without disrupting the flow of commerce is rather impractical and requires a significantly large number of suitably trained security officers. As a result, the current screening protocols in most CTs rely mainly on: (i) container selection based on a risk analysis, specific intelligence, or at random, (ii) non-invasive inspection of X-ray cargo images, and (iii) physical inspection as a last resort (Jaccard & Rogers, 2017). While the inspection of X-ray cargo images is favoured over random and physical container searching and allows the inspection of a much larger number of containers using fewer resources and at a much faster pace, it is still a challenging visual search task for security officers as the images tend to be significantly cluttered by the large variety of objects that are transported in cargo containers (Jaccard et al., 2016). BDA tools and techniques can come to assist this situation by partially automating the inspection process.

Jaccard, Rogers, Morton, and Griffin (2015) develop a deep learning framework based on convolutional NN for the classification of X-ray cargo images according to their content. Jaccard et al. (2016) develop a framework for automated X-ray cargo image inspection based on several machine learning approaches including deep learning. Their proposed system can help to improve the inspection time by enabling security officers to focus their attention on images that are likely to be anomalous. Che, Xing, and Zhang (2018) propose an ensemble model based on deep learning with human-in-the-loop embedded for cargo inspection. They integrate human intelligence particularly to correct inaccurate predictions and hence balance model specificity and accuracy.

BDA's anomaly detection tools have not been used merely for security and inspection purposes in the CT context, though; they have been also used in the detection of CT processes inefficiencies. Rahmawati and Sarno (2021) use fuzzy regression and verbal expert judgments on the rate of anomaly to detect deviations from standard operating procedures. They develop rules for detecting 5 anomaly attributes corresponding to skip sequences, wrong throughput time (min), wrong throughput time (max), wrong decision and wrong pattern.

4.3. Automating operations and other applications

While the BDA predictive arm and its application in forecasting key operational parameters is significantly dominating the BDA in CT operations literature, there are other prominent BDA applications that have had very limited penetration into the CT environment and the pertinent academic research community. One of these key areas is BDA's application in assisting operations automation which, despite the fast-paced global development of automated CTs, has surprisingly attracted very limited attention, at least in terms of the number of pertinent studies we have been able to identify (Li, Fang, & Fang, 2020; Mi et al., 2019). Mi et al. (2019) propose an algorithm based on regional clustering and two-stage SVM classifier to automate the detection and positioning of quay side container trucks precisely and quickly. Li et al. (2020) develop a deep NN algorithm for automatic positioning of container keyholes.

Industry reports from Trelleborg Marine Systems (2018) and Papadomanolakis (2020) also shed light on several other potential applications of the BDA in CT operations including the prediction of inspection-intensive importers, IoT analytics, predictive maintenance and personnel efficiency forecasts that have not been yet explored in the academic literature and are significantly lagging behind. These applications can contribute significantly to the efficiency and cost effectiveness of CT operations. For example, Trelleborg Marine Systems (2018) reports that using Cisco and IBM solutions for IoT analytics, the Port of Cartagena in Columbia has been able to forecast equipment failures and thus ensure proper and timely maintenance of port machinery. Predictive maintenance, in particular, is a well-researched area of BDA that has not been yet much exploited within the CT operations research. Interested readers may refer to Carvalho et al. (2019) for a systematic literature review of machine learning methods applied to predictive maintenance.

5. Incorporation of environmental considerations and synergistic outputs

This section focuses on reviewing synergistic outputs from the *OR+EC*, *BDA+EC*, *OR+BDA* and *OR+BDA+EC* areas identified in Fig. 1. The section starts with OR and environmental considerations and develops a new classification scheme for papers that incorporate environmental concerns explicitly into the optimisation of key CT operational problems. Other dedicated optimisation problems that arise within the container terminal ecosystem and implicitly, yet significantly, contribute to the decarbonisation of CT operations are also reviewed and presented within this part. Then, we refer to the very meagre literature on BDA and environmental considerations in CT operations and shed light on promising research directions that are yet pretty much underdeveloped. Synergistic OR and BDA outputs are then reviewed, and the section is concluded with an analysis of the interplay between OR and BDA in addressing environmental concerns.

5.1. OR and environmental considerations

Decarbonisation initiatives have been increasingly incorporated into different domains of OR such as the vehicle routing problem (Bektaş & Laporte, 2011; Raeesi & O'Sullivan, 2014; Raeesi & Zografos, 2019, 2020; Salimifard & Raeesi, 2015) and manufacturing scheduling (Mansouri & Aktas, 2017; Mansouri, Aktas, & Besikci, 2016), and have been recently picked up as an important component in the optimisation of CT decision problems. Several of these initiatives in ports environments have been recently reviewed in Iris and Lam (2019b), particularly in the part of their paper that focuses on "energy-aware optimisation" studies which is most pertinent to this review paper. While arguing that operational efficiency would typically lead to energy efficiency and as such most of the optimisation studies inherently contribute to energy efficiency at CTs, Iris and Lam (2019b) conjecture that the literature on energy-aware operations planning with an explicit energy consumption related objective function is still pretty meagre. They maintain that with the increasing penetration of autonomous and intelligent vehicles into the CT environment, and with the technological developments relating to speed, manoeuvring and sensors, energy-aware routing and scheduling of equipment and integrated planning of CT problems must be much further explored.

Container MHE (i.e., QC, YC, IMVs, etc.) and the mooring vessel, regardless of the fuel/energy type involved are the main sources of emissions (either locally or through their life cycle), and for ease of reference can be collectively referred to as "Emitting Resources (ERs)". Within any of the key optimisation problems discussed earlier, at least one of the ERs appear (e.g., vessels in BAP, and QCs or vessels in QCSP) depending on the objective function used, and as such, the corresponding decision problem can be extended to reduce/minimise emissions explicitly, and concurrent with maintaining the service level. When any two or more of these problems are integrated, all the ERs associated with each individual problem could be potentially targeted using an appropriate objective function in the integrated higher-level problem, and thus, extra opportunities are presented to reduce emissions over multiple ERs (of course at the cost of higher complexity).

As was earlier discussed, we identified a total of 47 papers within the review area of OR and environmental considerations. Around 47% of these papers can be categorised as OR papers with explicit incorporation of environmental considerations (the 'explicit' category). These are optimisation papers that address one or more of the key decision problem categories reviewed in Section 3 (i.e., BAP, QCSP, SYOP, and TOP) by incorporating an explicit objective function (or an objective function component) corresponding to environmental performance into the optimisation problem. In order to characterise and position these papers with respect to one another and highlight their key elements, we propose a dedicated classification scheme based on different groups of mutually exclusive attributes. This classification scheme is illustrated in Fig. 13.

Each attribute and its potential values is briefly described below:

- *Problem category*: refers to the problem categories discussed in Section 3; i.e., BAP, QCSP, SYOP, TOP and integrated problems.
- *Optimisation type*: determines whether the problem is studied as a deterministic (*deter*), stochastic (*stoch*), or robust (*robust*) optimisation problem.
- *Uncertain parameter*: if the problem is studied in an uncertain environment, this attribute specifies the considered uncertain parameter as vessel's earliest time of arrival (*ETA*), QC workload (*workload*), container volume (*contvol*), or QC handling rates (*QCrate*). When this is not relevant *NA* refers to not applicable.
- *No. of objectives*: determines whether the problem has been studied as a single (*single*), bi-ojective (*bi*), or multiobjective (*multi*) problem with more than two objectives.
- *EC incorporation as an objective function*: specifies whether a dedicated objective function (*dedicated*) has been developed for the incorporation of environmental considerations, or this has been built into a more generic objective function as an objective function component (*component*).
- *Multiobjective optimisation approach*: determines whether weighted sum scalarisation (*wsum*), Pareto frontier generation (*pareto*), lexicograhic optimisation (*lexi*), or normalised scalarisation (*norm*) has been used to address the multiobjective problem. If the problem is not multiobjective, then this is not applicable (*NA*).
- *Competing objective*: refers to the objective considered alongside the environmental objective in case of a dedicated environmental objective. This can be makespan minimisation (*makespan*), service level (*service*), operational cost minimisation (*cost*), tardiness minimisation (*tard*), vessel handling time minimisation (*vhand*), or not applicable (*NA*).
- *Explicit ER involved*: refers to the emitting resource explicitly impacted by the optimisation; this can be vessel, IMV, YC, QC, AGV, or AQC.
- *ER's fuel*: determines whether ER is running on the conventional diesel or heavy oil (*conv*), or alternative fuels such as electricity (*elec*), hydrogen (*hydr*), ammonia (*ammo*), *LNG* or other fuels (*other*).
- *Terminal type*: specifies whether the terminal is of legacy and conventional type (*conv*) or automated (*auto*).
- *EC function*: determines the focus of the environmental consideration function used. This can be on minimising energy consumption (*energy*), fuel consumption (*fuel*), carbon taxt (*Ctax*), or emissions (*emissions*).
- *EC function type*: specifies whether the environmental consideration function developed is linear (*linear*), piecewise linear (*piece*), or nonlinear (*nolin*).
- *Emissions inventory calculation approach*: emissions inventory of vessels and MHE can be calculated either using the fuel statistics approach (*stat*) or the activity-based approach (*act*). Regardless of whether the environmental considerations function focuses on energy, fuel, emissions, or carbon tax, whenever statistical rates such as QC energy consumption rate per hour (kWh/hr), or vessel fuel consumption rate per hour while mooring (ton/hr) are used, the classification scheme marks *stat*, and when operational data related to service activity, or other detailed data such as engine workload, ship speed, location, etc. are used the approach is marked as *act*.
- *Factors affecting EC function*: many factors have been cited as factors affecting the corresponding environmental function used. An indicative set of factors used here correspond to vessel sailing speed (*vessp*), QC working time (*QCwt*), QC non-working time (*QCnwt*), IMV travelling distance (*IMVdist*), YC travelling distance (*YCdist*), container weight (*weight*), vessel waiting time (*vtime*), vessel service time (*vserv*), vessel characteristics such as its engine rated power, load ratio, number of engines, etc. (*vchar*), IMV waiting (*IMVwait*), AQC travelling and hoisting factors such as the moving speed and distance of AQC trolley and AQC hoisting mechanism with no-load/heavy-load (*AQCfact*), AGV full and empty time (*AGVtime*) and YC turning 90 degrees (*YCturn*). It is worth mentioning that this cannot be an exhaustive list but can be helpful in identifying key features considered to date.

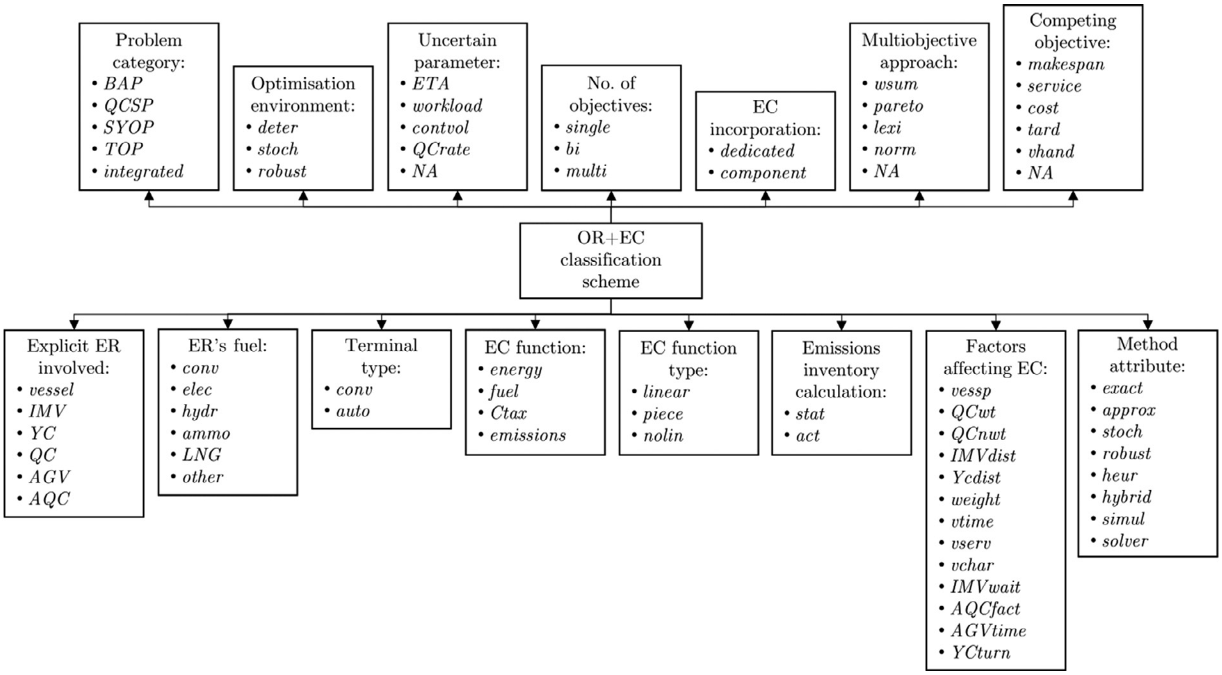

Fig. 13. Classification scheme developed for optimisation papers with explicit incorporation of environmental considerations.

Table 8
Classification of OR and explicit environmental considerations papers in CT operations.

Reference	Problem classification
Yu, Tang, and Song (2022a)	*integrated | deter | NA | multi | dedicated | pareto | Vessel | conv | fuel | act | nolin | vessp | heur*
Zhen, Sun, Zhang, Wang, and Yi (2021)	*integrated | stoch | ETA+workload | single | component | NA | QC | elec | Ctax | stat | linear | QCwt | exact*
Xin, Meng, D'Ariano, Wang, and Negenborn (2021)	*TOP | deter | NA | bi | dedicated | pareto | AGV | conv | energy | act | nolin | weight+othes | heur*
Tan et al. (2021)	*QCSP | deter | NA | bi | dedicated | norm | AQC | elec | energy | act | linear | AQCfact | solver*
Duan et al. (2021)	*integrated | deter | NA | bi | component | wsum | QC+IMV | conv+elec | emissions | stat | linear | YQCwt+IMVdist | heur*
Yue, Fan, and Zhai (2020)	*integrated | deter | NA | single | dedicated | NA | QC | elec | energy | stat | linear | QCwt+QCnwt | heur*
Wang et al. (2020b)	*integrated | deter | NA | bi | component | pareto | QC | elec | Ctax | stat | piece | QCwt | heur*
Hu (2020)	*BAP | deter | NA | multi | dedicated | pareto | Vessel | conv | fuel | act | nolin | vessp+vchar+QCwt+QCnwt+IMVdist+IMVwait | exact*
De et al. (2020)	*BAP | deter | NA | single | component | NA | Vessel | conv | fuel | stat | linear | vtime+vserv | heur*
Zhao, Ji, Guo, Du, and Wang (2019)	*integrated | deter | NA | single | component | NA | AQC+AGV | conv+elec | energy | stat | linear | AQCfact+AGVtime | heur*
Yu et al. (2019)	*TOP | stoch | workload | single | component | NA | YC | conv | emissions | stat | linear | YCdist | exact*
Wang et al. (2019a)	*integrated | deter | NA | bi | dedicated | pareto | Vessel+QC+IMV | conv+elec | emissions | act | nolin | vessp+vchar+QCwt+QCnwt+IMVdist+IMVwait | heur*
Sun, Zhen, Xiao, and Tan (2019b)	*integrated | robust | ETA+workload | single | component | NA | QC | elec | Ctax | stat | linear | QCwt | Solver*
Wang et al. (2018b)	*integrated | deter | NA | single | component | NA | QC | elec | Ctax | stat | piece | QCwt | exact*
Yu et al. (2016)	*QCSP | deter | NA | single | dedicated | NA | Vessel | conv | fuel | stat | linear | vessp | heur*
Sha et al. (2017)	*TOP | deter | NA | single | dedicated | NA | YC | conv | energy | stat | linear | YCturn+YCdist | solver*
Dulebenets et al. (2017)	*BAP | deter | NA | single | component | NA | Vessel | conv | emissions | stat | piece | vtime+vserv | heur*
He (2016)	*integrated | deter | NA | bi | dedicated | norm | QC | elec | energy | stat | linear | QCwt+QCnwt | heur*
He, Huang, Yan, and Wang (2015)	*integrated | deter | NA | bi | dedicated | wsum | IMV | conv | energy | stat | linear | IMVdist+IMVwait | heur*
Hu et al. (2014)	*integrated | deter | NA | bi | dedicated | norm | Vessel | conv | fuel | act | nolin | vessp | solver*
Du et al. (2011)	*BAP | deter | NA | bi | dedicated | pareto | Vessel | conv | fuel | act | nolin | vessp | exact*
Golias et al. (2009)	*BAP | deter | NA | single | component | NA | Vessel | conv | emissions | stat | linear | vtime+vserv | heur*

Table 8 classifies all *OR+EC* papers identified based on the proposed framework. Given that the majority of the emissions at CTs are from vessels, Table 8 shows that the existing literature on the incorporation of environmental considerations has thus far mostly focused on the quay side problems that more directly involve the vessel, i.e., the BAP and the QCASP, and the integration thereof. The table also shows that except for three cases (which consider workload and vessel arrival time as the key uncertain parameters), all papers have been studied in a deterministic optimisation environment. Half of the studies appear to have formulated the problem as a single objective optimisation problem and the environmental element has been incorporated as a term in a generic objective function; the other half (mostly bi-objective) have introduced a dedicated environmental objective to the problem in most cases, and the Pareto frontier has been investigated in some of these studies to illustrate the trade-off between environmental and business objectives. The competing business objective is found to be mostly makespan or tardiness minimisation. Vessel and QC are the most frequently targeted ERs within the classified papers, and energy and fuel consumption minimisation are more focused on than emissions and carbon tax.

We also observe that the fuel statistics approach and linear emissions functions are preferred over the more accurate activity-based approaches and nonlinear functions in most papers, mainly due to their simplicity. An example of fuel statistic approach usage is in the paper of Duan, Liu, Zhang, and Qin (2021) which considers the joint allocation of berths and QCs considering carbon cost through the use of linear functions with simple estimations for factors such as power consumption per unit time of a QC and per unit transport distance fuel consumption of a truck. To improve accuracy, other studies have tried to incorporate more compound calculations for fuel/energy consumption, emissions and carbon costs through the use of activity-based approaches. Wang, Li, and Hu (2019a) consider the multi objective berth-QC-IMV allocation problem where an activity-based approach composed of 4 main elements is used to estimate emissions inventory: (i) the total emissions of a vessel while shipping within the radium of the port area, (ii) the total emissions of a vessel while moored in port calculated by taking the rated power of the engine of the vessel, the load ratio, the number of engines of the vessel, and the total hoteling time into consideration (for the vessel auxiliary engines only), (iii) the total emissions of QCs in each state of working and waiting, where working energy is deduced based on the containers handling time which is in turn dependant on the containers volume and the QCs' work efficiency, and (iv) the total emissions of IMVs calculated by taking the energy requirement during the idle time and the transporting time of the IMV from berthing position to its corresponding block in the storage yard. Tan, Yan, and Yue (2021) focus on the AQC scheduling problem for an automated CT considering the trade-off between operational efficiency and energy consumption. To calculate the AQC energy consumption over a task they aggregate three components in their estimation equations corresponding to: (i) the power of the AQC multiplied by the time (i.e., distance over speed) the AQC takes to move in horizontal position with no-load and heavy-load, (ii) the power of the hoisting mechanism of the AQC multiplied by the time it takes to move in vertical position with no-load, and (iii) the power of the hoisting mechanism of the AQC multiplied by the time it takes to move in vertical position with heavy-load. There is also a group of studies that while relying on the fuel statistics approach, use more elaborate piecewise linear functions instead of simple linear estimations for emissions calculations. Wang, Du, Fang, and Li (2020b) extend a previous work (Wang, Wang, & Meng, 2018b) on the integrated BAP and QCSP with the consideration of carbon emission taxation as a bi-objective integer programming model. The authors use a stepwise linear function for the carbon emission taxation rate yielding a piecewise non-decreasing linear function for the total tax paid for a given level of carbon emissions. Carbon emission is calculated using estimates for the energy consumption of a QC during a unit time segment and the carbon emission factor for the given QC. Dulebenets, Moses, Ozguven, and Vanli (2017) consider the BAP with environmental considerations where a CO_2 emissions cost component is added to the generic objective function used for the problem. They consider a discrete set of potential handling rates for serving a vessel and associate a certain CO_2 emission factor to each handling rate in the set and allow the optimisation model to determine the value of the binary variable associated with each handling rate.

An unconventional approach towards the BAP with fuel consumption and vessel emissions considerations is to regard the arrival times of vessels as decision variables instead of exogenous parameters (Du, Chen, Quan, Long, & Fung, 2011; Golias, Saharidis, Boile, Theofanis, & Ierapetritou, 2009; Hu, 2020; Hu, Hu, & Du, 2014; Lang & Veenstra, 2009; Quan, Du, & Chen, 2011) which leads to nonlinear models for fuel consumption/emissions estimation. The main justification for this is that considering the arrival time of a vessel as a decision variable will provide the convenience of optimising fuel consumption and emissions as the vessel sails towards the port by exploiting the relationship between the fuel consumption and the sailing speed. Du et al. (2011) employ a nonlinear function for fuel consumption as a function of the sailing speed raised to power 3.5 for feeder containerships, 4 for medium-sized containerships, and 4.5 for jumbo containerships, and address the nonlinear complexity resulting from the incorporation of this function into BAP by casting it as a mixed integer second order cone programming. This approach has been improved in Wang, Meng, and Liu (2013) by proposing static and dynamic quadratic outer approximation approaches that can handle general fuel consumption rate functions more efficiently. One practical limitation of this "variable arrival time" strategy (Du et al., 2011) for optimising fuel consumption and emissions would be, however, the need for coordination between the terminal operator and the shipping line which are in practice two independent players with different objectives and limited ability to meddle with each other's operational decisions, especially when the vessel is not yet at the port.

As was earlier discussed, most of the economically efficient operations decided through the long-standing OR optimisation problems are usually also energy (and thus emission) efficient, and as a result it may be argued that OR has historically contributed to environmental performance of CTs (rather implicitly). However, new optimisation problems have been also increasingly arising within CTs with the increased level of automation, as well as with the adoption of new technologies and fuel and energy options, and while these optimisation problems do not essentially contain an explicit environmental element, they contribute significantly to the decarbonisation of CT operations in an implicit way (the 'implicit' category). We observe that these papers can be broadly categorised into two groups corresponding to: (i) optimisation for energy management and sizing (*OptEMS*), and optimisation for new technology, fuel, and equipment adoption (*OptTFE*). An indicative list of identified papers with a description of the paper focus is presented in Table 9. It is worth mentioning that only one of the studies cited in Table 9 (Gelareh et al., 2013) has been published in the mainstream OR and transportation journals discussed earlier, and these are mostly coming from engineering fields such as electrical engineering.

Finally, we must refer to an important (although meagre) group of studies that have very recently emerged at the intersection of explicit and implicit approaches discussed above (Iris & Lam, 2021; Peng, Dong, Li, Liu, & Wang, 2021; Yu, Voß, & Song, 2022b; Zhang, Liang, Shi, Lim, & Wu, 2022b; Zhang, Wang, & Zhen, 2022a). This category of interdisciplinary papers with 'hybrid' contributions (the 'hybrid' category) realises and incorporates the relationship between conventional optimisation problems of BAP, QCSP, SYOP and TOP, and the optimisation problems arising from energy management and sizing, and new technology and energy vectors adoption. Zhang et al. (2022b) propose an integrated day-ahead scheduling algorithm to jointly optimise the seaside and yard operations and the port energy system management within a unified framework. They develop a two-stage model, where the optimal berthing allocation for the incoming vessels considering their cargo volumes, energy demands, and the availability of onshore power supply facility and MHE is firstly determined, and then in the second stage, the optimal day-ahead scheduling of the container handling activities and operation of port microgrid assets for each time slot is optimised. They also incorporate the uncertainty from renewable energy generation and port load forecast in the problem formulation. Zhang et al. (2022a) develop a stochastic mixed-integer programming model to minimise the costs of purchasing, retrofitting, and chartering IMVs, as well as the operational costs that arise during the planning horizon. Yu et al. (2022b) propose a multi-objective optimisation model for the integrated BAP and QCSP that alongside optimising the conventional decision variables of the integrated problem (e.g., vessel's berthing position and berthing start and departure time), optimises the duration of using shore side electricity considering factors such as the availability of this at dif-

Table 9
Optimisation papers addressing environmental concerns in CT operations implicitly.

Reference	Category	Paper focus
Zhen, Jin, Wu, Yuan, and Tan (2022a)	*OptTFE*	IMV renewal problem optimisation considering three renewal modes of purchasing, retrofitting, and chartering
Fang, Wang, Liao, and Zhao (2022)	*OptEMS*	Optimal power scheduling for seaport microgrids, integrating logistics loads from cold ironing, quay and yard cranes, and reefer areas
Roy et al. (2021)	*OptEMS*	Optimisation for energy management and sizing within a multi-energy system considering electricity and hydrogen
Phiri (2021)	*OptEMS*	Optimal energy control of an RTGC with potential energy recovery
Hein, Xu, Gary, and Gupta (2021)	*OptEMS*	Operational scheduling of a seaport microgrid under uncertain renewable energy sources power output and load demand
Roy, Auger, Olivier, Schaeffer, and Auvity (2020)	*OptEMS*	Review on the development of harbour microgrids and studies dealing with sizing and energy management optimisation
Zhong, Hu, and Yip (2019)	*OptTFE*	Optimal strategy of measures including equipment changes for a CT to meet its statutory emissions reduction target
Wang et al. (2019b)	*OptEMS*	Optimal design problem of a hybrid renewable energy system for seaports
Li et al. (2019)	*OptEMS*	Optimising the installation capacity and operation strategy of a hybrid renewable energy system with offshore wind energy for CTs
Bolonne and Chandima (2019)	*OptEMS*	Sizing of a hybrid energy system for RTGCs
Antonelli, Ceraolo, Desideri, Lutzemberger, and Sani (2017)	*OptTFE*	Optimal energy management strategy for RTGCs with energy storage systems
Pietrosanti, Holderbaum, and Becerra (2016)	*OptEMS*	Power management strategy for an RTGC with a flywheel energy storage system
Peng, Wang, Song, and Zhang (2016)	*OptTFE*	Energy replacement problem for the adoption of electric RTGCs
Xin, Negenborn, and Lodewijks (2015)	*OptTFE*	Determining the trajectory of interacting MHE that transport containers between the quayside and the yard in an automated CT
Schmidt, Meyer-Barlag, Eisel, Kolbe, and Appelrath (2015)	*OptTFE*	Optimisation of the charging cost of battery-powered AGVs with a battery-swapping station
Kim, Choe, and Ryu (2013)	*OptTFE*	Dispatching strategy for operating AGVs in an automated CT
Gelareh et al. (2013)	*OptTFE*	Scheduling a new class of Intelligent and Autonomous Vehicles (IAVs)
Bui, Nguyen, and Nguyen (2021)	*OptEMS*	Review on optimisation of energy management systems in green seaports

ferent berths and the time-of-use electricity pricing. Peng et al. (2021) propose a multi-objective cooperative optimisation model for the problem of whether to allocate shore power for each berth minimising the total cost of installing and using shore power systems and maximising the environmental benefit of reducing emissions. Iris and Lam (2021) develop a mixed integer linear programming model to solve the integrated operations planning of the number of QCs and yard equipment assigned to each ship, and the energy management problem of the seaport smart grid considering uncertain renewable energy generation.

5.2. Big data analytics and environmental considerations

A key requirement for efficient inclusion of environmental considerations into CT operations is to estimate accurately fuel/energy consumption or emissions from the main ERs that operate at CTs. Given the available big data around each one of these resources in the port, BDA has a crucial role to play. Despite this intuitive expectation, literature on BDA and environmental considerations in CT operations is quite meagre and we have been able to identify only a few relevant papers focusing on the energy consumption and emissions prediction of ships in port (Peng, Liu, Li, Huang, & Wang, 2020; Sun, Tian, Malekian, & Li, 2018) and predicting energy consumption of RTGCs (Fahdi, Elkhechafi, & Hachimi, 2021; Papaioannou, Pietrosanti, Holderbaum, Becerra, & Mayer, 2017).

Peng et al. (2020) use five different machine learning models including gradient boosting regression, RF regression, backpropagation network, liner regression and kNN to predict the energy consumption of ships in Jingtang Port in China. They further find that net tonnage, deadweight tonnage, actual weight and efficiency of facilities are the top four features for predicting the energy consumption of ships. Sun et al. (2018) develop a BDA-based methodology to predict vessel emissions at Qingdao Port in China, and refer to the adoption of shore power and efficient cargo handling as a potential solution to reduce exhaust emissions. Fahdi et al. (2021) use multiple regression to analyse the operational data of daily energy consumption of 11 RTGCs in Casablanca Port in Morocco over two years. In their model, RTGC's emissions are assumed dependent on RTGC's hoist consumption, gantry consumption, trolley consumption, and idle mode consumption. Papaioannou et al. (2017) analyse the energy that is used by the RTGC motors in active and idle modes at the Port of Felixstowe in the UK based on the data collected during normal operation for eight days. Their analysis indicates that on average about half of the energy consumed is potentially recoverable and the recovery of this proportion of energy could lead to savings of 32,600 litre of fuel and 8100 tonnes of CO_2 per year at the port.

On top of BDA's application in forecasting energy consumption and emissions, and hand in hand with the 'implicit' category of contributions identified in the previous section on OR and environmental considerations, two other important categories of applications for BDA in implicit addressing of environmental concerns within CTs can be mentioned. These correspond to BDA's predictive capability in: (i) forecasting the energy or electricity demand by vessels and the CT's MHE, and (ii) forecasting the uncertain renewable energy generation within the port's microgrid. The general area of using BDA for such forecasting applications is rather well developed (Almaghrebi, Aljuheshi, Rafaie, James, & Alahmad, 2020; Guo, Gao, Zheng, Ning, & Zhao, 2020; Iliadis et al., 2019; Khan, Walker, & Zeiler, 2022; Lei & Mohammadi, 2021; Ogawa & Mori, 2019; Park, Park, & Hwang, 2020), but we were only able to identify two relevant papers within the context of seaports; Gopalakrishnan et al. (2022) use a variant of the gradient boost decision tree to forecast the hourly photovoltaic power generated in the Port of Gävle, to then perform peak shaving of electricity demand, and Alikhani, Tjernberg, Astner, and Donnerstal (2021) forecast the hourly peak load demand and short-term electricity demand profile in a container terminal using an ANN method. These are significantly useful approaches for integration with optimisation methods described before for energy management and sizing, and the adoption of new technology, fuel, and equipment options, and constitute an important direction for future research.

Table 10
Classification of *OR+BDA* papers.

Study	BDA application	Optimisation problem	Uncertain parameter	BDA approach
Kolley et al. (2022)	Input estimation	BAP	ETA	Linear regression, kNN, decision tree regressor, kNN and ANN
Cho et al. (2022)	Input estimation	SYOP	Weight class of containers	Gaussian mixture model
Zhang et al. (2021)	Input estimation and solution improvement	IMV routing	QCs operational times and parameter-controlled low-level heuristics	Deep reinforcement learning
Xiang and Liu (2021a)	Input estimation	Integrated BAP and QCSP	Uncertainties in the late arrival of ships and inflation of container quantity	k-means clustering
Xiang and Liu (2021b)	Input estimation	BAP	Operation time	k-means clustering
Kolley et al. (2021)	Input estimation	BAP	ETA	machine learning-based algorithm
Guo et al. (2021)	Input estimation	BAP	Vessel handling time due to uncertain weather conditions	NN and k-means
Chargui et al. (2020)	Input estimation	QCSP	Uncertain QC productivity rate	ANN
Zhang et al. (2020b)	Solution improvement	SYOP	Tightened upper bounds	RF classifier and association rules mining
Zhang and Guan (2020)	Solution improvement	SYOP	Tightened upper bounds	RF classifier and association rules mining
Hottung et al. (2020)	Solution improvement	SYOP	Lower bound determination	deep ANN
Caballini et al. (2020)	Input estimation	External trucks assignment in TAS	Associated containers	Hierarchical clustering
Maldonado et al. (2019)	Input estimation	SYOP	CDT	Multiple linear regression, decision trees, and RF
Yu et al. (2018)	Input estimation	Integrated BAP and QCSP	ETA	Back-propagation, CART and RF
De León et al. (2017)	Solution improvement	BAP	Best lower-level heuristic	machine learning-based algorithm
Choe et al. (2016)	Solution improvement	AGV dispatching	Adapt dynamically to the policy	ANN
Jeon et al. (2011)	Input estimation	AGV routing	AGV's waiting time	Q-learning
Fancello et al. (2011)	Input estimation	Human resource allocation	ETA	NN
Kang et al. (2006)	Input estimation	SYOP	Uncertain container weight information	Decision Tree and Naïve Bayes

5.3. OR and big data analytics

While BDA, machine learning and data mining techniques can play a significant complementary role with OR in overcoming the uncertainty of container terminal operations, the literature in the area is yet significantly underdeveloped. We identify a total of 19 papers where BDA and OR approaches are explicitly unified to address CTs' decision problems (over 60% of them were published after 2020 which indicates the rising interest in the topic). It may be worth adding that out of these, only 6 papers have been published in our 20 journal outlets. A complete classification of all *OR+BDA* papers is given in Table 10. These papers could be broadly classified into three groups corresponding to studies that use BDA: (i) to forecast problem domain inputs such as ETA and CDT which are then passed on to the related optimisation problems of BAP, QCSP, SYOP, etc. (Caballini et al., 2020; Chargui, Zouadi, El Fallahi, Reghioui, & Aouam, 2020; Fancello et al., 2011; Guo, Wang, & Zheng, 2021; Jeon, Kim, & Kopfer, 2011; Kang, Ryu, & Kim, 2006; Kolley, Rückert, & Fischer, 2021; Maldonado et al., 2019; Yu et al., 2018), (ii) to reinforce the exact or heuristic solution algorithms developed for the CT key optimisation problem considered (Choe, Kim, & Ryu, 2016; De León, Lalla-Ruiz, Melián-Batista, & Marcos Moreno-Vega, 2017; Hottung, Tanaka, & Tierney, 2020; Zhang & Guan, 2020; Zhang et al., 2020b), and (iii) to both forecast problem inputs and parameters and reinforce the solution in a hybridised mode (Zhang, Bai, Qu, Tu, & Jin, 2021).

Kolley et al. (2022) use four different machine learning algorithms to estimate the ETA of vessels in the optimisation of BAP. Cho et al. (2022) propose an online optimisation method for the container stacking problem in which the container weight is classified into data-driven weight classes based on the Gaussian mixture model. Guo et al. (2021) consider the BAP with vessel handling time uncertainty due to uncertain weather conditions. Vessel handling times considering the influence of weather conditions is in turn predicted using an NN algorithm, which uses the wind speed and direction, wave height and direction, wave cycle, visibility, and precipitation as inputs. To reduce the fitting difficulty, k-means clustering algorithm is used to cluster historical data into several groups of data based on their similarity. Kolley et al. (2021) study a robust BAP with uncertain vessel arrival times. Within their approach, ETAs are predicted using machine learning techniques and uncertainty is proactively considered in the planning phase, resulting in a robust berthing schedule. Xiang and Liu (2021b) consider the BAP at a tactical level with uncertain operation time. They propose a data-driven robust optimisation model in which available historical data is first analysed using k-means clustering to construct the uncertainty set, and then a column-and-constraint generation algorithm is used to solve the model. The proposed approach is later extended to the case of the integrated BAP and QCSP problem by Xiang and Liu (2021a). Yu et al. (2018) compare the performance of back-propagation network, CART and RF in estimating the delay or advance of ship arrivals, and use the predictions in optimising the integrated BAP and QCSP. Chargui et al. (2020) consider the QCSP with uncertain productivity rate of QCs. The authors use an ANN coupled with a variable neighbourhood search as their training algorithm to build a productivity rate predictive model. The resulting productivity rate forecasts from the predictive model are then passed as input to the QCSP optimisation model. The productivity rate of QCs in the proposed predictive model is assumed dependent on the type of containers on the vessels and the expected equipment failure rate. Caballini et al. (2020) deal with the assignment of external trucks to time slots in CTs equipped with TAS. They combine a clustering analysis (hierarchical clustering method) aimed at matching export and import containers in tuples, with a Mixed Integer Programming (MIP) formulation that assigns the identified tuples to time slots such that trucks deviation from their preferred time slots and turnaround times are minimised. Maldonado et al. (2019) address the stacking problem for import containers via a two-step strategy in which dwell times are first predicted for each container using multiple linear regression, decision trees, and RF, and then used as an input to minimise container rehandles. The authors use historical data of the Port Terminal of Arica in Chile from 2016 for their predictive models. Fancello et al. (2011) develop a dynamic learning predictive algorithm based on NN to reduce the ETA uncertainty in port and use the predicted values within an optimisation algorithm for human resource allocation. Jeon et al. (2011) develop a method for AGVs routing, where the AGVs waiting time is estimated using a Q-learning technique and then shortest time routing matrices are constructed for each given set of positions. Kang et al. (2006) consider export containers stacking with uncertain weight information and use different machine learning algorithms such as the decision tree and Naïve Bayes to improve the weight group estimation.

The application of BDA and machine learning in improving the performance of exact and heuristic solution algorithms for difficult optimisation problems has also attracted considerable attention in recent years. Within the context of (meta-)heuristic search procedures, machine learning has been efficiently used in hyper-heuristics to select the best heuristic out of a portfolio of options for a given problem instance, and to determine and train parameters of metaheuristics (Hottung et al., 2020), for example; and within exact solvers data analytics has been effectively used in the selection of variables and nodes in MIPs, deciding when to apply a primal heuristic while solving an MIP, and improving the performance of branch-and-price algorithms by predicting an upper bound for each iteration of the pricing problem; to name but a few applications (Hottung et al., 2020). Other interesting areas such as objective function and constraint learning have been also emerging (Fajemisin, Maragno, & Hertog, 2021; Maragno et al., 2021; Matsuoka, Nishi, & Tiemey, 2019). It may be worth mentioning that within this area, the interplay of OR and BDA is pretty much mutual, and OR contributes significantly to BDA, machine learning and data mining algorithms through the optimisation of the loss function in machine learning algorithms, optimisation of the nonconvex objective function in different machine learning algorithms such as deep NN, and hyperparameter tuning (Fajemisin et al., 2021), for instance.

Within the area of CT operations, we identify only five papers that focus on the co-application of OR and BDA in reinforcing the performance of solution algorithms for different CT optimisation problems. Zhang et al. (2020b) and Zhang and Guan (2020) develop a machine learning-driven optimisation method for the container relocation problem aiming at finding the optimal movement sequence such that the total number of container relocation operations is minimised. Within the proposed approach a new upper bound method is proposed that incorporates branch pruners derived from machine learning techniques (e.g., RF classifier and association rules mining) with the optimal solution values of many small-scale instances. These tightened upper bounds are then used within an exact branch-and-bound algorithm and a hybrid beam search heuristic. Hottung et al. (2020) propose a deep learning assisted heuristic tree search for the container pre-marshalling problem. They use a heuristic tree search in which decisions pertaining to which branches to explore and how to bound nodes are made by a deep ANN. The algorithm is further used at some levels of the search tree to determine a lower bound and reduce the branching factor. De León et al. (2017) consider the BAP at bulk terminals and propose a machine learning-based algorithm in which machine learning is used to select the best lower-level heuristic for the problem instance at hand based on collected data from past problems with similar features. Choe et al. (2016) study the AGV dispatching problem in an automated CT with the objective of minimising the average QC processing time and the total empty travel distance of AGVs. To solve the problem, the authors propose an online preference learning algorithm based on ANN that adapts dynamically to the policy for dispatching AGVs to changing situations in the terminal**.**

Finally, the simultaneous application of BDA to forecast problem inputs and parameters to reinforce the solution algorithm has been considered in only one study. Zhang et al. (2021) develop a deep reinforcement learning based hyper-heuristic framework that is applied on an IMV routing problem with the objective of minimising the aggregated QCs waiting times, where the QCs operational times are assumed uncertain due to factors such as container stacking requirements complexities, operator proficiency, weather conditions and differences among QCs. Their proposed algorithm enhances existing hyper-heuristics with deep reinforcement learning on parameter-controlled low-level heuristics to improve their handling of uncertainties.

5.4. OR, big data analytics and environmental considerations

The *OR+BDA* papers reviewed above indicate no explicit incorporation of environmental considerations, and despite significant research opportunities which will be shortly discussed, the literature on the co-application of OR and BDA to address environmental considerations in CT operations is significantly underdeveloped. In total, we observe that there is only one paper within the area that uses BDA in improving estimates on input data used within an integrated BAP and QCSP problem addressing environmental considerations. He (2016) investigates the trade-off between time-saving and energy-saving in a bi-objective integrated BAP and QCSP. The objective function corresponding to the total handling energy consumption of a vessel is composed of two parts for the working and non-working states. The working energy consumption component is basically formulated as a linear function of the estimated QC energy required per move, but the non-working energy consumption (i.e., energy required for the running of auxiliary equipment during the QCs' idle time) is assumed dependent on the number of QCs assigned to the vessel and is estimated using a regression analysis of more than 30,000 historical data collected from different CTs in China.

This situation clearly indicates the current significant gap in the literature focusing on the synergistic effect of OR and BDA in decarbonising CT operations. To identify and discuss prominent ways in which this collaboration can be reinforced in forthcoming research, we begin by summarising the key findings of this review paper in terms of the synergistic outputs from the *OR+BDA*, *OR+EC* and *BDA+EC* literature reviewed so far in Table 11. This table indicates the key subcategories identified within each category and the distribution of papers within each of these. As it is clear from the table, most of the studies are saturated at sub-categories II.a and II.b, while the general category of *BDA+EC* (i.e., category III) is quite meagre. The table also implies that research under category I (i.e., *OR+BDA*) has just started to take-off and with rapid advances in other fields of OR, many more outputs in this research category may be expected.

Not only does Table 11 function as a concise summarisation of all the foregoing discussions on collective outputs, but it also helps identifying ways in which the presented sub-categories I.a to III.c can be synergised to bring forward new research with significant impact. One such way which was already discussed with the example from He (2016), is to hybridise I.b and II.a (i.e., I.b+II.a). Along the same lines, many different combinations can be thought of; however, we tend to refer to two particular areas for new interdisciplinary research with significant methodological and practical impacts: (i) II.a+III.a, which refers to the incorporation of accurate forecasts of emissions inventory from BDA predictive modelling tools into the environmentally-oriented objective function (or objective function component) of CT decision problems, and (ii) II.b+III.b+III.c, which corresponds to tackling the uncertainty in the CT's energy/load demand and renewable energy/microgrid output, and feeding the forecasts into the optimisation models used for energy management of the vessel cold ironing or energy required by CT's MHE, for instance. Suitable research in these areas

Table 11
Identified synergistic research paths and the corresponding classified literature.

Category	Sub-category	Reference
I. *OR+BDA*	**I.a.** BDA for reinforcing exact or heuristic solution algorithms	(Choe et al., 2016; De León et al., 2017; Hottung et al., 2020; Zhang & Guan, 2020; Zhang et al., 2020b)
	I.b. BDA for forecasting problem domain inputs, e.g., ETA, dwell times, etc.	(Caballini et al., 2020; Chargui et al., 2020; Fancello et al., 2011; Guo et al., 2021; Jeon et al., 2011; Kang et al., 2006; Kolley et al., 2021; Maldonado et al., 2019; Yu et al., 2018)
	I.c. Hybridisation of I.a and I.b	(Zhang et al., 2021)
II. *OR+EC*	**II.a.** Explicit incorporation of an environmental considerations-oriented objective function or component into conventional CT decision problems	(De et al., 2020; Du et al., 2011; Duan et al., 2021; Dulebenets et al., 2017; Golias et al., 2009; He, 2016; He et al., 2015; Hu, 2020; Hu et al., 2014; Sha et al., 2017; Sun et al., 2019b; Tan et al., 2021; Wang et al., 2020b; Wang et al., 2019a; Wang et al., 2018b; Xin et al., 2021; Yu et al., 2019; Yu et al., 2022a; Yu et al., 2016; Yue et al., 2020; Zhao et al., 2019; Zhen et al., 2021)
	II.b. Optimisation for energy management and sizing, and adoption of new net-zero technology, fuel, and equipment options	(Antonelli et al., 2017; Bolonne & Chandima, 2019; Bui et al.; Fang et al., 2022; Gelareh et al., 2013; Hein et al., 2021; Kim et al., 2013; Li et al., 2019; Peng et al., 2016; Phiri, 2021; Pietrosanti et al., 2016; Roy et al., 2020; Roy et al., 2021; Schmidt et al., 2015; Wang et al., 2019b; Xin et al., 2015; Zhen et al., 2022a; Zhong et al., 2019)
	II.c. Hybridisation of II.a and II.b	(Iris & Lam, 2021; Peng et al., 2021; Yu et al., 2022b; Zhang et al., 2022a; Zhang et al., 2022b)
III. *BDA+EC*	**III.a.** BDA for predicting ER's energy/fuel consumption or emissions	(Fahdi et al., 2021; Papaioannou et al., 2017; Peng et al., 2020; Sun et al., 2018)
	III.b. BDA for predicting energy/electricity load/demand by the CT, vessels and MHE	(Alikhani et al., 2021)
	III.c. BDA for forecasting the uncertain renewable energy generation	(Gopalakrishnan et al., 2022)

can bring in significant real-life impact on the decarbonisation of CT operations. An example of this might be the study of Alasali et al. (2019) reviewed before in Section 4, which uses BDA to forecast expected day-ahead RTGCs electrical demand for use within an optimal management system that controls the energy storage systems at the Port of Felixstowe, UK.

6. Summary and future research directions

With the ever-increasing reliance of the global economy on shipping of containerised goods, CTs have been facing with an unprecedented level of significantly interdependent and highly uncertain operations. Intensity of operations at container ports has also resulted in increasing environmental concerns, and stakeholders from the public and local governments are pressurising CTs to yet cut down on their emissions.

OR, with its long-lasting role in the optimisation of the key decision problems that arise from the quay and land sides of CTs, has been therefore presented with new challenges (and of course opportunities) to incorporate sustainability considerations into decision making and better utilise the big data generated and stored from the never-stopping CT operations. Despite these significant challenges and opportunities in the face of OR, however, the extant literature on OR's incorporation of environmental considerations and its interplay with BDA is still underdeveloped, fragmented and divergent, and a guiding framework is missing.

This review paper tried to address this gap by presenting a review of the most relevant literature in the six key areas of *OR*, *BDA*, *OR+EC*, *BDA+EC*, *OR+BDA* and *OR+BDA+EC* in CT operations, and deriving a research framework to shed light on promising research avenues for the better exploitation of the synergistic effect of the two disciplines in addressing CT operations, while incorporating uncertainty and environmental concerns efficiently. The review makes it obvious that despite the significant benefits that lie in the co-application of OR and BDA, corresponding research in addressing CT operations is significantly lagging behind and there are multiple important directions for future developments. Below, we summarise some of the identified gaps and opportunities for future research for each of the six areas considered in this paper:

6.1. OR in CT operations

We reviewed recent developments in BAP, QCSP, SYOP, TOP and integrated problems, and provided updates within the existing classification schemes. In line with previous review papers, we observe that the literature is still significantly lagging behind in terms of incorporating the uncertainty that is widespread in various key input parameters to the decision problems reviewed, and only less than 15% of the papers in our selected set consider one or several uncertain problem inputs, and incorporate them into optimisation mainly through stochastic and robust optimisation approaches. This is particularly an area of underdevelopment reported also in previous review papers, and hence requires revitalised attention. One key development would definitely be to exploit BDA in addressing uncertainty more proactively as will be discussed shortly. Our review also reveals a rise in the number of papers addressing integrated problems. This is a key requirement for addressing CT decision problems in a more efficient way. Given the extra complexity of the integrated problem, however, adding uncertainty would be yet more challenging and this is hence mostly missing from the literature and constitutes a promising direction for future research.

6.2. BDA in CT operations

Our review of BDA applications in addressing CT operational problems identified three main areas of application for BDA corresponding to parameter prediction, anomaly detection, and operations automation. We find that parameter prediction is by far the most widely used application of BDA in the extant literature. While this is perfectly expected due to the significance of the predictive analytics benefits of BDA, there are many more important applications which are yet untapped and very much underdeveloped. In particular, with the increasing trend of CT automation, there is a great opportunity for BDA to facilitate operations automation and this is where the current literature is currently extremely meagre. We also observe that literature on other very useful applications of BDA such as IoT analytics and predictive maintenance are fully missing from the existing literature.

While most of the arguments in this paper centred around how BDA can contribute to OR modelling and solution development, this is not a one-way relationship, and research on strengthening BDA methodologies using optimisation and its application in parameter prediction, anomaly detection, and operations automation and more in CT operations is quite needed. In all, despite the significant connection between OR and analytics, the reluctance of OR community and publication outlets reflected by the very low amount of research into analytics published in journals associated with OR is one key issue requiring further attention.

6.3. OR + EC in CT operations

Acknowledging the fact that the long-standing OR optimisation problems pertaining to CT operations have traditionally led to improved environmental performance of CTs indirectly, we classified the literature pertaining to the *OR+EC* area into three categories of ‘explicit’, ‘implicit’ and ‘hybrid’ approaches.

A new classification scheme was developed for papers within the ‘explicit’ category to position the existing literature and shed light on attributes that must be considered carefully when planning future developments in the field. It is observed that the explicit incorporation of environmental considerations into the CT operations optimisation is yet rather immature and there are still significant potentials for OR to unlock and deliver its contributions. For one thing, we observe that in most of the existing papers rather rudimentary calculations based on fuel statistics approaches are employed for the estimation of fuel/energy consumption or emissions inventory, which clearly lack accuracy and can lead to sub-optimal solutions. We suggest that this situation can be to a large extent addressed by establishing a better interaction with the vast literature that is dedicated to energy/fuel consumption and emissions estimation of the vessel and CT’s MHE. As will be discussed shortly, the use of BDA can be also quite helpful in improving the required estimates.

In most of the studies reviewed in this paper, environmental considerations have been either incorporated as just a term in the single objective of the problem, or if a dedicated objective function is defined, this is usually aggregated with the service-related objective(s) and only in few studies an attempt has been made to generate the Pareto optimal solutions on the efficient frontier of the problem of concern. This is, however, a highly desired approach in addressing optimisation problems with environmental considerations as it allows the decision maker to visualise the trade-offs between environmental and business objectives more obviously and consider the best compromise.

As regards the ‘implicit’ category of papers, we reviewed optimisation problems that have naturally emerged due to the increased level of automation, and adoption of new technologies and fuel and energy options in seaports. These optimisation problems do not essentially contain an explicit environmental element, but they contribute significantly to the decarbonisation of CT operations in an implicit way. We observe that these papers can be broadly categorised into two groups corresponding to optimisation for energy management and sizing, and optimisation for new technology, fuel, and equipment adoption. Despite their significance, and the clear role for OR, these have been much less appeared in key OR outlets and has mostly attracted researchers from other fields such electrical engineering. New interdisciplinary research within this area with more proactive participation from the OR community is highly desired.

Along the same lines, a very interesting wave of research which has just recently been partially activated and is expected to grow much more, corresponds to the research at the intersection of ‘explicit’ and ‘implicit’ categories referred to as the ‘hybrid’ category. This category of interdisciplinary research realises and incorporates the relationship between conventional CT optimisation problems, and the optimisation problems arising from energy management and sizing, and new technology and energy vectors adoption and are methodologically and practically important. New research within this area is very much encouraged.

6.4. BDA + EC in CT operations

As discussed above, a key requirement for efficient inclusion of environmental considerations into CT operations is to estimate accurately fuel/energy consumption or emissions from the main ERs that operate at CTs. Given the available big data around each ER within CTs, one attractive way to increase the accuracy of these estimates is to use BDA. Despite this intuitive expectation, literature on BDA and environmental considerations in CT operations is quite meagre and underdeveloped. Overall, it may be argued that using BDA to perform ER’s emissions inventories has an added value over existing fuel-based (top-down) approaches in terms of the delivered accuracy, and over activity-based (bottom-up) approaches in terms of its relative simplicity in implementation, and independence form detailed and hardly accessible input data.

In addition to emissions prediction, we also shed light on the important role BDA research can play in forecasting the energy or electricity demand by vessels and the CT’s MHE, and the uncertain renewable energy generation within the port’s microgrid. As will be shortly discussed, these are significantly useful information for the efficient optimisation of energy management and sizing problems, and problems associated with the adoption of new technology, fuel, and equipment options.

6.5. OR + BDA in CT operations

BDA can play a significant complementary role with OR in overcoming the uncertain environment of CT operations; however, the extant literature in the area is significantly lagging behind. We identify three main ways in which future research can exploit the synergy of OR and BDA in CT operations better.

BDA capability of predictive modelling can be used to forecast OR problem domain inputs such as ETA and CDT. Although still very limited, this is where most of the existing relevant papers are concentrated. There are lots of potentials yet to untap within this research theme and this is a largely open research avenue.

BDA can also contribute to tailoring better solutions to CT optimisation problems and reinforce the developed exact or heuristic solution algorithms. It can be efficiently used in hyper-heuristics to select the best heuristic out of a portfolio of options for a given problem instance, determine and train parameters of metaheuristics, select variables and nodes in MIPs, help in deciding when to apply a primal heuristic while solving an MIP, improve the performance of branch-and-price algorithms by predicting an upper bound for each iteration of the pricing problem, and so on and so forth. Other emerging areas such as objective function and constraint learning also imply interesting research directions.

The simultaneous application of BDA to forecast problem inputs and to reinforce the solution algorithm comprises a significant opportunity for future research at the intersection of OR and BDA in CT operations; however, there is currently not much literature within this theme.

6.6. OR + BDA + EC in CT operations

One of the key objectives of this review paper was to understand how the interplay of OR and BDA can contribute to addressing environmental considerations in CT operations. We observe that, despite its importance and relevance, there is hardly any literature in this area. The conducted review of *OR+EC*, *BDA+EC*, and *OR+BDA* in this paper, however, sheds light on several obvious ways in which OR and BDA can work together to promote environmental performance of CT operations; for example, adding an environmentally explicit objective function to an optimisation problem with uncertain problem inputs that are estimated using BDA, is a research path already exploited in the literature. Another significantly promising research direction at the intersection of OR and BDA in incorporating environmental considerations into CT operations is to exploit BDA's predictive modelling capability in improving ER's energy/fuel consumption or emissions estimation, and then using the obtained estimate within the explicit environmental considerations-oriented objective function of the optimisation problem of concern. This capability can be particularly helpful in addressing integrated problems with environmental considerations, where highly accurate estimates on multiple ER's can be generated via BDA and used within the unified optimisation model. Research to report the value of this integration by carrying out a comparative analysis of using high-level and judgmental estimates, estimates based on fuel-based or activity-based approaches, and estimates based on BDA is also highly desirable. Such research can provide very useful insights into the sub-optimality of solutions obtained just due to lack of accuracy in the provided estimates. Finally, we believe new research that tackles the uncertainty in the CT's energy/load demand and renewable energy/microgrid output using BDA, and feeds these forecasts into the optimisation models used for energy management of the vessel cold ironing or energy required by CT's MHE can bring in significant real-life impact on the decarbonisation of CT operations.

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Appendix A. List of the acronyms

Acronym	Meaning	Acronym	Meaning
AGV	Automated Guided Vehicle	MHE	Material Handling Equipment
ALV	Automated Lifting Vehicle	MIP	Mixed Integer Programming
ANN	Artificial Neural Network	NN	Neural Network
AQC	Automated Quay Crane	OR	Operational Research
BAP	Berth Allocation Problem	QC	Quay Crane
BDA	Big Data Analytics	QCSP	Quay Crane Scheduling Problem
CART	Classification and Regression Tree	RF	Random Forest
CDT	Container Dwell Time	RMGC	Rail-Mounted Gantry Crane
CT	Container Terminal	RTGC	Rubber-Tired Gantry Crane
EC	Environmental Considerations	SOM	Self-Organizing Map
ER	Emitting Resource	SVM	Support Vector Machine
ETA	Estimated Time of Arrival	SYOP	Storage Yard Operations Problems
GP	Gaussian Processes	TAS	Truck Appointment System
IMV	Internal Movement Vehicle	TEU	Twenty-foot Equivalent Unit
IoT	Internet of Things	TOP	Transport Operations Problems
kNN	k-Nearest Neighbours	YC	Yard Crane

Appendix B. Adopted classification schemes for OR papers

Table B.1
BAP papers classification scheme adopted from Bierwirth and Meisel (2015).

Attribute group	Attribute	Description
Spatial attribute describing the berth layout and water depth constraints	*disc*	Discrete berth layout considered
	cont	Continuous berth layout considered
	hybr	Hybrid berth layout considered
	draft	Vessel's draft considered
Temporal attribute describing the arrival process of vessels	*stat*	Static arrivals considered
	dyn	Dynamic arrivals considered
	cycl	Cyclic arrivals considered
	stoch	Stochastic arrival times considered
	due	A pre-set due date or a maximum waiting time considered
Handling time attribute describing the way vessel handling times are considered	*fix*	Known and unchangeable handling times considered
	pos	Handling times based on the berthing positions considered
	QCAP	Handling times determined by including QC assignment decisions
	QCSP	Handling times determined by incorporating QC scheduling
	stoch	Stochastic handling times considered
Performance measure describing the objective of the optimisation problem	*wait*	Minimising waiting times before berthing
	hand	Minimising handling times of vessels
	compl	Minimising service completion times
	tard	Minimising tardy vessel departures
	speed	Speeding vessel up at the expense of additional bunker cost
	res	Optimising the utilisation of resources
	pos	Positioning vessels close to the yard
	misc	Other performance measures

Table B.2
QCSP papers classification scheme adopted from Bierwirth and Meisel (2015).

Attribute group	Attribute	Description
Task attribute specifying the aggregation of a vessel's containers into crane tasks	*area*	All containers within a certain area of vessel bays
	bay	All containers at a bay of a vessel
	group	Single container groups of a bay
	stack	Container stacks of a bay
	container	Single container movements
	prec	Precedence relations (i.e., unloading before loading)
	prmp	Preemption (i.e., the interruption of executing a task is allowed
Crane attribute capturing the properties of the crane resource	*ready*	Individual ready times considered
	pos	Initial positions are considered
	TW	Availability of QCs is restricted to given time windows
	move	The time for moving cranes alongside the vessel is considered
Interference attribute indicating restrictions for the movements of cranes	*cross*	QCs are rail-mounted and cannot pass each other
	safe	Safety distance among QCs during operation observed
Performance measure describing the objective of the optimisation problem	*compl*	The completion times of tasks
	finish	The finishing times of cranes
	util	The crane utilisation rate
	through	The throughput of cranes
	move	The time spent for moving cranes along the quay

Table B.3
SYOP papers classification scheme adopted from Carlo et al. (2014a).

Attribute group	Attribute	Description
Decision problem attribute describing the type of problem considered	*stocap*	Storage space capacity is the decision problem
	stoassig	Storage space assignment is the decision problem
	routing	Routing of MHE is the decision problem
	dispatch	Focus is on dispatching policies for MHE
	compare	Focus is on comparing MHE
	reshuffle	Number of reshuffles is the decision problem
	layout	Focus is on finding the best storage yard layout
Yard layout attribute characterising the layout assumptions made	*asian*	Asian layout (i.e., with truck lanes) is considered
	european	European layout (i.e., I/O points at ends) is considered
	3D	The height of the stacks is considered (e.g., reshuffling)
	Grouped	Requests are for container group (not individual)
MHE characteristics attribute characterising the MHE considered	*dedicated*	MHE is dedicated to one block
	straddle	Straddle carriers are used as storage equipment
	RTGC	RTGCs are used
	RMGC	RMGCs are used
	singlecrane	A single crane per block is used
	dualpass	Dual passing RMGCs arrangement is used
	twinGC	Twin (non-passing) GCs arrangement is used
	triple	A triple crane arrangement is used
Temporal attribute specifying situation with ready and due times	*readyd*	Container ready times are assumed deterministic
	readys	Container ready times are assumed stochastic
	dued	Container due times are assumed deterministic
	dues	Container due times are assumed stochastic
	horiz	The planning horizon is dynamic
Uncertainty environment attribute indicates if stochastic optimisation is used	*stochop*	Stochastic optimisation is used
	nonstoch	No stochastic or robust optimisation is used
Performance measure specifying the most used terms in the objective function	*num*	The number of moves required
	compl	Task completion time (typically makespan)
	dist	MHE distance travelled-related metric
	due	Due times-related metrics
	space util	Utilisation of yard space
	GC util	Utilisation of gantry cranes
	other	Other metrics

Table B.4
TOP papers classification scheme adopted from Carlo et al. (2014b).

Attribute group	Attribute	Description
Decision variables attribute specifying the decision problem considered	*compare*	Multiple types of transfer vehicles considered
	number	The number of vehicles is optimised
	route	The transfer vehicles' routing is optimised
	dispatch	The vehicle dispatching is optimised
	deadlock	Focus on deadlock prevention and resolution

(*continued on next page*)

Table B.4 (*continued*)

Attribute group	Attribute	Description
Operations attribute specifying vessel loading/unloading and transport operations	*load*	Addresses the vessel loading operation
	unload	Addresses the vessel unloading operation
	double	Transfer vehicles are allowed to double-cycle
	inter	Inter-terminal movements are considered
Vehicle capabilities attribute specifying vehicles capabilities and technologies	*self-lift*	Self-lifting vehicles considered
	non-lift	Non-lifting vehicles considered
	self-stack	Vehicle self-performs the stacking operation
Interaction attribute indicating congestion or collisions among vehicles	*interference*	Congestion or collisions are considered
	prec_l	Precedence constraints are imposed for loading operation
	prec_u	Precedence constraints are imposed for unloading operation
Temporal attribute specifying situation with ready and due times	*readyd*	Container ready times are assumed deterministic
	readys	Container ready times are assumed stochastic
	dued	Container due times are assumed deterministic
	dues	Container due times are assumed stochastic
	horiz	The planning horizon is dynamic
Uncertainty environment attribute indicates if stochastic optimisation is used	*stochop*	Stochastic optimisation is used
	nonstoch	No stochastic or robust optimisation is used
Performance measure specifying the most used terms in the objective function	*num*	Number of vehicles
	compl	Task completion time (typically makespan)
	dist	Transfer vehicle distance travelled-related metrics
	lateness	Due times-related metrics
	QC	Average quay crane work rate (maximise)
	vessel	Average vessel processing time
	cost	Other financial cost not related to number of vehicles
	other	Other metrics

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