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Contemporary challenges and AI solutions in port operations: applying Gale–Shapley algorithm to find best matches

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Abstract

Artificial intelligence (AI) developments enable human capability to deliver the same outcome at a lower cost. This research performs a high-level matching between AI solutions and challenges within the port area by developing a novel academic approach. This way, the matching is carried out more structured than when one (manager, developer, challenge owner, etc.) fulfils it based on their opinion without following any structured approach. Therefore, the study defines first a comprehensive typology of port stakeholders' challenges, which can be solved via AI solutions. This typology presents challenges, including their main issues, widespread impact, and potential solutions. A state-of-the-art review of AI solutions that can address these challenges is carried out in parallel. Secondly, this review clearly distinguishes between AI solutions based on their technology and functionality. Thirdly, this research selects an appropriate AI solution for addressing each identified challenge in the port operation by upgrading the Gale–Shapley algorithm. Finally, it shows that the most critical presented AI solutions in this study use various machine learning (ML) techniques. Besides, concerning the AI solution's reusability feature and the result of high-level matching, this research shows that the implementation phase effort can be drastically reduced by using the recently developed matching algorithm.

Keywords: Port challenges, AI solutions, Matching, Gale–Shapley algorithm, Ports

Introduction

Ports constitute an important economic activity in coastal areas, being gates to the world for transportation within the international trade process. They also act as a crucial connection between sea and land transport. There are many challenges in this area, making port operations relatively complex, with recent research showing that solving these challenges will bring various benefits to the local and regional economy and the environment (Jeevan et al. 2015), (DeChant 2019). Furthermore, container shipping is one of the broadest industries in the world and can reap the most considerable benefits from applying AI technologies within its operations (Chui et al. 2018). Then there would be several motivations for availing AI technology in the port and shipping industry. For instance, AI can help optimize port and shipping operations, reduce waiting times and congestion, increase vessel and cargo throughput, and improve overall efficiency (Chargui et al. 2021; Darendeli et al. 2021; Martins et al. 2020). AI technology can also enhance safety by analyzing and predicting potential hazards, preventing accidents, and mitigating risks (Lee et al. 2020; Michail et al. 2015). By automating specific tasks and optimizing operations, AI can help reduce labor, fuel consumption, and maintenance costs (Ma et al. 2020; Yan et al. 2021). AI can furthermore help reduce the environmental impact of the port and shipping industry by optimizing vessel routes, lowering emissions, and promoting more sustainable practices (Cammin et al. 2020; El Mekkaoui et al. 2020). AI technology can finally help ports and shipping companies stay competitive by improving operational efficiency and effectiveness (Niestadt et al. 2019; Shen et al. 2017).

Similarly, developers put considerable effort into AI-based solutions that can solve challenges in both logistics and ports. However, managers tend to make decisions based on their personal preferences, knowledge, or experience to implement those AI solutions or by looking at consultant advice. Therefore, it is not a reliable decision when stakeholders would implement an AI solution to solve a challenge. In addition, AI technologies are new and experimental, so there is limited information about related projects (Davenport 2018). Choosing the right AI solution requires specialized IT knowledge, which port stakeholders may lack (Murphy 2012). Sharing this valuable knowledge with port stakeholders can enhance their awareness of the appropriate types of AI solutions that can be employed to surmount challenges effectively.

A matching process is required to find the best AI solution for solving a challenge in the port area and effectively link the specific requirements of port challenges with the capabilities and features of AI solutions (Abououf et al. 2018). Nevertheless, no structured method exists to help stakeholders match AI solutions and challenges and determine the right decision. Moreover, the lack of a clear structure for matching AI solutions with existing challenges would affect the final results (DIckerson et al. 2021).

Therefore, a high-level matching under academic and scientific approach builds a structure that can assist port stakeholders in perceiving which AI solution with specific functionalities can solve which challenge(s) with certain attributes. To that purpose, a three-level approach is utilized to answer the following research question. *"What is the structured method to find the best AI solution for overcoming a challenge in port and shipping industries?".*

This approach contains both desk and empirical research to fill the gap in the literature. The study objective is to find the best AI solution to solve a challenge for port stakeholders. In this manner, one facet of this approach involves formulating an exhaustive list of challenges within port operations, which can be addressed through AI-based solutions. The port challenges list is compiled after conducting a comprehensive literature review. In parallel, the study generates a review of AI solutions that can address these challenges by organizing interviews. Finally, another approach's level is dedicated to developing and applying a new method for matching identified challenges and AI solutions.

This high-level matching turns into a guideline when stakeholders tend to implement an AI solution and gives insight into which AI solution from a potential list should be customized for solving their challenge. Moreover, as stated by Moscoso-López et al. (2021), all stakeholders in port areas can benefit from scientifically-founded indications in which AI technology addresses multiple problems, being the foundational future of businesses in the port ecosystem. Consequently, this can also increase the maturity level of port stakeholders from the digitalization viewpoint, including AI technology development (Sadiq et al. 2021).

On the other hand, AI developers also need access to a new academic structured methodology for decision-making regarding implementing AI solutions. Providing AI developers with this knowledge can also assist them in identifying the most promising areas for further exploration. Therefore, novel research is needed to provide advice on implementing AI solutions that address most port challenges and reduce the effort in the implementation phase by choosing the right solution right from the beginning, with the help of the matching algorithm. Accordingly, this can also contribute to raising the overall market maturity level regarding digital solutions like AI.

Besides, due to the adherence of the port and shipping industry to traditional techniques and its challenging nature for digitalization (Alop 2019; Babica et al. 2019; ESPO 2021; Fruth and Teuteberg 2017), a lack of alignment has always persisted between the expectations of stakeholders engaged in port operations and what the technology developers provide. The present study and its matching concept also have the potential to expedite this alignment process and enhance the operational efficiency of operations in ports through the availing of developed AI solutions.

This study is structured as follows: after this brief introduction, Sect. "Literature review" presents the current paper's approach, providing details regarding the steps taken to identify a matching algorithm to collect data regarding challenges and determine AI solutions' characteristics. Section 3 then presents a comprehensive literature review regarding the existing gap and the methods associated with matching algorithms. Afterward, Sect. "Maritime challenges and AI solutions" delivers the identified challenges and AI solutions in detail. Sect. "Case study: matching AI solutions and challenges" exhibits the empirical results of matching port challenges with AI solutions. Finally, Sect. "Conclusion" presents conclusions and indications for further research.

Approach

Three research steps are carried out to gather the related data for matching port challenges and AI solutions. Firstly, as this study aims to find the appropriate AI solution to address port challenges, an in-depth literature review is conducted to identify the best algorithm for matching challenges with AI solutions. The method applied to gather data for this investigation process is detailed in Sect. "Matching algorithm". The second step then collects data on a comprehensive list of challenges. The method used for this step is presented in Sect. "Identifying port challenges". Next, a list of AI solutions is also put forward in a parallel research step, which is explained in Sect. "Identifying AI solutions".

Figure 1 illustrates the approach taken by this research to match AI solutions and challenges. The dark grey-colored boxes here indicate the data collection methods followed in this study. In contrast, the light grey-colored boxes show how this data and information is collected in each intermediary step. Besides, the light grey-colored circles represent the investigation results of the collected data.

The primary aim of this study is to identify the most effective AI solutions for specific challenges faced by port stakeholders. The research objective is two-fold: first, to develop a robust matching algorithm to determine the best match between the two

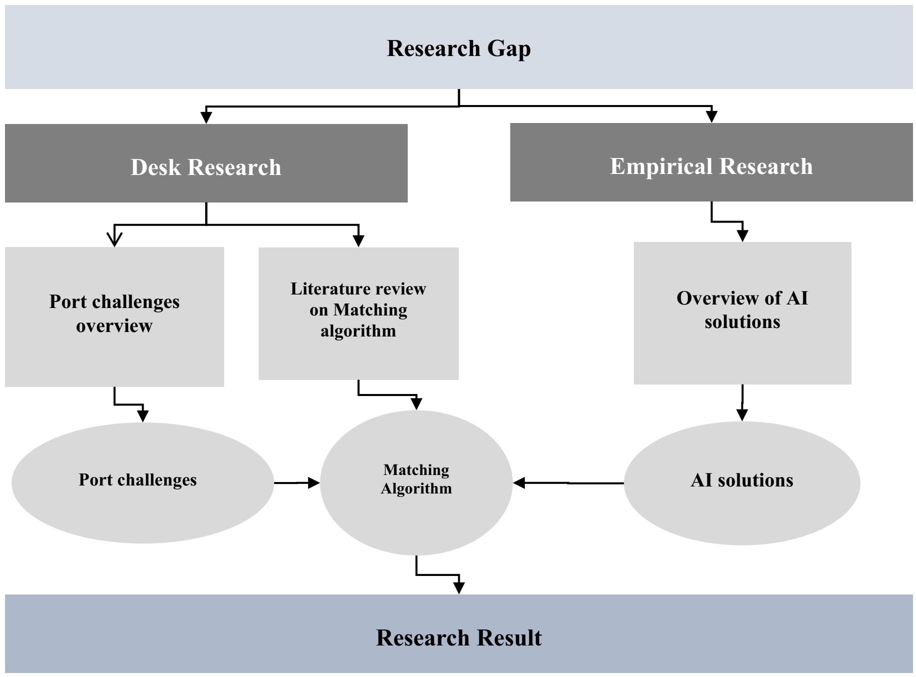

Fig. 1 Approach

sides (challenges and AI solutions), and second, to advise industry stakeholders on the optimal AI solutions for addressing their specific challenges. The initial objective is aligned with the research question as it aims to discover a structured approach for matching challenges with AI solutions. A second objective is to validate the designated matching algorithm. Given the dual nature of the problem, involving both AI solutions and port challenges, two distinct research steps are necessary to collect the data required for validating the matching algorithm.

The first step of the research explores the functionality of a proper matching algorithm to be used in this specific issue. As such, this step entails conducting a comprehensive literature review to identify existing matching algorithms and techniques that have successfully addressed similar problems across different domains. This step provides valuable insights into the most effective and efficient algorithms currently available.

As mentioned earlier, validating the matching algorithm between challenges and AI solutions requires equally gathering data on both sides. Therefore, as a second step, this study collects information on challenges through a desk research approach, utilizing a literature review method for two key reasons. First, a literature review provides a comprehensive and systematic approach to identifying and gathering information on various challenges. By analyzing a wide range of sources, including academic journals, books, and other publications, this study can ensure that it captures the most relevant and exhaustive information on challenges faced by port stakeholders. Second, a literature review allows for a standardized and replicable approach to data collection. This is important in ensuring that the study's findings are reliable and can be replicated in future research. By using a literature review, this study can be confident that it has collected a representative sample of challenges faced by the industry and that these challenges have been identified using a standardized approach. Besides, the academic database mainly contains applied research in which use cases from the industry have been included.

In contrast to the desk research approach used to collect information on challenges, this study employs an experimental research method to gather data on AI solutions within the third research step. There are several advantages to using interview-based research methods to collect data on AI solutions in the port and shipping industries. Firstly, interviews with developers can provide detailed and in-depth information on the functionality and technical aspects of AI solutions. This can be especially useful in identifying AI solutions' specific features and capabilities, most effectively addressing different challenges. Secondly, interviews with individual developers with direct experience or expertise with AI solutions can provide valuable first-hand perspectives on the unique use cases associated with implementing AI in the field. This can help identify practical insights and best practices that may not be readily apparent from desk research. Finally, since this paper aims to investigate innovative research on AI solutions in the port and shipping industries, interviews can be a valuable source of new and previously unidentified insights.

Matching algorithm

A thorough literature review is undertaken to discern a scientific methodology for effectively pairing challenges with AI solutions within port environments. This literature review investigates studies released since 1950. The entire literature review process is depicted in Fig. 2.

Table 1 shows the results of searching "Query 1" in Fig. 2 based on journals. The right column here presents the proportion of successful results for all searches in each journal. These fractions represent the ratio of publications related to the matching algorithm to the number of publications searched for in that particular journal. For instance, in the first row of Table 1, "1/5" indicates that among five publications found in the "Discrete Applied Mathematics" journal, only one introduces an algorithm for tackling matching

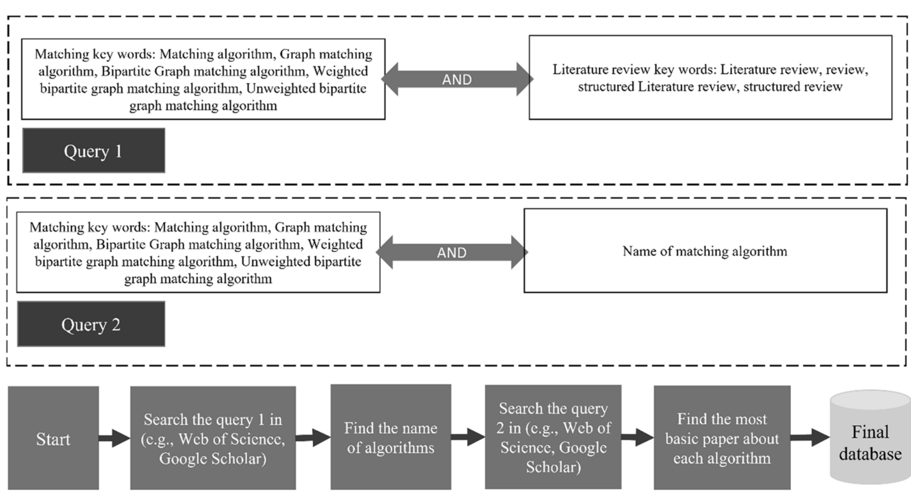

Fig. 2 Literature review process for identifying matching algorithm

Table 1 Overview of search results for Matching methods literature review

Journal	Keywords: Matching algorithm, Graph matching algorithm, Bipartite Graph matching algorithm, Weighted bipartite graph matching algorithm, Unweighted bipartite graph matching algorithm
Discrete Applied Mathematics	1/5
Computer vision and image understanding	0/3
Computer science	1/5
Pattern recognition letter	1/3
Naval research logistics quarterly	2/2
Association for computing machinery	1/2
Political Economy	1/3
The American Mathematical Monthly	1/2
Information processing letter	1/4
Mathematical Programming	2/4
IEEE Xplor	0/7
Transportation Research Record	1/6
Computability journal	1/1
Total results	13/47

challenges and AI solutions. The following sub-section puts forward the method used to identify challenges that port stakeholders face within their operations.

Identifying port challenges

Identifying and presenting port challenges begins with an exhaustive literature review (see Fig. 3). The main purpose is to provide a comprehensive and categorized list of the port and maritime transport industry's challenges, which AI can solve. There have been many studies on these terms, with this study gathering all challenges data from the port, marine, and shipping transport journals.

The resulting list of challenges is presented from a three-level perspective: micro (optimization and prediction of own operation), macro (prediction of external factors and

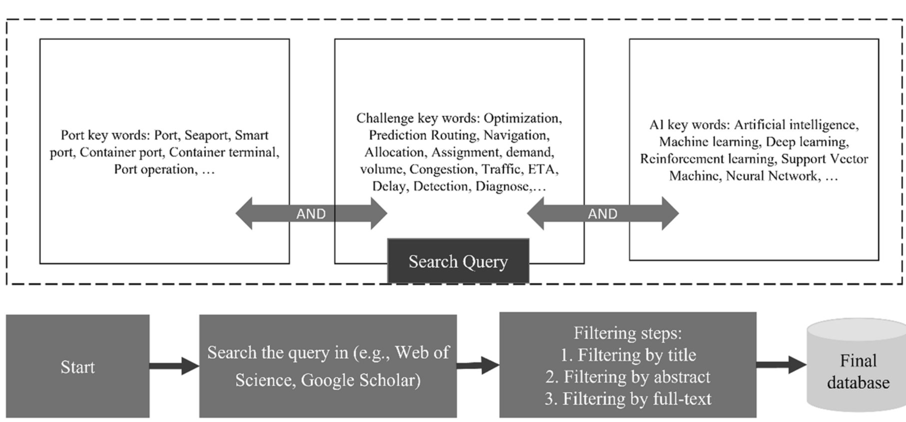

Fig. 3 Literature review process for identifying challenges

optimization in a process that involves more than one organization), and sustainability. All these challenges are concerned with a specific port operation area, presented below:

- Waterside: This section includes infrastructure such as berth, quay, and sea carriers.
- Landside: This operation area performs activities such as importing and exporting containers, managing empty containers, and moving containers in the yard.
- Hinterland: This section is known as the truck, barge, and train operation area.

The following sub-section presents the method for identifying AI solutions implemented before, in, or beyond port areas.

Identifying AI solutions

Extra research is carried out here as a response to a lack of overview concerning whether and which AI solutions can be used in ports up to the present date. Therefore, a list of associated AI solutions has been made, which provides an overview of AI solutions that could address the challenges of the maritime transport industry, especially regarding port operations and their stakeholders.

Data regarding various AI solutions is collected through semi-structured interviews, addressing comprehensive questions. This way, knowledge from two research groups, Internet, Technology and Data Science Lab (IDlab) Antwerp and IDlab Ghent, is collected.

- The IDLab Antwerp research group is associated with the University of Antwerp and Imec. Researchers affiliated with this group perform fundamental and applied research on wireless technology, AI, and the Internet of Things (IoT).
- IDLab Ghent performs fundamental and applied research on internet technology and data science. Major research areas here are ML and data mining; semantic intelligence; distributed intelligence for IoT; cloud and big data infrastructures; multimedia processing; wireless and fixed networking; and electromagnetic, and high-speed circuits and systems.

These questions addressed to researchers have the goal of extracting the necessary information about the technology and infrastructure used to develop AI solutions, their target (optimization or prediction), the outcomes of these AI solutions after implementation, required input and data to develop them, and the future of these AI solutions. Eventually, these outcomes were gathered in a consistent report and are provided in brief in this research effort.

The AI solutions collected through experimental research within this step have already been developed to address specific challenges in port operations. The underlying concept behind adopting this particular approach is to simultaneously contribute to both practice and academia. Hence, the research gathers data pertaining to those AI solutions and broadens practical insights. It highlights additional challenges that can potentially be addressed using these solutions. Equally, existing port challenges identified during the literature review are listed within the study. This approach also enriches the existing academic literature by identifying suitable AI solutions for each of the established challenges within the literature.

Literature review

AI encompasses various branches within the field of computer science that aim to develop intelligent solutions capable of performing tasks that typically require human intelligence. Recently, organizations have moved beyond the experimental stage and are actively implementing AI technologies, leading to the widespread adoption of AI across numerous industries (Daitan 2021). Mckinsey (2019) stated that approximately 60% of companies have experienced revenue growth, while around 40% have effectively reduced costs by adopting AI technologies. However, specific barriers may cause companies to become conservative in investing further or expanding their AI capabilities. This hesitation often arises from a lack of understanding regarding which type of AI solution can effectively address the existing challenges within a company. Consequently, many enterprises have yet to embark on developing these innovative technologies.

Moreover, AI technologies are relatively novel innovations, and as projects related to AI implementation are inherently experimental, there is limited information available about these projects (Davenport 2018). Identifying the optimal AI solution to address a challenge necessitates specialized IT knowledge in AI solution development (Murphy 2012). This knowledge might not exist on the port stakeholders' side. Therefore, disseminating this knowledge among port stakeholders can heighten their awareness regarding the appropriate AI types for overcoming their challenges. Additionally, this can elevate the maturity level of port stakeholders regarding digital solution development, including AI technology (Sadiq et al. 2021). Moreover, providing AI developers with this knowledge can also assist them in identifying the most promising areas for further exploration.

Consequently, this can raise the overall market maturity level from a digitalization perspective. To that purpose, a matching algorithm is needed to effectively connect the specific requirements of port challenges with the capabilities and features of AI solutions. Besides, by considering various factors such as problem characteristics, and solution capabilities, the algorithm can identify the most suitable AI solutions for each challenge (Abououf et al. 2018).

A matching algorithm can also consider each challenge's unique characteristics and requirements and suggest AI solutions that align with those specific needs (Flach 2012). This ensures that the selected AI solutions are tailored to address the port industry's specific challenges, leading to more effective and targeted problem-solving approaches. Besides, evaluating multiple AI solutions based on their performance metrics, compatibility, and applicability to the identified challenges helps to maximize the effectiveness and impact of the AI solution in addressing the identified challenge (DIckerson et al. 2021).

In addition, by utilizing data on the characteristics of challenges and the capabilities of AI solutions, a matching algorithm facilitates data-driven decision-making. It enables decision-makers to make informed choices based on objective evaluations and comparisons, reducing biases and increasing the likelihood of successful AI implementation (Kitahara and Okumura 2021). Finally, matching AI solutions and port challenges expedites the process of identifying suitable AI solutions for port challenges, saving time and effort that would otherwise be spent on manual evaluation. It helps avoid potential trial-and-error approaches, reducing costs associated with ineffective or mismatched AI implementations (Aouad and Saritaç 2020).

Despite the existing literature on AI technologies in the port and shipping industries, which highlights the extensive research conducted in AI development, there is no framework for matching AI solutions and challenges (see Appendix 1). Only a few publications have examined the barriers to implementing AI technology in port and maritime companies. In contrast, most publications have dedicated their efforts to developing AI solutions and demonstrating the specific advantages of AI implementation in various segments of port operations and the shipping industry.

The following sub-section presents the literature review results on matching algorithms and discusses the characteristics of the best algorithm to be applied within the desired application case.

Literature review regarding matching algorithms

Since the matching problem in this study consists of two elements—AI solutions and challenges—it is expected that a bipartite matching in the graph theory will be able to address this issue. A graph in this context is made up of vertices (also called 'nodes' or 'points'), which are connected by edges (also called 'links' or 'lines') (Carlson 2020).

A bipartite graph is a graph whose vertices can be divided into two disjoint sets (Skiena 1990). There are several applications in this regard, such as matching candidates to jobs, chairs to desks, surfers to surfboards, etc.

A bipartite graph can be weighted or unweighted. In this respect, a weighted graph is one in which each branch has a numerical weight. In a weighted graph, relationships between nodes have a magnitude, which is vital for the connection. In an unweighted graph, however, the existence of a relationship is the subject (Elliot Bettilyon 2019). Subsequently, Table 2 lists the bipartite matching algorithms extracted in this literature review. These algorithms are presented as follows, with one of them selected to tackle matching challenges and AI solutions.

Table 2 shows three unweighted and three weighted algorithms have been identified. Nevertheless, although all the algorithms in graph theory science can solve the matching problems, convenience in implementing and being appropriate to the current study is a significant matter. Therefore, the comparison of algorithms is summarized in Table 3.

This comparison was performed based on the characteristics of algorithms, namely the algorithms' time complexity, the input that needs to run algorithms, and the algorithms' limitations. Finally, one algorithm is selected for matching AI solutions and challenges.

Table 2 Algorithms of bipartite graph

Bipartite graph	
Unweighted	**Weighted**
Gale–Shapley algorithm	Hungarian algorithm
Hopcroft–Karp algorithm	Cycle cancelling algorithm
Ford–Fulkerson algorithm	LP network simplex algorithm

Table 3 Conclusion of literature review

Algorithms	Run time	Input	Limitations
Gale–Shapley (Gale and Shapley 1962; Roth 1984)	$n \times m$	$n \times m$ matrix for each set of vertices (List of preferences)	–
Hopcroft-Karp (Micali and Vazirani 1980; Motwani 1994)	$(n \times m - \min(n, m))\sqrt{n + m}$	$n \times m$ matrix (A unweighted bipartite graph)	Does not satisfy assumption 2 and 1
Ford-Fulkerson (Backman and Huynh 2018)	$(n \times m - \min(n, m)) \times f$	$n \times m$ matrix (A unweighted bipartite graph) and capacity of each vertices	Does not satisfy assumption 2
Hungarian (Kuhn 1956)	$(n + m)^3 = n^3 + m^3 + 2n^2m + 2nm^2 + 1$	$n \times m$ matrix (Cost of matching vertices)	Does not satisfy assumption 1
Cycle cancelling (Shepherd and Zhang 1999; Nassir et al. 2014)	$(n \times m - \min(n, m)) \times C \times U$	$n \times m$ matrix (Cost of matching vertices) and capacity and supply/demand of vertices	–
LP Network Simplex (Orlin 1997; Tarjan 1997)	$(n + m)(n \times m - \min(n, m)) \log(n + m) \log((n + m)C)$	$n \times m$ matrix (Cost of matching vertices)	Does not satisfy assumption 1

According to the run time, the following observations are made: if there are V vertices in a bipartite graph, then n numbers belong to one set, and m numbers belong to another. This study presents vertices by V $(V = n + m)$. Besides, f is the maximum flow in the graph, C is the maximum weight (cost) of edges and U is the maximum edges' capacity. U, f, and C here are positive and higher than 1. Moreover, in some instances, the runtime of algorithms has been approximately calculated. Therefore, the Gale–Shapley algorithm can probably match AI solutions and challenges in less time.

Table 3 illustrates that weighted algorithms always need more input than unweighted algorithms. Moreover, among unweighted algorithms, the Hopcroft-Karp can run with less input.

This study aims to match AI solutions and challenges based on a set of assumptions as follows: 1. Each AI solution can solve more than one challenge, with no limitation regarding the maximum number of challenges that one AI solution can solve; 2. Since finding the best match is the study's objective, it is mandatory to compare potential matching alternatives.

The Ford-Fulkerson, cycle cancelling, and Gale–Shapley algorithms satisfy assumption 1. Moreover, they can also set a capacity for each vertex to match other vertices. Therefore, if one AI solution can solve multiple challenges, assigned capacity to each AI solution can let this occur.

The second assumption refers to making the best match among all the potential alternatives. This way, if two respective AI solutions can solve a particular challenge, the algorithm must decide upon the best choices. To overcome the above matter, deciding based on each alternative's value is required. For example, weighted bipartite graphs indicate this value by the weight of each edge. Furthermore, the Gale–Shapley algorithm can define this value by each vertex's list of preferences. Accordingly, if the Gale–Shapley algorithm can match two different vertices in set A with a vertex in set B, it will match the vertex in set B with the best vertex in set A, based on the list of preferences of the vertex in set B.

According to the assumptions of the problem, Table 3 shows the algorithm that does not satisfy those assumptions. Therefore, this matter can limit utilizing this particular algorithm for matching AI solutions and challenges. In this respect, the Gale–Shapley and cycle cancelling do not have any limitations among any algorithms. Therefore, the Gale–Shapley algorithm is preferred over the cycle-canceling algorithm for several reasons.

Firstly, the Gale–Shapley algorithm guarantees a stable matching solution, meaning no incentives exist for any participant to deviate from their assigned match. On the other hand, the cycle-canceling algorithm may result in unstable solutions where participants have motives to break their matches and form new ones. Secondly, the Gale–Shapley algorithm is quicker than cycle canceling. This makes it efficient even for larger datasets. Besides, the cycle-canceling algorithm typically has exponential time complexity, making it less scalable for more significant problem instances.

Additionally, the Gale–Shapley algorithm exhibits an elegant and intuitive mechanism for matching participants based on their preferences. It optimizes the participants' preferences while ensuring stability. Conversely, the cycle-canceling algorithm may involve more complex steps and require additional optimizations to achieve similar results.

To sum up, the Gale–Shapley algorithm offers a compelling combination of stability, efficiency, and simplicity, making it a superior choice for matching AI solutions and challenges in this research.

Modified Gale–Shapley matching algorithm

This subsection modifies the selected algorithm for matching AI solutions and challenges. Accordingly, the keywords associated with the Gale–Shapley algorithm terminology are clarified as follows:

Proposing/Sending proposal: the bipartite graph has two sides, in which sending a proposal happens when one member of one side matches with the other side's members. This proposal can either be rejected or accepted by the proposal receiver.

List of preferences: each member in the Gale–Shapley algorithm must rank other members of the other side based on their preferences. This list can be incomplete.

The Gale–Shapley algorithm starts by sending a proposal from a member of one side of the bipartite graph to a member of the other side. This way, the algorithm ends when it processes the preferences list of all members of the proposer side. There are two possibilities for this: 1. The algorithm matches the member of the proposer side with one member from another side; 2. If one member of the proposer side has received rejection by its preference list members, it remains unmatched.

The input of this method is retrieved from two sides, which might conflict with each other. In this study, challenge preferences are gathered through a literature review, and AI solution preferences have been collected from developers. Hence, it is necessary to propose from one side and check whether another accepts the proposal.

The Gale–Shapley algorithm is used to solve stable matching problems. The stability of the matching between challenges and AI solutions is needed because this research tends to find the most appropriate AI solution for solving each challenge. Therefore, a pair (Challenge A, Solution B) shouldn't exist in which both members prefer each other to their partner under the Gale–Shapley algorithm.

There are two variants of the Gale–Shapley algorithm: the classical version, which solves the stable marriage problem for two sets of agents with equal size, and the "college admissions" version, which solves a related problem where a set of students are seeking to be admitted to a set of colleges (two sets of agents with unequal size) (Fenoaltea et al. 2021). The second version is considered in this study. Both variants of the Gale–Shapley algorithm are only optimal for the proposer side. For instance, if the study runs the algorithm through proposing by the challenges side, the result is optimal only for the challenges side. On the other hand, if the algorithm operates by proposing from the AI solutions side, the result is optimal for AI solutions.

Nevertheless, the equitable, stable matching problem (ESMP) aims to find a stable matching solution with avoiding bias towards either side. ESMP is more appropriate for the current study scenario than the classic SMP. Several heuristic methods have been proposed concerning ESMP. For instance, Gelain et al. (2010) developed a local search algorithm to find a fair solution for a small problem. Roth and John H. Vande Vate (1990) showed that randomly pairing two sides starting from an arbitrary matching can result in a stable solution with probability 1, but it does not guarantee fairness. Iwama et al. (2010) designed an approximation algorithm that can produce a stable solution with time complexity of $n^3 + 1$.

Giannakopoulos et al. (2016) created a heuristic algorithm that allows both men and women to make proposals, repeatedly leading to a fair solution. Since this study aims to find the best match for both sides, it also modifies the Gale–Shapley algorithm by running it twice (phase 1—Challenges proposed and phase 2—AI solution proposed) to avoid discrimination between the two sides of the problem. It then avails a heuristics-weighted approach to deal with inequality in each phase's results.

First, the algorithm runs by sending proposals from challenges to AI solutions at phase 1. Second, the algorithm runs in reverse, which means it operates by sending proposals from AI solutions to the challenges at phase 2. Finally, the results of these two phases might be different. Therefore, phase 3 compares the result. In other words, phase 2 validates the result of phase 1, and in case of a difference between the results of phases (phase 1 and phase 2), phase 3 will decide which phase's result is better. These phases are explained in the following sub-sections.

Phase 1. Proposing by challenges

In this phase, challenges send a proposal to AI solutions in their list of preferences. Due to assumption 1, it would be better to implement AI solutions that can solve more challenges. Hence, the algorithm in this phase sets the capacity of AI solutions as infinite, which means that each AI solution can accept the proposal of numerous challenges. Therefore, if a challenge sends a proposal to an AI solution and exists in that AI solutions preferences list, the AI solution will accept the proposal. The algorithm run in phase 1 is presented in Appendix 2.

Phase 2. Proposing by AI solutions

In phase 2, the procedure starts as in phase 1, but with two significant differences. The first point distinguishing these two phases is sending proposals by AI solutions instead of challenges, broadly affecting the algorithm. Second, during the interviews, AI solutions developers validated that each identified challenge could be solved totally by one of the identified AI solutions. Therefore, this phase considers each challenge can be paired with one AI solution. The capacity of each challenge in accepting AI solutions proposals is one.

Consequently, based on hypotheses in the Gale–Shapley algorithm, only one AI solution pairs with each challenge. Accordingly, if the number of AI solutions is less than the number of challenges, the algorithm of phase 2 must run more than once. Each time the algorithm runs here, the number of challenges that pair with AI solutions is less or equal to the number of AI solutions. Thus, the algorithm runs on several occasions to pair all the challenges. The algorithm of phase 2 is presented in Appendix 2.

Phase 3. Comparing pairs that are made in phases 1 and 2

The result of phase 1 is optimal from the challenges' perspective, and, in contrast, phase 2 provides results that satisfy the AI solutions' perspectives. Therefore, phase 3 intends to compare the results of the two previous phases while finding the most appropriate AI solution for each challenge.

First, phase 3 validates the duplicate pairs within these two phases because they are optimal for both sides simultaneously. Subsequently, this phase compares the AI solution assigned to a challenge in phases 1 and 2 in other pairs. This comparison finds the more effective pair between the two pairs with the same challenge. Although the selected pair is optimal for only one side, this is better than the other pair for the other side.

To compare pairs, the new algorithm sequence is as follows: a) the differentiation between AI solutions' ranking in the preferences list of the challenge must be calculated; b) the algorithm finds the difference of the challenge's rank in the preferences list of the AI solutions assigned to it. Since the number of challenges and AI solutions might be non-equal, to normalize the amount of (a) and (b), the count of AI solutions and challenges multiply by (a) and (b), respectively. The reason for this is that if one challenge gets the rank X among Y amount of challenges, and an AI solution gets rank X among Z amount of AI solutions, and $Y > Z$, then the position of the challenge is better than the AI solution's position. The following sub-section puts forward the overview of challenges AI solutions that are used further in the empirical part of this research.

Maritime challenges and AI solutions

This section presents the challenges and AI solutions identified within port areas. Table 4 shows the description of the challenge. The AI solutions implemented before in or beyond port areas by the developer in this field are listed in Table 5.

Table 4 Overview of challenges in port operation area

Title of challenge (Area)	Description	Source
Optimizing ship stowage planning (Waterside)	Finding containers' optimal position on the ship Increasing economic and safety impact Optimizing cranes' planning using AI	Shen et al. (2017)
Reducing sea going vessel delays (Waterside)	Not sailing in a predetermined time window Using infrastructure capacity better Using AI by including weather and route conditions in ETA	Parolas (2016)
Predicting of inland vessel ETA (Waterside)	Estimating arrival time of inland vessel Planning infrastructure better Using AI instead of manually data entering in AIS	Meijer (2017)
Optimizing ship queuing (Waterside)	Planning the sequence of loading/unloading of ships Reducing ship waiting time Finding the required numbers of infrastructure at the berth by using AI	Shahpanah et al. (2014a, b)
Centralizing berth allocation (Waterside)	Assigning vessel to berth for loading/unloading Reducing turnaround time Simulating by including the planning of vessels and the number of berths	Leon et al. (2017)
Optimizing quay Crane (QC) assignment (Waterside)	Assigning vessel to QC for loading/unloading Enhancing handling capacity Planning time of the QC by using AI	Atak et al. (2021)
Detecting ship and ships traffic (Waterside)	Measuring and monitoring a ship's activity Increasing economic and maritime impact Identifying and classifying ships by AI	Song et al. (2020)
Reducing vessel turnaround time (Waterside)	Reducing the time from arrival to departure of the vessel Increasing customer satisfaction and attracting more vessels Addressing vessel scheduling by using AI	Stepec et al. (2020)
Predicting the risk range of ship's berthing velocity (Waterside)	Controlling the vessel's speed during mooring Reducing the occurrence of damage to the berth equipment or the hull Finding safe speed	Lee et al. (2020)
Reducing vessel waiting time (Waterside)	Reducing the time between arrival and load/unloading Increasing advantages of container terminals and attracting more vessels Analyzing berthing time based on demand and capacity	Shahpanah et al. (2014a, b)
Predicting loading and unloading container demand (Waterside)	Preparing guidelines of requirements at the quayside Optimizing the loading and unloading of vessels Predicting by Artificial Neural Network (ANN)	Yang and Chang (2020)
Lowering emissions in shipping (Waterside)	Reducing emission Reducing air pollution Reducing wasted time and developing process	El Mekkaoui et al. (2020)

Table 4 (continued)

Title of challenge (Area)	Description	Source
Optimizing yard truck routing (Landside)	Determining the optimal route for transporting containers between the yard and the quayside Enhancing the capacity of the yard and quayside Assigning a truck to a specific quay crane	Stojaković and Twrdy (2021)
Optimizing of yard truck scheduling (Landside)	Controlling delay and waste of time Reducing congestion and waiting time of yard trucks Simulating trucks at the yard	Wang et al. (2015)
Predicting container relocation (Landside)	Obtaining a sequence of containers moves Reducing required space to retrieve containers Retrieving container by including destination and departure time	Zhang et al. (2020)
Optimizing scheduling of yard crane (Landside)	Scheduling YC to reduce the sum of job waiting times Facilitating yard operations Scheduling YC by including space and workloads	Sharif et al. (2012)
Generating optimal yard block allocation (Landside)	Allocating of required space for container storage Reducing space limitations Considering containers information for assigning block	Kim and Park (2003)
Reducing congestion at terminals' gates (Hinterland)	Generating inefficiency and costs in the hinterland Optimizing the pattern of truck arrival Employing AI technologies for upgrading equipment	Alagesan (2017)
Predicting unforeseen trucks delays (Hinterland)	Affecting port's customer satisfaction index Gaining benefits from the prediction of trucks' arrival time Pre- collecting info on containers that are transported by road	Azab and Eltawil (2016)
Optimizing truck queuing at gate (Hinterland)	Reducing long waiting times for trucks in queues Reducing freight costs Using data analysis for prioritizing gate-ins	Jin et al. (2021)
Complex scheduling of rail mounted gantry crane (Hinterland)	Mapping of loading and unloading, as well as cargo storage tasks Scheduling by including complexity and workload	Wang and Zhu (2019)
Reducing truck and train waiting time excess (Hinterland)	Reducing the unproductive time between arrival and load/unloading Reducing undesirable impact on the operation of other companies	Jin et al. (2021)
Integrating individual appointment systems (Hinterland)	Appointment systems determine the arrival times based on internal capacity It contributes to reducing traffic and congestion	Ramadhan and Wasesa (2020)
Reducing truck and train turnaround time (Hinterland)	Optimizing the total time spent in the terminal Reducing the number of resources Increasing economic and reducing environmental impact	Karam et al. (2019)

Table 4 (continued)

Title of challenge (Area)	Description	Source
Recognizing assets like containers, truck or vessels (All Port area)	Monitoring and positioning of the container Preventing inefficient movement	Mi et al. (2019)
Registering container damage (All Port area)	Registering and centralizing container damage Reducing waste time to filling assertion	Panchapakesan et al. (2018)
Predicting container demand (All Port area)	Predicting the precise number of containers entering the yard Enhancing the efficiency of container terminal	Yang and Chang (2020)
Reducing container dwell time (All Port area)	Reducing the amount of time that a container spends within a port Enhancing throughput Planning by including space limitation and departure time	Heilig et al. (2020)
Reducing emission and noise (All Port area)	Reducing prolong queues Reducing traffic congestion Reducing waiting and turnaround time	Xiaoju et al. (2013)
Predicting fuel and energy consumption (All Port area)	Preventing global warming and energy shortages Reducing emission Predicting consumption of renewable energy by AI	Kim and Kim (2018)

Table 5 Overview of AI solutions to tackle port challenges

Title of AI solution	Description	Source
Smart waterway	Developing autonomous barges in urban waterways with low-cost sensor systems Detecting and localizing obstacles in the waterway Finding the optimal path by a navigation agent localizing seamless handovers, even blind spots (e.g., under bridges) Using computer vision and sensor fusion technology	IDlab Antwerp (2021)
Demand prediction	Predicting demand for better matching with supply Using reinforcement learning as a technology	IDlab Antwerp (2020a, b, c)
Resource allocation	Optimizing gate allocation in a warehouse to reduce the distance Using reinforcement learning as a technology	IDlab Antwerp (2020a, b, c)
Optimized shelf placement	Optimizing shelf placement in the warehouse Using reinforcement learning as a technology	IDlab Antwerp (2020a, b, c)
Resource-efficient AI	Designing computational power- and resource-efficient autonomous robotic platform for an industrial warehouse Improving human worker job satisfaction and safety Using ML as a technology	IDlab Antwerp (2020a, b, c)

Table 5 (continued)

Title of AI solution	Description	Source
Data-driven control	Controlling chemical plants, processes, systems, robotics, ships Employing reinforcement learning as a technology	IDlab Antwerp (2022a, b)
Lock optimization	Navigating and scheduling solutions for inland waterway transport Predicting ETA and accurate vessel positioning Using ML as a technology	IDlab Antwerp (2020a, b, c)
Large-scale simulation	Simulation-based testing of large-scale Internet of Things applications Focusing on efficiency and accuracy Simulating operations of various port-related activities Using digital twin as a technology	IDlab Antwerp (2022a, b)
Control flexibility in industrial processes	Controlling algorithm to characterize Reducing CO_2 emissions to bed for the overall industrial and energy ecosystem Employing deep learning and the Markov decision process as a technology	IDlab Gent (2021)
Applied building photovoltaics	Improving the energy yield prediction of solar panels Developing techniques for predictive maintenance of solar panels Reducing the overall carbon footprint Employing neural networks as a technology	IDlab Gent (2020a, b)
Electric vehicle charging	Reducing the port's carbon emissions Shifting from fossil fuels to electricity Reducing energy consumption by smart charging Employing reinforcement learning and the Markov decision process as a technology	IDlab Gent (2020a, b)
Truck guidance system	Optimizing engine trading off local versus global cost functions Optimizing logistic flows when global information is available Using ML as a technology	Carlan et al. (2019), IDlab Gent (2019)
Predictive planning	Optimizing statistical forecasting Forecasting traffic conditions for trucks to optimize the planning Employing ML as a technology	Carlan et al. (2019)
Booking of slots	Optimizing matching of free slots in container terminals Making faster handling time Employing ML as a technology	Carlan et al. (2019)
Optimized maintenance scheduling	Predicting accessibility for offshore assets taking context, weather, vessel, routes Detecting anomaly, semantic stream reasoning, rule mining Using neural networks as a technology	IDlab Gent (2023)
Boat landing	Predicting accessibility for offshore assets taking context, weather, vessel, routes Employing neural networks as a technology	IDlab Gent (2023)
Detection of fouling using AI	Modeling the performance of a ship Preventing extreme fouling on the hull and propeller of the ship Reducing fuel consumption Using ML as a technology	Gillis et al. (2017)

Case study: matching AI solutions and challenges

This section puts forward a case study, along with the matching of the challenges and AI solutions identified in Sect. "Maritime challenges and AI solutions". This case study aims to find the best AI solution developed in the "COOCK smart port" project for addressing the challenges identified in the literature review of the port and shipping industries. In doing so, the designated modified algorithm takes care of the matching process in this study. "COOCK" stands for Collective Research and Development and Collective Knowledge Dissemination. Therefore, this project encourages port stakeholders to leverage AI to overcome their challenges. According to the project motto, this goal should be achieved by transferring knowledge from academia to industry. This way, the "COOCK" project plays a crucial role in advancing the AI technology perspective and enhancing the maturity level of port stakeholders in this regard.

Nevertheless, the research intends to match those AI solutions and challenges by applying the algorithm modified in Sect. "Modified Gale–Shapley matching algorithm". In other words, this study uses 30 challenges and 17 AI solutions to verify the modified algorithm. The following sub-section defines the required input to run this algorithm.

Input of matching algorithm

The necessary inputs to run the Gale–Shapley algorithm are two matrices called 'preferences lists'. The first is associated with AI solutions, while the second is provided for challenges. This way, AI solution developers rank challenges, which relies on the relevance of challenges with AI solutions. Afterward, challenges also rank AI solutions based on the relevancy of their functionality. Furthermore, the list of AI solutions and challenges preferences are presented in a table later, which presents challenges and AI solutions by codes.

Table 6 AI solutions' preferences list

Title of AI solutions	AI solutions' code	List of preferences
Smart waterway	S1	C7, C9, C12
Demand prediction	S2	C27, C11, C30
Resource allocation	S3	C5, C6, C18, C20, C4
Optimizing shelf placement	S4	C17, C1, C15, C13
Resource efficient AI	S5	C29, C17, C1, C15
Data driven control	S6	C29
Lock optimization	S7	C3, C2, C10, C19, C22
Large scale simulation	S8	C19, C3, C15, C9
Control flexibility in industrial processes	S9	C29
Developing applied building photovoltaics	S10	C12, C30
Electric vehicle charging	S11	C29, C12
Truck guidance system	S12	C13, C14, C18, C23, C16, C21, C29
Predictive planning	S13	C18, C19, C3, C30
Booking of slots	S14	C17, C1, C15, C5, C6, C18
Optimizing maintenance scheduling	S15	C3, C8, C24, C28
Boat landing	S16	C9, C3, C8, C24, C28
Detection of fouling using AI	S17	C7, C12, C29

AI solutions' preferences list

This research effort presents numerous AI solutions for solving challenges in port operations. However, the impact of these AI solutions on the challenges they can solve is different. For instance, one AI solution can solve challenge A better than challenge B. Moreover, it also can solve challenge B better than challenge C. Therefore, the preferences list of this AI solution is (Challenge A, Challenge B, Challenge C). In this case study, developers of AI solutions provide this preferences list about their AI solutions, with data presented in Table 6 as an AI solutions' preferences list. More information regarding the AI solutions preferences list is presented in Appendix 3.

Challenges' preferences list

Drawn on the preferences list of AI solutions and challenges description in Table 4, the challenges' preferences list can be prepared. For instance, this section presents the reasons for ranking AI solutions for one challenge as follows:

Table 7 Challenges' preferences list

Title of challenges	Code of challenges	List of preferences
Optimizing ship stowage planning	C1	S14, S4, S5
Reducing sea going vessel delays	C2	S7
Predicting of inland vessel ETA	C3	S7, S16, S15, S8, S13
Optimizing ship queuing	C4	S3
Centralizing berth allocation	C5	S3, S14
Optimizing quay Crane (QC) assignment	C6	S14, S3
Detecting ship and ships traffic	C7	S1, S17
Reducing vessel turnaround time	C8	S16, S15
Predicting the risk range of ship's berthing velocity	C9	S8, S1, S16
Reducing vessel waiting time	C10	S7
Predicting loading and unloading container demand	C11	S2
Lowering emissions in shipping	C12	S11, S17, S10, S1
Optimizing yard truck routing	C13	S12, S4
Optimizing of yard truck scheduling	C14	S12
Predicting container relocation	C15	S8, S14, S4, S5
Optimizing scheduling of yard crane	C16	S12
Generating optimal yard block allocation	C17	S14, S4, S5
Reducing congestion at terminals' gates	C18	S13, S12, S5, S14
Predicting unforeseen trucks delays	C19	S13, S7, S8
Optimizing truck queuing at gate	C20	S3
Complex scheduling of rail mounted gantry crane	C21	S12
Reducing truck and train waiting time excess	C22	S7
Integrating individual appointment systems	C23	S12
Reducing truck and train turnaround time	C24	S16, S15
Recognizing assets like containers, truck or vessels	C25	
Registering container damage	C26	
Predicting container demand	C27	S2
Reducing container dwell time	C28	S16, S15
Reduction of emission and noise	C29	S11, S9, S5, S6, S12, S17
Predicting fuel and energy consumption	C30	S2, S10, S13

An "Optimizing quay Crane (QC) assignment" was placed in two AI solutions' preferences lists. These AI solutions are "Resource allocation" and "Booking of slots." Both of these AI solutions rely on assignment problems but have different goals. "Resource allocation" here attempts to reduce distance, while "Booking of slots" can create faster handling time. The most significant reason for optimizing QC here is to minimize idle time and handle more containers. Therefore, it is clear that "Booking of slots" can be placed at the first slot in the preferences list of this challenge. In this way, current research prepares other challenges' preferences list as above. Finally, by utilizing these reasons, the preferences list of challenges is provided in Table 7. More information regarding the challenges preferences list is located in Appendix 3.

Result of the matching algorithm

Results associated with the matching algorithm are provided in three phases based on the structure of the modified algorithm. Equally, this section also discusses the implications of these results and using the matching algorithm.

Table 8 Result of phase 1

Challenges	AI solutions	Pairs
C1	S14	C1,S14
C2	S7	C2,S7
C3	S7	C3,S7
C4	S3	C4,S3
C5	S3	C5,S3
C6	S14	C6,S14
C7	S1	C7,S1
C8	S16	C8,S16
C9	S8	C9,S8
C10	S7	C10,S7
C11	S2	C11,S2
C12	S11	C12,S11
C13	S12	C13,S12
C14	S12	C14,S12
C15	S8	C15,S8
C16	S12	C16,S12
C17	S14	C17,S14
C18	S13	C18,S13
C19	S13	C19,S13
C20	S3	C20,S3
C21	S12	C21,S12
C22	S7	C22,S7
C23	S12	C23,S12
C24	S16	C24,S16
C25	–	NOT Match
C26	–	NOT Match
C27	S2	C27,S2
C28	S16	C28,S16
C29	S11	C29,S11
C30	S2	C30,S2

Result of phase1

According to the previous section, the challenges' preferences list was provided based on a preferences list of AI solutions. Thus, if a challenge sends a proposal to the first AI solution in its preferences list, this proposal will undoubtedly be approved. Each challenge can be matched by the first member of its preferences list in this phase. The result of running the algorithm associated with phase 1 is provided in Table 8. In this table, each challenge pairs with an AI solution except C25 and C26.

Result of phase 2

Since the number of AI solutions is less than the number of challenges, the algorithm must run more than once. The number of challenges paired with AI solutions is less or equal to the number of AI solutions each time the algorithm runs. Thus, the algorithm runs several times to pair all the challenges with AI solutions. Therefore, the steps below present the algorithm's running process, with each step showing its result at the end.

Table 9 Result of phase 2

Step	AI solutions	Challenges	Pairs
1	S1	C7	S1,C7
	S2	C27	S2,C27
	S3	C5	S3,C5
	S4	C1	S4,C1
	S5	C15	S5,C15
	S6	–	NOT Match
	S7	C3	S7,C3
	S8	C19	S8,C19
	S9	–	NOT Match
	S10	C30	S10,C30
	S11	C29	S11,C29
	S12	C13	S12,C13
	S13	C18	S13,C18
	S14	C17	S14,C17
	S15	C8	S15,C8
	S16	C9	S16,C9
	S17	C12	S17,C12
2	S2	C11	S2,C11
	S3	C20	S3,C20
	S7	C2	S7,C2
	S12	C14	S12,C14
	S14	C6	S14,C6
	S15	C28	S15,C28
	S16	C24	S16,C24
3	S3	C4	S3,C4
	S7	C10	S7,C10
	S12	C23	S12,C23
4	S7	C22	S7,C22
	S12	C16	S12,C16
5	S12	C21	S12,C21

Step 1: In this step, the algorithm of phase 2 runs just once. As a result, it matches AI solutions with challenges, except for two AI solutions. The results concerning this step and the following steps are provided in Table 9**.**

Step 2: This step first removes all the challenges selected by AI solutions in the previous step. Afterward, the preferences lists must be updated, and the algorithm can run again.

Step 3: Up to this step, some AI solutions are connected with two challenges, which can be increased later in this step. As in the previous steps, if the algorithm assigns one AI solution to a challenge, the algorithm will remove the challenge from the process within the following steps.

Step 4: Only three challenges remain without an AI solution following the preceding steps. Therefore, the algorithm deletes the rest of the challenges from the process.

Step 5: Finally, the algorithm pairs the last challenge to the AI solution.

Result of phase 3

Eventually, the result associated with phase 3, which compares the result of two previous phases, is shown in Table 10. All the challenges (except C25, C26) were matched with AI

Table 10 Final result of matching algorithm

Challenge	AI solution	Final pair
C1	S14	C1,S14
C2	S7	C2,S7
C3	S7	C3,S7
C4	S3	C4,S3
C5	S3	C5,S3
C6	S14	C6,S14
C7	S1	C7,S1
C8	S15	C8,S15
C9	S16	C9,S16
C10	S7	C10,S7
C11	S2	C11,S2
C12	S11	C12,S11
C13	S12	C13,S12
C14	S12	C14,S12
C15	S8	C15,S8
C16	S12	C16,S12
C17	S14	C17,S14
C18	S13	C18,S13
C19	S13	C19,S13
C20	S3	C20,S3
C21	S12	C21,S12
C22	S7	C22,S7
C23	S12	C23,S12
C24	S16	C24,S16
C27	S2	C27,S2
C28	S15	C28,S15
C29	S11	C29,S11
C30	S10	C30,S10

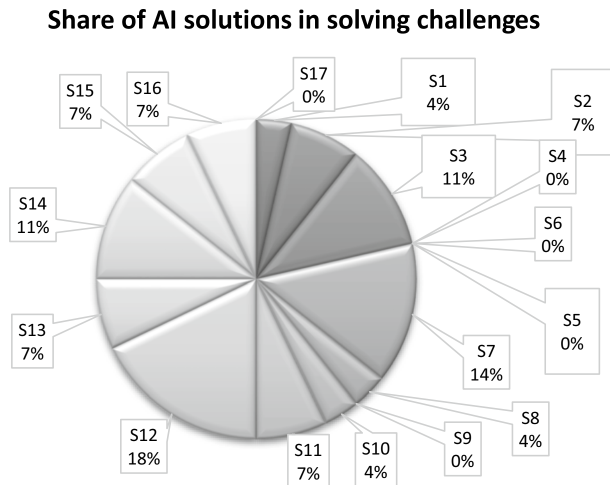

Fig. 4 Result of matching algorithms

solutions in this table. These pairs are the best choice for tackling challenges by AI solutions within the port operation area.

The result of the matching algorithm in phase 3 illustrates that only four AI solutions can solve more than half of the challenges in this study. The ranking of these AI solutions, due to the number of challenges that they can solve, is as follows: "Truck guidance system" (18% of challenges); "Lock optimization" (14% of challenges); "Resource allocation" (11% of challenges); and "Booking of slots" (11% of challenges) Fig. 4. These AI solutions are more critical than others in this research effort. Thus, their implementation can help port operations more than other AI solutions.

Managerial implications

Managerial implication 1

AI solutions can be effectively classified based on their functionalities, allowing IT developers to conveniently identify which solution aligns with the specific requirements of a given challenge. However, stakeholders in the port and shipping industry may lack the necessary knowledge in this domain, hindering their ability to make informed decisions. The designed matching algorithm can be a solid foundation for organizing and structuring this knowledge. The outcome of this matching would empower anyone in the port and shipping industry, regardless of their level of expertise, to access and understand the appropriate AI solutions for addressing their unique challenges.

Managerial implication 2

Adopting AI solutions in port operations can significantly enhance productivity and managerial efficiency. With AI, the knowledge gained from developing specific models can be repurposed to tackle related challenges. Hence, it saves time and resources in data collection, model training, and computation efforts for port stakeholders. The main issue of many challenges within the current study is similar, and they are matched with the same AI solution. For instance, "optimizing ship stowage planning" and "Generating optimal yard block allocation" are linked to "Booking of slots", "Optimizing ship queuing" and "Optimizing truck queuing at the gate" are solved by solutions like "Resource allocation", "Reducing vessel waiting time" and "Reducing truck and train waiting time excess" could be tackled by "Lock optimization", "Optimizing scheduling of yard crane" and "Complex scheduling of rail-mounted gantry crane" have been matched with "Truck guidance system".

Therefore, by utilizing AI solutions to overcome one challenge, port operators can apply the same solution to tackle similar challenges with less effort, increasing overall efficiency and productivity. Moreover, those AI solutions tackling multiple challenges can potentially revolutionize the port and shipping industry. This way, implementing such AI solutions becomes cost-effective for port stakeholders and enables them to improve their operational productivity significantly. This phenomenon can be a game-changer for port operators seeking to stay ahead of the curve in the competitive global market.

Managerial implication 3

Many AI solutions presented in this study utilize ML techniques to address challenges in port operations. Among these, Reinforcement Learning (RL) is a crucial algorithm used by approximately 25% of the identified AI solutions in this research. Therefore, investing in the development of RL algorithms could bring significant benefits in the long term for port operators seeking to enhance their operational productivity and efficiency.

RL algorithms have shown promising results in optimizing various port-related processes such as resource allocation, vessel service scheduling, and container stacking. Allocating capacities to develop these algorithms further could lead to more efficient and effective port operations, saving time and resources while increasing productivity. As such, port stakeholders should consider the potential benefits of investing in RL and other cutting-edge ML algorithms.

Managerial implication 4

The challenges identified by this research belong to one of the three operation areas (waterside, landside, hinterland) or all of them. The waterside operation area possesses 12 challenges matched with 8 AI solutions. 5 challenges are associated with the landside operation area, and 3 with other AI solutions. This study identifies 7 challenges within the hinterland operation area, which have been matched with 5 distinct AI solutions.

The effort factor for solving challenges is defined based on the ratio of AI solutions to challenges (waterside: 8/12 = 67%, landside: 3/5 = 60%, hinterland: 5/7 = 71%). Therefore, the results show that less effort is needed to address challenges belonging to landside operations.

The terminal is often considered the bottleneck in the port supply chain due to its limited space. However, it is worth noting that similar AI solutions can address many challenges terminals face. Port stakeholders can leverage this insight by adopting appropriate AI solutions to overcome landside challenges, turning potential threats into opportunities. Despite the possible slowdown of port operations and increased shipping costs caused by terminal limitations, AI solutions can improve overall efficiency and productivity, helping port operators remain competitive.

Theoretical implications

Theoretical implication 1

Implementing a suitable AI solution in a port area can lead to a higher level of digitalization for port stakeholders. By matching proper AI technology to solve specific challenges, such as improving operational efficiency, enhancing security, or optimizing supply chain management, port stakeholders can better understand the potential of digital technologies and become more comfortable with using these types of technologies. This also can lead to a higher level of digital maturity and create a culture of innovation and continuous improvement. Additionally, as port stakeholders become more digitally mature, they may be more willing to invest in further digital transformation initiatives, leading to even more significant benefits for the port ecosystem as a whole.

Theoretical implication 2

There is often a gap between port stakeholders and AI developers, each with unique perspectives and objectives. Introducing AI technology to established industries can be challenging due to the inherent uncertainty of adopting novel solutions. However, demonstrating the economic viability of implementing AI in the port industry can help bridge this gap.

This research aims to identify which AI solutions with specific features can best address particular challenges in certain port operations. The matching algorithm used in this study can provide valuable input for assessing the economic feasibility of implementing AI solutions in the port industry. By analyzing each matching pair from an economic standpoint, the results can determine whether or not each match is financially viable.

Furthermore, the outcome of the investigation of economic feasibility can guide port stakeholders in identifying which AI solutions with specific attributes can be most beneficial for their particular type of operation. This information can inform decision-making processes and help port actors to make more informed choices about implementing AI solutions in their operations. By leveraging these findings, port stakeholders can become more knowledgeable about the potential benefits of AI technology and make strategic decisions to drive economic growth and efficiency in their operations.

Conclusion

Contemporary port stakeholders face various difficulties within their operations. In contrast, technology providers (recently focusing on AI, big data, or ML) claim to solve numerous port issues. In this regard, there is a lack of a marketplace in which the supply can meet the demand, as in traditional markets. Moreover, there are difficulties in structurally matching the right AI solution provider with the respective challenge owner. This research develops and applies a new academic approach that structurally identifies the AI solution that solves the appropriate challenge within port operations.

This research sets pioneering steps in matching AI solutions with challenge owners. It has the following tangible results: first, it conducts an in-depth literature review to investigate matching algorithms. Accordingly, the research intends to identify innovative methods to link the two market sides (challenges and AI solutions), in which the Gale–Shapley algorithm is found to provide the best results. Since this algorithm is only optimal if applied from the perspective of one side of the market (the proposer's side), this research contributes to the literature associated with this algorithm by using these principles, developing a novel integrated sequence that runs this algorithm from two perspectives, then provides comprehensive matching results satisfying the conditions of the two market sides.

Secondly, this research carries out some desk/empirical research to provide an overview of contemporary challenges and AI solutions within ports. It briefly describes the challenges by presenting their underlying issues, impact, and potential solution characteristics. Similarly, an overview of AI solutions is exhibited. In this respect, an intermediary observation is made that while AI technology is highly likely to be applied in several port operations areas, technology providers integrate their conceptual models in highly focused and dedicated AI applications. For instance, the technological concept that uses AI to "predict vessels' ETA" is almost equally helpful in predicting the delay of trucks and trains in hinterland operations.

As its main and third outcome, this research identifies the AI solutions matching contemporary challenges within port operations by applying the newly developed sequence based on the Gale–Shapley algorithm. Accordingly, the data regarding which AI solutions can solve these port challenges is collected due to face-to-face meetings between technology providers and challenge owners. Subsequently, the in-depth literature review collects data regarding the characteristics and preferences of challenge owners.

The results here show that the concepts of several AI solutions also tackle challenges from other port operational areas than initially intended. For example, a "Truck guidance system", developed to reduce queues in both landside and hinterland operational areas, solves most port challenges (5 out of 30). Moreover, a "Lock optimization" solution using AI and operational in the waterside area of ports tackles 4 out of 30 port challenges in total. Similarly, the use of a solution that enables digital "booking of time slots" at terminals and/or "Recourse allocation" can tackle an equal share of challenges (3 out of 30). Besides, the concept of "Booking of time slots" is matched with challenges that solve issues in container warehousing, with "Resource allocation" linked to queuing problems. On the other hand, when selecting one port operational area, the landside operation area would benefit the most from implementing an AI solution.

Furthermore, the foundation of these critical AI solutions is implemented once. Concerning the reusability feature of AI technologies, stakeholders can customize those AI solutions with less effort to solve the challenges. Moreover, the AI solution overview shows that the key technology these solutions use is ML, specifically the RL algorithm, which can be worth investing in.

This study develops a structured methodology to match port challenges and AI solutions. The main limitation of applying and gaining meaningful results from this method lies in the data collection. Although the buildup of the preference list from both challenges and AI solutions perspectives is supported by strong arguments, there is no theoretical paradigm for collecting this data. Therefore, as a future step, new research is undertaken to employ a scientific method that objectively obtains the preferences of each market side. This method will consider the characteristics of solutions and challenges for defining these preferences. These measures can then make the input of this research more reliable, and the final result can be more accurate.

Appendices

Appendix 1

See Table 11.

Table 11 Overview of the literature adhering to the AI technologies in port and shipping industries

Author (year)	Publication	Challenge addressed	Studied port	Scope of study
Parolas (2016)	ETA prediction for containerships at the Port of Rotterdam using Machine Learning Techniques	ETA	Rotterdam (Netherlands)	AI Advantages
Flapper (2020)	ETA Prediction for Vessels using Machine Learning	ETA	Rotterdam (Netherlands)	AI Advantages
Moscoso-López et al. (2021)	A machine learning-based forecasting system of perishable cargo flow in maritime transport	Prediction of cargo flow	Algeciras (Spain)	AI Advantages
Ansorena and Ansorena (2020)	Managing uncertainty in ferry terminals: a machine learning approach	Congestion	Ceuta (Spain)	AI Advantages
Viellechner and Spinler (2020)	Novel Data Analytics Meets Conventional Container Shipping: Predicting Delays by Comparing Various Machine Learning Algorithms	Congestion	No port mentioned	AI Advantages
Cammin et al. (2020)	Applications of Real-Time Data to Reduce Air Emissions in Maritime Ports	Emission, ETA	Hamburg (Germany)	AI Advantages
Martins et al. (2020)	A Dynamic Port Congestion Indicator—A Case Study of the Port of Rio de Janeiro	Congestion	Rio de Janeiro (Brazil)	AI Advantages
Atak et al. (2021)	Container Terminal Workload Modeling Using Machine Learning Techniques	Quay Crane planning	No port mentioned (Turkey)	AI Advantages
Chargui et al. (2021)	A quay crane productivity predictive model for building accurate quay crane schedules	Quay Crane planning	No port mentioned	AI Advantages
Yang and Chang (2020)	Forecasting the Demand for Container Throughput Using a Mixed-Precision Neural Architecture Based on CNN–LSTM	Predicting Container's Demand	No port mentioned (Taiwan)	AI Advantages
Darendeli et al. (2021)	Container Demand Forecasting Using Machine Learning Methods: A Real Case Study from Turkey	Predicting Container's Demand	Mersin (Turkey)	AI Advantages

Table 11 (continued)

Author (year)	Publication	Challenge addressed	Studied port	Scope of study
Luo and Huang (2020)	Port Short-term Truck Flow Forecasting Model Based on Wavelet Neural Network	Congestion, Truck Flow forecasting	Guangzhou (China)	AI Advantages
Kunnapapdeelert and Thepmongkorn (2020)	Thailand port throughput prediction via particle swarm optimization based neural network	Port throughput forecasting	Bangkok (Thailand)	AI Advantages
Wang et al. (2018)	A Forecast Model of the Number of Containers for Containership Voyage	Predicting container volume	No port mentioned	AI Advantages
Shen et al. (2017)	A deep Q-learning network for ship stowage planning problem	Ship stowage	Ningbo (China)	AI Advantages
Shahpanah et al. (2014a, b)	Optimization Waiting Time at Berthing Area of Port Container Terminal with Hybrid Genetic Algorithm (GA) and Artificial Neural Network (ANN)	Ship Queuing	Tanjung Pelepas (Malaysia)	AI Advantages
Gao et al. (2018)	Deep learning with long short-term memory recurrent neural network for daily container volumes of storage yard predictions in port	Yard equipment Planning	No port mentioned	AI Advantages
El Mekkaoui et al. (2020)	A Way Toward Low-Carbon Shipping: Improving Port Operations Planning using Machine Learning	Low-Carbon Shipping	North African (Morocco,)	AI Advantages
Oucheikh et al. (2021)	Rolling Cargo Management Using a Deep Reinforcement Learning Approach	Cargo Management	No port mentioned	AI Advantages
Adi et al. (2020)	Interterminal Truck Routing Optimization Using Deep Reinforcement Learning	Yard Truck planning	Busan (South korea)	AI Advantages
Kourounioti et al. (2016)	Development of models predicting the Dwell Time of containers in port container terminals	Dwell Time forecasting	No port mentioned	AI Advantages, AI barriers
Mi et al. (2019)	Research on regional clustering and two-stage SVM method for container truck recognition	Container recognition	Taicang (China)	AI Advantages, AI barriers
de León et al. (2017)	A Machine Learning-based system for berth scheduling at bulk terminals	Berth assignment	No port mentioned	AI Advantages

Table 11 (continued)

Author (year)	Publication	Challenge addressed	Studied port	Scope of study
Gao et al. (2019)	The Daily Container Volumes Prediction of Storage Yard in Port with Long Short-Term Memory Recurrent Neural Network	Yard block forecasting	No port mentioned	AI Advantages
Zhang et al. (2020)	Machine learning-driven algorithms for the container relocation problem	Container relocation planning	No port mentioned	AI Advantages
Garrido et al. (2020)	Predicting the Future Capacity and Dimensions of Container Ships	Capacity prediction	Barcelona (Spain)	AI Advantages
Zhang et al. (2020)	Motion Planning Using Reinforcement Learning Method for Underactuated Ship Berthing	Ship Berthing	No port mentioned	AI Advantages
Lee et al. (2020)	Development of Machine Learning Strategy for Predicting the Risk Range of Ship's Berthing Velocity	Control Berthing Risk	No port mentioned	AI Advantages
Niestadt et al. (2019)	Artificial intelligence in transport Current and future developments, opportunities and challenges	AI in road transport, aviation, railway transport shipping, navigation and ports	No port mentioned	AI Advantages, AI barriers
Alop (2019)	The Main Challenges and Barriers to the Successful "Smart Shipping"	AI in smart shipping	No port mentioned	AI Advantages, AI barriers
Babica et al. (2019)	Digitalization in Maritime Industry: Prospects and Pitfalls	AI in maritime industry	No port mentioned	AI Advantages
Stepec et al. (2020)	Machine Learning based System for Vessel Turnaround Time Prediction	Vessel's Turnaround time prediction	Bordeaux (France)	AI Advantages, AI barriers
Xie et al. (2017)	Data characteristic analysis and model selection for container throughput forecasting within a decomposition-ensemble methodology	Container throughput prediction	Singapore (Singapore), Los Angeles (USA)	AI Advantages
Yan et al. (2021)	An Artificial Intelligence Model Considering Data Imbalance for Ship Selection in Port State Control Based on Detention Probabilities	Ship detention	Hong Kong (China)	AI Advantages

Appendix 2

Algorithm phase 1 Proposing by challenges

See Fig. 5.

1. Select a challenge that is not already matched with any AI solutions,
2. If all members of the preferences list of this challenge have already rejected it, or its preferences list is empty,
3. This challenge cannot match with any AI solutions, then delete it,
4. go to line 1,
5. Else,
6. Send a proposal from the challenge to the first AI solution among AI solutions who have not rejected this challenge's proposal before,
7. If this challenge exists in the list of preferences of that particular AI solution,
8. Match the AI solution with this challenge, then go to line 1,
9. Else,
10. Go to line 2,

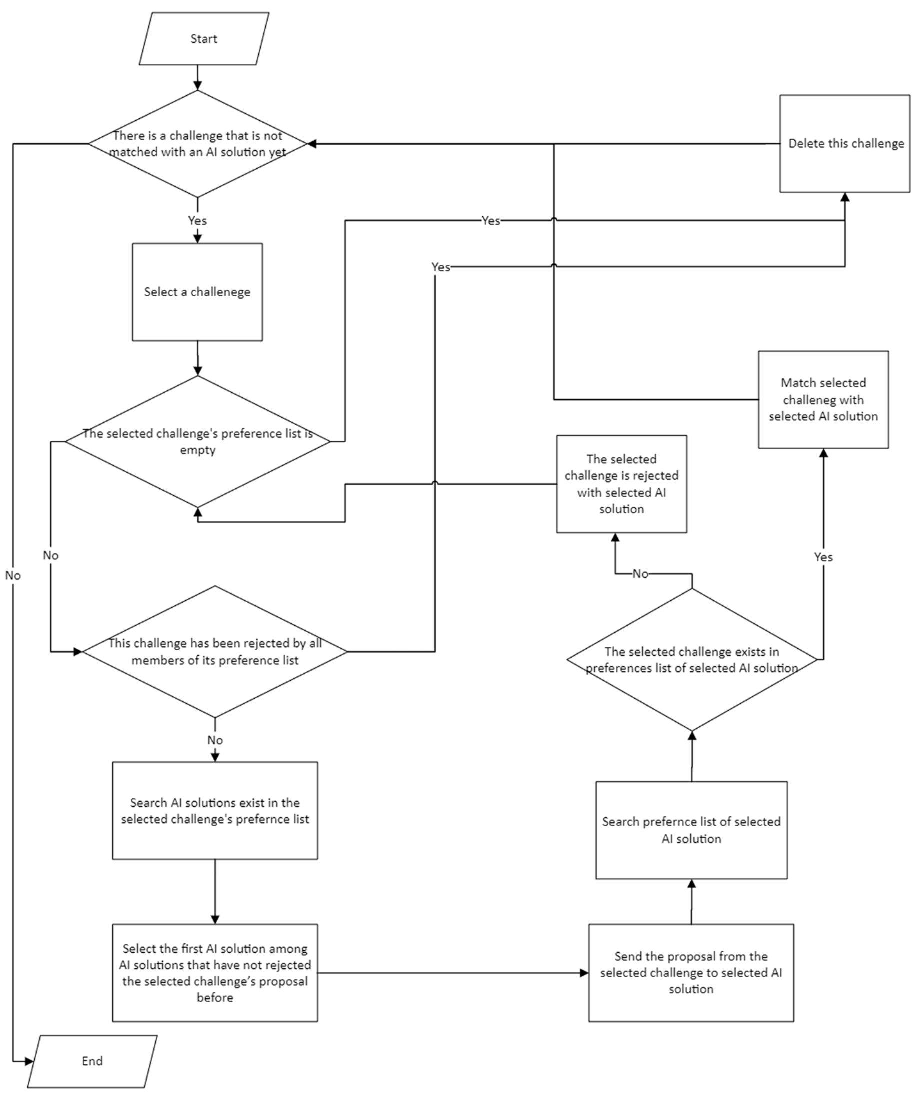

Fig. 5 Algorithm phase 1 flowchart

Algorithm phase 2 Proposing by AI solutions

See Fig. 6.

```
1. Select an AI solution that is not already matched with any challenges,
2. If all members of the preferences list of this AI solution have already rejected it, or its preferences list is empty,
3.      This AI solution cannot be matched with any challenges, then delete it,
4.      go to line 1,
5. Else,
6.      Send a proposal from the AI solution to the first challenge among challenges that have
        not rejected this AI solution's proposal before,
7       If this AI solution exists in the list of preferences of that particular challenge,
8.           If the challenge has already been matched with another AI solution,
9.                Compare AI solutions based on their order in the challenge's preference list,
10.               If both have the same rank
11.                    Match new AI solution with that challenge,
12.               Else,
13.                    Match the AI solution which has been ranked higher by that challenge,
14.                    Reject the proposal of another AI solution to this challenge and
             select that AI solution, then go to line 2,
15.          Else,
16.               Match the AI solution with that challenge,
17.               go to line 1,
18.     Else,
19.          Reject the proposal of the AI solution, then select it and go to line 2
```

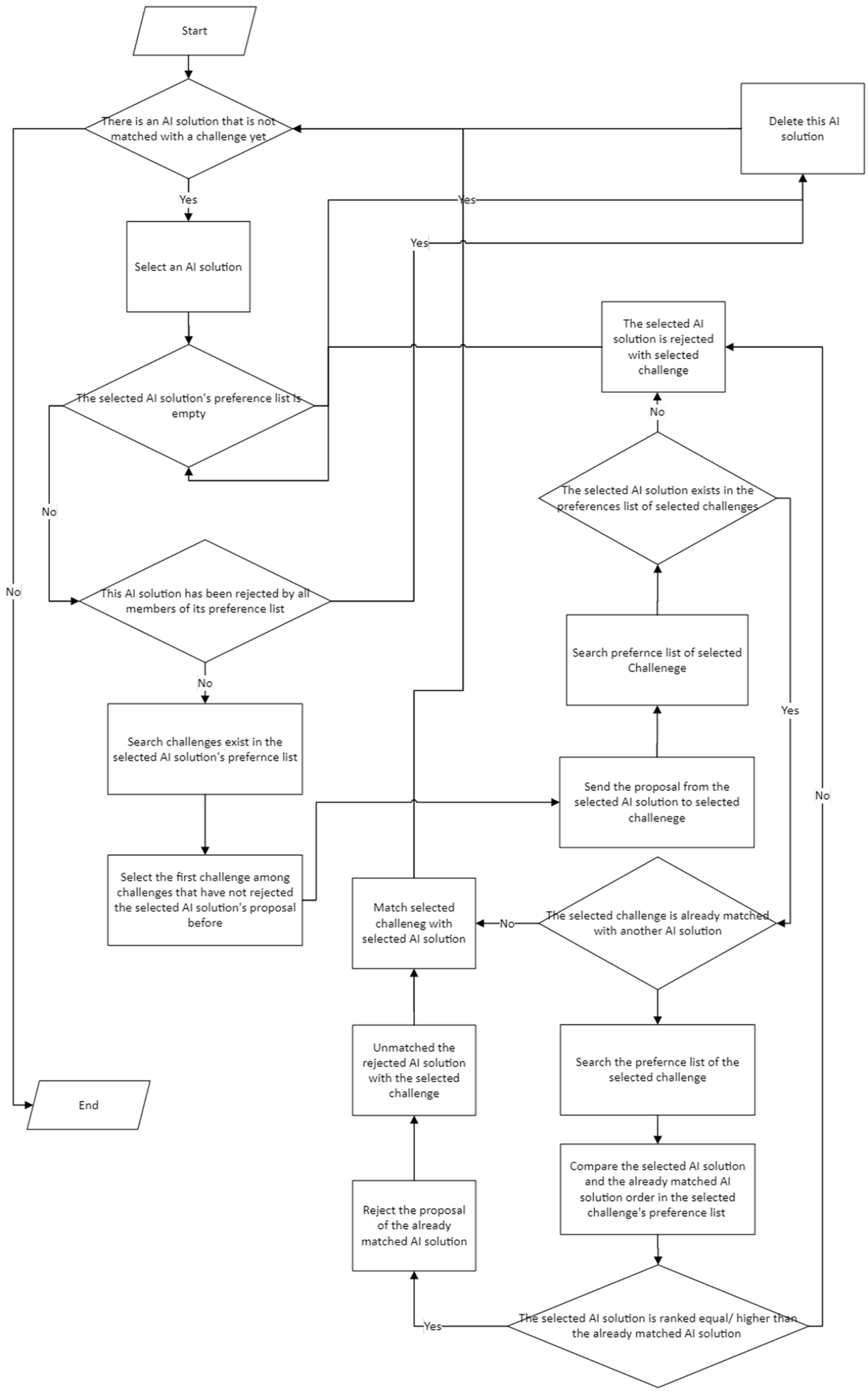

Fig. 6 Algorithm phase 2 flowchart

Algorithm phase 3 Comparing pairs that are made in phases 1 and 2

See Fig. 7

1. Select a challenge,
2. If the challenge is matched with different AI solutions in phases 1 and 2,
3. Comparison value (AI solution phase 1, AI solution phase 2)=(rank of challenge in AI solution phase 1 preference list - rank of challenge in AI solution phase 2 preference)* (count of challenges) + (rank of AI solution phase 1 in challenge's preference list-rank of AI solution phase 2 in challenge's preference list)* (count of AI solutions)
5. If Comparison value =<0,
    Finalize pair (Challenge, AI solution phase 1),
   Else,
    Finalize pair (Challenge, AI solution phase 2),
6. Repeat the procedure for the next challenge,
7. Else,
8. Finalize the pair that challenge exists in it,
9. Repeat the procedure for the next challenge,

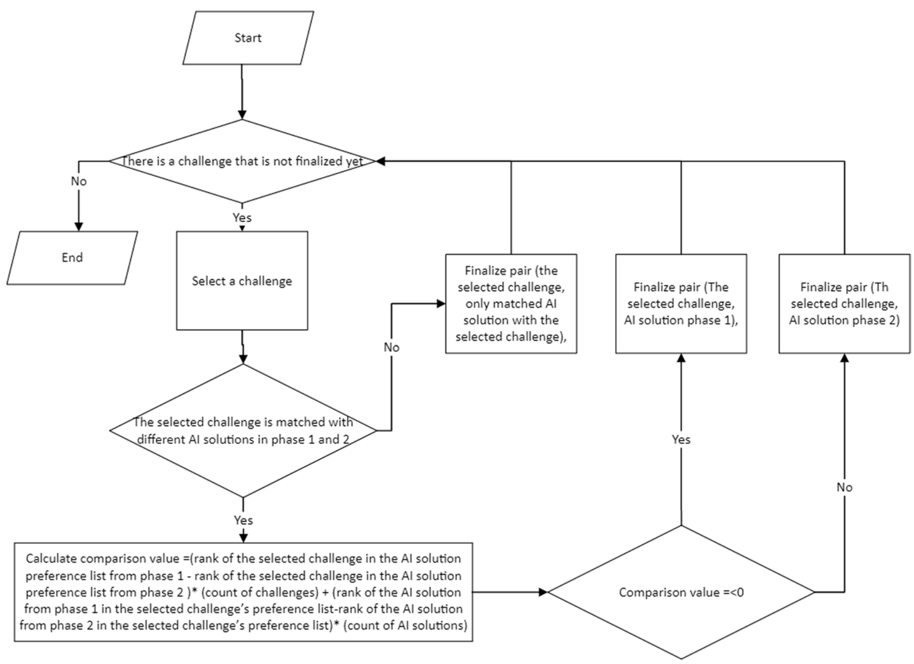

Fig. 7 Algorithm phase 3 flowchart

Appendix 3

See Tables 12 and 13.

Table 12 AI solutions preferences list details

Smart waterway: this solution concerned autonomous barges in urban waterways with low-cost sensor systems, enabling a shift from road to water for sustainable last-mile logistics. The ship detection challenge might be the best match for this solution because one of the technologies used for this solution is computer vision and sensor fusion algorithms to detect and localize obstacles in the waterway. This technology can throw this challenge This solution has been designed for affordable sensors. Although this sensor is employed for navigation and localization, this solution might be useful for predicting a ship's berthing risk range velocity. The goal of low-carbon shipping is reducing air pollution. On the other hand, this solution by researching autonomous barges causes to reduce pollution. Hence, there is a weak connection between them. Hereby the preferences list for this solution is as follows: **Smart waterway LP: *Detecting ship and ships traffic, Predicting the risk range of ship's berthing velocity, Lowering emissions in shipping***
Demand prediction: this solution indicates the demand for fresh food by prediction methods. The challenge of container demand prediction is the best match with this solution because an approach employed for predicting demand for fresh food must be appropriate for this challenge. Also, this solution can predict load and unload containers' demand. However, this challenge is after container demand prediction because it needs to concentrate on the waterside operation area and is not general like container demand. The prediction approach designed in this solution is related to demand. The amount of consumption is related to the demand, and then this approach can help to predict fuel and energy consumption as well. According to the fact relevant to this solution, the list of references is provided below **Demand prediction LP: *Predicting container demand, Predicting loading and unloading container demand, Predicting fuel and energy consumption***
Resource allocation: this solution assigns trucks to the optimal gate in a distribution center. Therefore, berth allocation to vessels has the most connected with this solution. Assigning quay cranes to load or unload vessels is based on the task assignment problem, which is unrelated to this solution as much as the berth allocation problem. One measure that can reduce congestion at the gate is optimizing the assignment of trucks to the gate. Hence, this solution can help reduce congestion at the gate. Also, assigning trucks to the gate is one part of the queuing algorithm. Thus this solution might help optimize truck queuing at the gate. Although this solution is employed for assigning trucks to the gate, it might solve ship queuing like truck queuing at the berth. Finally, the preferences list of this solution is presented based on the above reasons **Resource allocation LP**: ***Centralizing berth allocation, Optimizing quay Crane (QC) assignment, Reducing congestion at terminals' gates, Optimizing truck queuing at gate, Optimizing ship queuing***
Optimizing shelf placement: this solution finds the optimal place to put goods on a shelf in a distribution center. Hence, the personnel can take the least amount of kilometers per day. Therefore, yard block allocation and ship stowage planning are the best matches. The reason for yard block allocation is more related to this solution's goal than the reason for ship stowage planning. The container terminal will prepare ship stowage planning because of safety and security After ship stowage planning, the most appropriate problem this solution can solve is predicting container relocation because allocating blocks to the container can help predict the future movement of containers. One of the goals for tackling yard truck routing is to reduce the number of kilometers that trucks take. Therefore, this solution can address the yard truck routing problem partly. Lastly, the list concerned preferences of this solution is as follows: **Optimizing shelf placement LP: *Generating optimal yard block allocation, Optimizing ship stowage planning, Predicting container relocation, Optimizing yard truck routing***
Resource efficient AI: this solution creates a computational power- and resource-efficient autonomous robotic platform for an industrial warehouse setting that can scale to multiple interacting agents. Therefore, at first, this solution leads to reduce emissions. Also, according to the warehousing knowledge in this solution, the challenges related to allocating containers to block and relocate them in the yard or vessels might be solved by this solution. This solution's challenges related to warehousing have been ranked like the previous solution. At last, the list of preferences indicates the ranking associate challenges for this solution **Resource efficient AI LP: *Reduction of emission and noise, Generating optimal yard block allocation, Optimizing ship stowage planning, Predicting container relocation***
Data driven control: this solution is an innovation project of catalysts, the spearhead cluster that facilitates innovation in the Flemish chemistry and plastics sectors. These methods specifically could be of value in process and system control. Process control can reduce emissions. Hence, this solution only can solve one challenge. The list of preferences for this solution is as follows: **Data driven control LP: *Reduction of emission and noise***
Lock optimization Novimove: this solution is about end-to-end navigation and scheduling for inland waterway transport. Thus, this solution is the most appropriate to predict the ETA of an inland vessel. After that, sea-going vessels delay can be reduced through this solution. Also, this solution leads to reduced waiting times at bridges, locks, and docks while creating smoother sailing. This solution can address challenges like the above but in the hinterland. It can reduce truck delays and truck waiting time. The list of preferences for this solution is as follows: **Lock optimization Novimove LP: *Predicting of inland vessel ETA, Reducing sea going vessel delays, Reducing vessel waiting time, Predicting unforeseen trucks delays, Reducing truck and train waiting time excess***

Table 12 (continued)

Large scale simulation: this solution has been implemented for larger-scale simulations. Other simulation frameworks cannot simulate large-scale experiments in enough detail with an acceptable runtime. This simulation scheme was developed to be applied in traffic cases and could tackle future data prediction challenges. Therefore, the most related challenge with this solution is predicting truck delay. This solution also can address predicting ETA based on the power of the simulation method. This simulation can solve the prediction of container relocation and berthing risk range. However, "prediction of container relocation" is more related to the traffic concept than "prediction of berthing risk range", which is located higher in the preferences list **Large scale simulation LP: *Predicting unforeseen trucks delays, Predicting of inland vessel ETA, Predicting container relocation, Predicting the risk range of ship's berthing velocity***
Control flexibility in industrial processes: this solution combines model predictive control and deep learning techniques. Also, it considers the characteristics of energy-intensive industrial processes. Thus, the best match for this solution is the challenge of fuel and energy consumption prediction
Developing applied building photovoltaics: this solution develops tools to improve the energy yield prediction of solar panels, guidelines to maximize performance and reliability, and techniques for predictive maintenance. Therefore, according to the use of solar panels in vessels, this solution can reduce carbon emissions by vessels. Besides, if solar panels are energy sources, this solution can also predict energy consumption. However, this is not common, so the challenge of "predicting energy consumption" is ranked second in this solution's list of preferences **Developing applied building photovoltaics LP: *Lowering emissions in shipping, Predicting fuel and energy consumption***
Electric vehicle charging: this solution control strategies for the smart charging of electric vehicles. Also, their goals are to shift part of energy consumption towards more appropriate moments of the day or week, increasing the consumption of locally produced renewable energy, reducing peak loads, and avoiding grid congestion Since the equipment in the terminal often uses electricity fuel thus, this solution can help reduce energy consumption, and as a result, this solution can reduce emissions. Also this measure can perform for vessels as well. However, this can occur for some engines in vessels, not all parts of vessels. Therefore, the challenge of "Lowering emissions in shipping" accommodates the second rank in this solution's list of preferences **Electric vehicle charging LP: *Reduction of emission and noise, Lowering emissions in shipping***
Truck guidance system: this solution's first goal is optimizing the truck guidance system, and the second one is optimizing logistic flows when global information is available. Therefore, the most relevant challenge to this solution is the routing of trucks in the yard. After this challenge scheduling of trucks is most related to this solution. If one optimizes the routing of the truck, then the traffic congestion will reduce The second goal of this solution is to address challenges like Integrating individual appointment systems and scheduling cranes in the yard and hinterland, respectively. The appointment system impacts all logistics flow, so it accommodates right before scheduling cranes. Also, the yard crane is more involved in logistics than the rail-mounted gantry crane. Because the yard crane handles all containers, the rail-mounted gantry crane only handles containers moved by rail mode. Finally, by solving problems like the above, this solution can also reduce emissions. According to the above reasons list of preferences for this solution is provided as follows: **Truck guidance system LP: *Optimizing yard truck routing, Optimizing of yard truck scheduling, Reducing congestion at terminals' gates, Integrating individual appointment systems, Optimizing scheduling of yard crane, Complex scheduling of rail mounted gantry crane, Reduction of emission and noise***
Predictive planning: This solution is based on "optimizing statistical forecasting" and "forecasting traffic conditions for trucks to optimize the planning." This solution can predict data related to traffic and cause traffic reduction. Hence, the most relevant challenge to this solution is "Reducing congestion at terminals' gates". After that, the most related challenge is predicting delays that lead to traffic. As this solution is related to trucks, the challenge of "Predicting unforeseen truck delays" ranks second—also, the challenge of "Predicting of inland vessel ETA" rank as a third challenge. Lastly, as this solution is related to predicting data for reducing traffic, the prediction of the amount of energy and fuel that vehicles or vessels need can be addressed by this solution. The list of preferences for this solution is presented below **Predictive planning LP: *Reducing congestion at terminals' gates, Predicting unforeseen trucks delays, Predicting of inland vessel ETA, Predicting fuel and energy consumption***
Booking of slots: this solution relies on optimizing matching free slots in container terminals and making faster handling time. Hence, yard block allocation and ship stowage planning are the most appropriate challenges that can be solved by this solution, respectively. The yard block allocation is more related to this solution than ship stowage planning because the container terminal will prepare ship stowage planning because of safety and security aspects that do not make faster handling time. After ship stowage planning, the most related problem to this solution is predicting container relocation because allocating blocks to the container can help predict the future movement of containers. Although this solution is concerned with assigning slots, a challenge like "berth allocation" could be solved by this solution. Also, the challenges of assigning tasks like "Quay crane assignment" could be related to place assignment. Finally, it is obvious; if this solution optimizes the "allocation gate to the truck," traffic congestion will be reduced. Now, the list of preferences shows the rank of each challenge **Booking of slots LP: *Generating optimal yard block allocation, Optimizing ship stowage planning, Predicting container relocation, Centralizing berth allocation, Optimizing quay Crane (QC) assignment, Reducing congestion at terminals' gates***

Table 12 (continued)

Optimizing maintenance scheduling: this solution works on predicting accessibility for offshore assets taking context, weather, vessel, and routes. Also, it is related to anomaly detection, semantic stream reasoning, and rule mining for optimizing maintenance The most related problem to this solution is "Predicting of inland vessel ETA" because this time's prediction involves all the contexts like weather, vessel, and routes. The other problem with this solution is reducing turnaround time by preventive asset maintenance. As this solution was developed for vessels, "Reducing vessel turnaround time" ranks higher than "Reducing truck and train turnaround time" in the list of preferences Generally, this solution would address the "Reducing container dwell time" challenge in all the port's operation areas, so this solution also has a weak connection with this solution. The list of preferences for this solution testifies to all the above reasons **Optimizing maintenance scheduling LP: *Predicting of inland vessel ETA, Reducing vessel turnaround time, Reducing truck and train turnaround time, Reducing container dwell time***
Boat landing: This solution is exactly like the previous solution. Still, in the context of the boat landing, the most related challenge to this solution is "Predicting the risk range of the Ship's berthing velocity" Then, other challenges are like the previous solution, even rank of them in the preferences list **Boat landing LP: *Predicting the risk range of ship's berthing velocity, Predicting of inland vessel ETA, Reducing vessel turnaround time, Reducing truck and train turnaround time, Reducing container dwell time***
Detection of fouling using AI: the goals of this solution are modeling the performance of a ship, preventing extreme fouling on the hull and propeller of ship, and reducing fuel consumption. The first goal is more important than the second one, and the second one is more important than the last one. Therefore, the most relevant challenge for this solution is "Detecting ship and ship traffic". Also, challenges like "Lowering emissions in shipping" and "Reduction of emission and noise" are related to the third goal ranked respectively after "Detecting ship and ships traffic". The reason for ranking "Lowering emissions in shipping" higher than "Reduction of emission and noise" is the relation of the solution with the ship. The list of preferences provide for this solution is as follows: **Detection of fouling using AI LP: *Detecting ship and ships traffic, Lowering emissions in shipping, Reduction of emission and noise***

Table 13 Challenges preferences list details

Recognizing assets like containers, truck or vessels: according to the AI solutions' list of preferences, this challenge cannot address by AI solutions in this study. This challenge does not belong to the list of preferences of any AI solutions. Therefore, it will not be considered in the matching algorithm process
Registering container damage: this challenge is not concerned with any AI solution provided in this study. AI solutions did not rank this challenge in their preferences list. Hence, if this challenge is involved in the matching algorithm, it will not match any AI solutions. It is better to remove it from the algorithm process
Reducing sea going vessel delays: this challenge has been ranked by "Lock optimization" solution, then it is obvious there is no issue with ranking AI solutions in the list of preferences of this challenge. This list only has one member, and it is "Lock optimization"
Optimizing ship queuing: according to the preferences list of AI solutions. This challenge exists only in one list, which belongs to the "Resource allocation" solution. Therefore, the list of preferences for this challenge includes this solution
Reducing vessel waiting time: "Lock optimization" accommodated this challenge in its preferences list. Hence, this challenge can be solved by this solution and not with the rest of them. The list of preferences associated with this challenge only includes "Lock optimization"
Predicting loading and unloading container demand: " demand prediction " can only solve this challenge among all the AI solutions presented in this study. Thus, ranking AI solutions for this challenge is not difficult because its list of preferences solely contains "Demand prediction"
Optimizing of yard truck scheduling: list of preferences of this challenge comprising "Truck guidance system" AI solution. Undoubtedly only this solution ranked this challenge in its preferences list
Optimizing scheduling of yard crane: AI solutions' list of preferences indicates "Truck guidance system" can tackle this challenge. The rest of the AI solutions did not consider this challenge in their preferences list. Drawn on this, the list of preferences for this challenge consists of the "Truck guidance system"
Optimizing truck queuing at gate: preferences list of this challenge only encompasses one AI solution: "Resource allocation." Because among all the AI solutions, only this solution ranked this challenge in its preferences list
Complex scheduling of rail mounted gantry crane: "Truck guidance system" AI solution corresponds to this challenge. The rest of the AI solutions can not address this challenge. Therefore, the preferences list for this challenge is foreseeable to include only this solution

Table 13 (continued)

Reducing truck and train waiting time excess: among all the AI solutions in this study, only "Lock optimization" complies with this challenge, and this solution is involved in this challenge's preferences list

Integrating individual appointment systems: amid AI solutions in this research, only the "Truck guidance system" can tackle this challenge. Subsequently, this AI solution is a lonely member of this challenge's preferences list

Predicting container demand: "Demand prediction" is the only AI solution that can send a proposal to this challenge. Thus, the list of preferences associated with this challenge solely contains this solution

Centralizing berth allocation: The title of this challenge is self-explanatory. This challenge is about the assignment berth to vessels. "Resource allocation" and "Booking of slots" have accommodated this challenge in their preferences list. It means they can address this challenge. "Resource allocation" concerns gate allocation in the warehouse, and "Booking of slots" works on optimizing the matching of free slots in container terminals. The above explanations of AI solutions suffice to distinguish these AI solutions. Therefore, "Resource allocation" corresponds to this challenge more than "Booking of slots." Drawn on this result, the list of preferences for this challenge is as follows:
Centralizing berth allocation LP: *Resource allocation, Booking of slots*

Optimizing quay Crane (QC) assignment: This challenge involves two AI solutions' preferences list. These AI solutions are "Resource allocation" and "Booking of slots." Both of these AI solutions rely on assignment problems, but either of them has different goals. "Resource allocation" effort to reduce distance and "Booking of slots" can make faster handling time. The most significant reason for optimizing QC is to reduce idle time and handle more containers with them. Therefore, "Booking of slots" can be placed at the first spot in the list of preferences for this challenge. The preferences list for this challenge is presented below
Optimizing quay Crane (QC) assignment LP: *Booking of slots, Resource allocation*

Detecting ship and ships traffic: this challenge encompasses measuring and monitoring the ship's activity. Two solutions can solve this challenge among all AI solutions, so they have put this challenge in their preferences list. These AI solutions are "Smart waterway" and "Detection of fouling using AI". According to this challenge, "Smart waterway" is a better choice. "Smart waterway" was developed to detect obstacles in voyages with affordable sensors, but "Detection of fouling using AI" only detects fouling on the ship's hull and propeller. Therefore, a list of preferences for this challenge is provided as follows:
Detecting ship and ships traffic LP: *Smart waterway, Detection of fouling using AI*

Reducing vessel turnaround time: the time from arrival to departure of the vessel is the turnaround time. There are many measures to reduce it, but in this study, only two AI solutions can tackle it. "Optimizing maintenance scheduling" and "Boat landing" have ranked these challenges in their preferences list. Both of these solutions have the same objective: "Predicting accessibility for offshore assets taking context, weather, vessel, routes," but "Boat landing" is more related to this challenge. "Boat landing" can consider all needs to reduce the turnaround time, but "Optimizing maintenance scheduling" only concentrates on repair planning. Based on this result, the preferences list for this challenge figures out below
Reducing vessel turnaround time LP: *Boat landing, Optimizing maintenance scheduling*

Optimizing yard truck routing: this challenge concerned determining the optimal route for transporting containers between the yard and quayside. Two AI solutions are related to this challenge. "Truck guidance system" and "Optimizing shelf placement" have considered this challenge in their preferences list. Regarding their objectives, "Truck guidance system" is more practical to tackle this challenge than "Optimizing shelf placement." "Truck guidance system" optimizes route directly but "Optimizing shelf placement" decides to "where is the right place for goods" and as a result, the milage which needs to take will reduce. Hence, the "Truck guidance system" was placed at the first spot in the preferences list of this challenge
Optimizing yard truck routing LP: *Truck guidance system, Optimizing shelf placement*

Reducing truck and train turnaround time: the time from arrival to departure of the truck and train is the turnaround time. "Optimizing maintenance scheduling" and "Boat landing" have been ranked this challenge in their list of preferences like "Reducing vessels turnaround time." Both of these challenges have the same objective, then all the reason for ranking AI solutions is like the reasons which figure out for "Reducing vessels turnaround time." Therefore, the preferences list for this challenge is like "Reducing vessels turnaround time"
Reducing truck and train turnaround time LP: *Boat landing, Optimizing maintenance scheduling*

Table 13 (continued)

Reducing container dwell time: this challenge is about reducing the time a container spends within a port. If the "Optimizing maintenance scheduling" and "Boat landing" tackle challenges associated with the turnaround time of vessels, trucks, and trains, this challenge will also be fixed. Therefore, the AI solutions which can address this challenge are like "Reducing turnaround time," and all the reasons for ranking these solutions are the same. Hereby the list of preferences for this challenge is presented below **Reducing container dwell time LP:** ***Boat landing, Optimizing maintenance scheduling***
Optimizing ship stowage planning: Containers' optimal position on a ship is called ship stowage planning. This challenge is one of the members of the preferences list of three AI solutions which are "Optimizing shelf placement," "Resource-efficient AI," and "Booking of slots." Among these solutions, "Booking of slots" is the most related solution to this challenge because it is exactly concerned with optimizing the allocation of the free slots to containers. "Optimizing shelf placement" and "Resource-efficient AI" work on warehousing goods, but among these solutions, "Optimizing shelf placement" is the better choice to solve this challenge. The main objective of "Resource-efficient AI" is developing warehousing robots, but "Optimizing shelf placement" relies on assigning shelves to goods in a warehouse. Eventually, the preferences list for this challenge is presented as follows: **Optimizing ship stowage planning LP:** ***Booking of slots, Optimizing shelf placement, Resource efficient AI***
Predicting the risk range of ship's berthing velocity: The vessel's speed may go high during mooring, and there is the possibility of damaging the berth equipment or the hull. Therefore, the simulation approach maybe can find a safe speed. Three AI solutions have been considered for this challenge in their list of preferences. Among them, "Large scale simulation" is the most match solution. "Smart waterway" and "Boat landing" must also rank here. Both AI solutions rely on predicting some data relevant to vessels, but "Smart waterway" because of exploiting affordable sensors and predicting data like obstacles is better than "Boat landing." "Boat landing" works on predicting the accessibility of vessels based on route and weather. Finally, the preferences list for this challenge is provided as follows: **Predicting the risk range of ship's berthing velocity LP:** ***Large scale simulation, Smart waterway, Boat landing***
Generating optimal yard block allocation: This challenge is about allocating the required space for container storage. This challenge is one of the members of the preferences list of three AI solutions which are "Optimizing shelf placement," "Resource-efficient AI," and "Booking of slots." Among these solutions, "Booking of slots" is the most related solution to this challenge because it is exactly concerned with optimizing the allocation of the slots to containers. "Optimizing shelf placement" and "Resource-efficient AI" are concerned with warehousing goods, but among these solutions, "Optimizing shelf placement" is the better one to solve this challenge. The primary objective of "Resource-efficient AI" is to develop warehousing robots, but "Optimizing shelf placement" is assigning shelves to warehouse goods. Lastly, the preferences list for this challenge is as follows: **Generating optimal yard block allocation LP:** ***Booking of slots, Optimizing shelf placement, Resource efficient AI***
Predicting unforeseen trucks delays: This particular challenge is one of the members of the list of preferences for "Predictive planning," "Lock optimization," and "Large scale simulation" solutions. Among these solutions, the best one to tackle this challenge is "Predictive planning." "Predictive planning" forecasts traffic conditions for trucks to optimize the planning. The second choice for solving this challenge is "Lock optimization" because it predicts the ETA of the vessel. Lastly, "Large scale simulation" can address this challenge by simulation power that exists in this solution. This challenge's preferences list figure out below **Predicting unforeseen trucks delays LP:** ***Predictive planning, Lock optimization, Large scale simulation***
Predicting fuel and energy consumption: "Demand prediction," "Developing applied building photovoltaics," and "Predictive planning" ranked this challenge in their preferences list. The most appropriate solution for tackling this challenge is "Demand prediction" because consumption is the same as demand. In the end, demand consumes by the user. The second choice for this challenge is "Developing applied building photovoltaics." "Developing applied building photovoltaics" improves the energy yield prediction of solar panels, then maybe it can solve this challenge too. Finally, "Predictive planning" Optimizes statistical forecasting, but it does this in a general situation, but the previous solution at least predicts some energy-related data. The list of presences for this challenge is provided below **Predicting fuel and energy consumption LP:** ***Demand prediction, Developing applied building photovoltaics, Predictive planning***

Table 13 (continued)

Lowering emissions in shipping: Four AI solutions can solve this challenge based on their power to reduce emissions. The first alternative is "Detection of fouling using AI." This solution can reduce the ship's fuel consumption, and as a consequence, the emission will reduce too. The second choice is "Electric vehicle charging." This solution also can reduce emissions, but not emissions associated with ships. The third one is "Developing applied building photovoltaics," which can reduce emissions using solar panels. However, using solar panels is not so custom on the ship. Finally, the "Smart waterway" by optimizing the path for ships may reduce emissions. The list of preferences for this challenge is determined based on the above reasons
Lowering emissions in shipping LP: ***Detection of fouling using AI, Electric vehicle charging, Developing applied building photovoltaics, Smart waterway***

Predicting container relocation: This challenge has been accommodated in the list of preferences of four AI solutions. The most related AI solution among all of them is "Large scale simulation." This solution, by simulation, can obtain a sequence of container moves. The second related solution is "Booking of slots." This solution can find the best slot for the container so it knows about the relocation of the containers before. The third one is "Optimizing shelf placement." This solution also is related to this challenge but not exactly for relocating containers in slots. Lastly, "Resource-efficient AI" with warehousing knowledge can tackle this problem, but the first objective of this solution is developing warehousing robots. The list of preferences for this challenge is prepared as follows:
Predicting container relocation LP: ***Large scale simulation, Booking of slots, Optimizing shelf placement, Resource efficient AI***

Reducing congestion at terminals' gates: Four AI solutions have considered this challenge. These AI solutions are "Predictive planning," "Truck guidance system," "Resource allocation," and "Booking of slots." The best choice for addressing this challenge is "Predictive planning" because it forecasts truck traffic conditions to optimize the planning. The second alternative is the "Truck guidance system" because it optimizes logistic flows when global information is available. It does not mention traffic, but logistics flow could be related to traffic. The third one is "Resource allocation" because it can optimize the allocation of gates to trucks. Hence, the traffic can be reduced as a result. Eventually, "Booking of slots" can also optimize the gate's allocation to the truck, but it has been employed for allocating slots to containers. The list of preferences for this challenge is as follows:
Reducing congestion at terminals' gates LP: ***Predictive planning, Truck guidance system, Resource allocation, Booking of slots***

Predicting of inland vessel ETA: Five AI solutions have ranked this challenge in their preferences list. These solutions are "Lock optimization," "Boat landing," "Optimizing maintenance scheduling," "Large scale simulation," and "Predictive planning." The best option for addressing this challenge is "Lock optimization." It is employed for the prediction of ETA and accurate vessel positioning. "Boat landing," "Optimizing maintenance scheduling," predict accessibility for offshore assets taking context, weather, vessel, and routes, but "Boat landing" is more related to this challenge because it concentrates on landing and "Optimizing maintenance scheduling," relies on repair planning of vessels. "Large scale simulation" is more related than "Predictive planning" to this challenge because it can find out accurate ETA by simulation, but "Predictive planning" optimizes statistical forecasting and does not mention exact to ETA. The preferences list of current challenges is presented below
Predicting of inland vessel ETA LP: ***Lock optimization, Boat landing, Optimizing maintenance scheduling, Large scale simulation, Predictive planning***

Reduction of emission and noise: Six AI solutions have ranked this challenge. These are "Electric vehicle charging," "Control flexibility in industrial processes," "Resource-efficient AI," "Data-driven control," "Truck guidance system," and "Detection of fouling using AI." Among all these solutions, "Electric vehicle charging" is the best option to address this challenge. That reduces the port's carbon emissions because electric vehicles exist everywhere. The second one is "Control flexibility in industrial processes." That can control the emission as the first objective, then reduce CO2 emission afterward. "Resource-efficient AI," by Designing computational power- and resource-efficient autonomous robotic platforms for an industrial warehouse, can help to reduce emissions. Hence, it can be ranked in third place. The next place belongs to "Data-driven control" because it only reduces emissions related to chemical plants. One of the "Truck guidance system" objectives is to optimize logistics flow, which can cause to reduce emissions. The last choice is "Detection of fouling using AI" because it only reduces emissions related to ships. Finally, the list of preferences for this challenge is presented based on the above reasons
Reduction of emission and noise LP: ***Electric vehicle charging, Control flexibility in industrial processes, Resource-efficient AI, Data-driven control, Truck guidance system, Detection of fouling using AI***

Appendix 4

Table 14 presents the process of finalizing pairs due to the algorithm phase 3.

Table 14 Comparing process

Challenge	AI solution assigned by phase 1	AI solution assigned by phase 2	Are assigned AI solutions by two phases the same?	Rank of Challenges in the preferences list of AI solution assigned by phase 1	Rank of AI solutions in the preference list of challenges assigned in phase 1	Rank of Challenge in the preferences list of AI solution assigned by phase 2	Rank of AI solutions in the preference list of challenges assigned in phase 2	Comparison Value	Final pair
C1	S14	S4	No	2	2	2	1	−17	C1,S14
C2	S7	S7	Yes	Not compare	Not compare	Not compare	Not compare	Not compare	C2,S7
C3	S7	S7	Yes	Not compare	Not compare	Not compare	Not compare	Not compare	C3,S7
C4	S3	S3	Yes	Not compare	Not compare	Not compare	Not compare	Not compare	C4,S3
C5	S3	S3	Yes	Not compare	Not compare	Not compare	Not compare	Not compare	C5,S3
C6	S14	S14	Yes	Not compare	Not compare	Not compare	Not compare	Not compare	C6,S14
C7	S1	S1	Yes	Not compare	Not compare	Not compare	Not compare	Not compare	C7,S1
C8	S16	S15	No	2	2	3	1	11	C8,S15
C9	S8	S16	No	1	3	4	1	50	C9,S16
C10	S7	S7	Yes	Not compare	Not compare	Not compare	Not compare	Not compare	C10,S7
C11	S2	S2	Yes	Not compare	Not compare	Not compare	Not compare	Not compare	C11,S2
C12	S11	S17	No	2	2	2	1	−17	C12,S11
C13	S12	S12	Yes	Not compare	Not compare	Not compare	Not compare	Not compare	C13,S12
C14	S12	S12	Yes	Not compare	Not compare	Not compare	Not compare	Not compare	C14,S12
C15	S8	S5	No	4	4	3	1	−79	C15,S8
C16	S12	S12	Yes	Not compare	Not compare	Not compare	Not compare	Not compare	C16,S12
C17	S14	S14	Yes	Not compare	Not compare	Not compare	Not compare	Not compare	C17,S14
C18	S13	S13	Yes	Not compare	Not compare	Not compare	Not compare	Not compare	C18,S13
C19	S13	S8	No	1	3	2	1	−6	C19,S13
C20	S3	S3	Yes	Not compare	Not compare	Not compare	Not compare	Not compare	C20,S3
C21	S12	S12	Yes	Not compare	Not compare	Not compare	Not compare	Not compare	C21,S12
C22	S7	S7	Yes	Not compare	Not compare	Not compare	Not compare	Not compare	C22,S7
C23	S12	S12	Yes	Not compare	Not compare	Not compare	Not compare	Not compare	C23,S12
C24	S16	S16	Yes	Not compare	Not compare	Not compare	Not compare	Not compare	C24,S16
C27	S2	S2	Yes	Not compare	Not compare	Not compare	Not compare	Not compare	C27,S2
C28	S16	S15	No	4	2	5	1	11	C28,S15
C29	S11	S11	Yes	Not compare	Not compare	Not compare	Not compare	Not compare	C29,S11
C30	S2	S10	No	2	2	3	1	11	C30,S10

Abbreviations

AI Artificial intelligence
ML Machine learning
RL Reinforcement learning
IDlab Internet, technology and data science lab
IoT Internet of Things
SMP Stable matching problem
ESMP Equitable stable matching problem
COOCK Collective research and development and collective knowledge dissamination
QC Quay crane

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Author contributions
MF performed the literature review, modified the matching algorithm and wrote the first draft of the paper. He also wrote the method section of the paper and presented managerial insight and conclusion. TV and VC also supervised MF during the development of the paper and contributed by improving the quality of the paper with various meetings. All authors read and approved the final manuscript.

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Declarations

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