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The effect of autonomous systems on the crew size of ships – a case study

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ABSTRACT
Recently, autonomous ships have gotten a lot more attention both in the media and in research. However, very little research has focussed on the effects of automation on the size of the crew. This paper analyses the effects of added automation on the required size and composition of the crew on a 750 TEU short sea container vessel. A Crew Analysis Algorithm is used to determine the cheapest crew composition to perform the tasks required to operate a ship. Using this algorithm, two potential automation options are investigated: automating the navigation tasks and automating the mooring tasks. Automating the navigation tasks decreases the required crew size in the normal sailing and arrival & departure phases by 3 and 1 crew members, respectively. The loading & unloading phase is unaffected. Automating the mooring tasks reduces the required crew in the arrival & departure phase to 2. It is concluded that since individual automation options do not affect the crew requirements for all travel phases, their effect on crew reduction is limited unless several options are combined. However, with a change in task assignment and different training of crew members, a reduction of the required number of crew members is possible.

KEYWORDS
Autonomous ships; crew reduction; autonomous navigation; manning; merchant ships

1. Introduction

It is estimated that in 2025 there will be a shortage of 147.500 officers in the world merchant fleet (BIMCO, and ICS 2015). This expected shortage could potentially disrupt world trade, which is largely dependent on maritime transport. To counteract this, the maritime industry must address several challenges in workforce planning and training. One of the suggested solutions to combat this shortage is to increase the level of automation on ships in order to decrease the required number of crew members. New technologies, such as advanced communication methods, image recognition software, and more robust propulsion methods, make this possible (Lloyds Register, QinetiQ, and University of Southhampton 2017).

The minimum required size of the crew is governed by the Flag State of the ship. Many flag states, such as Panama (Panama Maritime Authority 2019), the Marshall Islands (Maritime Administrator Republic of the Marshall Islands 2011) and the Netherlands (Netherlands Regulatory Framework—Maritime 2011) follow the IMO Principles of Safe Manning. This document states that a ship must have enough crew on board to perform the crucial tasks on board. It is up to the ship owner to prove that this is the case. It is then up to the Flag State to accept or reject the proposed manning plan for a ship. In this article, we develop several such proposals based on an altered task load for the crew.

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Increased automation and autonomy are hot topics in many aspects of transportation research, spanning the automotive, aviation, rail and maritime industries. Within the automotive industry, several companies such as Waymo, Apple, and Uber have managed to drive millions of kilometres with autonomous cars (Waymo 2019; McCarthy 2019). Driverless metro systems are now considered standard (Thales Group 2018) and research is currently being conducted into running long distance trains without a driver (Franzen 2015). Planes are capable of flying practically all of their journey on autopilot, even though a pilot still remains on board (Charlton 2019).

The main differences between ships and other modes of transport for which autonomy is researched are the number and diversity of tasks of the operators. In a car, train, or plane the main function of the operator is to navigate, (i.e., control the vehicle, plan a route and have situational awareness) whereas on a ship the crew has other many tasks to perform in addition to the navigation. Additionally, the ship has to interface with an infrastructure in ports which is currently set up to work with manned ships. This poses an additional challenge, as it is unlikely that ports will invest heavily in alternative mooring solutions for unmanned ships before this will be widely used.

A ship is a complicated system of systems and each of these systems have different levels of automation or autonomy. This makes defining what an autonomous ship is relatively difficult and it has resulted in many different definitions of autonomous ships (Eriksen 2019). When assessing the impact of autonomy on crewing levels it is important to remember that a ship is complex system of systems. Therefore, the autonomy level of the ship should be defined at a systems level and not for the ship as a whole. For example, a ship could have fully autonomous navigation, while maintenance of the propulsion system still requires human interaction.

Autonomous shipping has gotten a significant amount of attention in the last decade. This is not only because the implied removal of the crew is a way to deal with the impending crew shortage, but also because of the potential to lower the operational cost of the ship and decreased fuel consumption and, as a result, emissions. A significant portion of research into autonomous shipping has focussed on automating the navigation duties of the ship, which follows the line of research in the other transportation areas. One of the first major projects in autonomous shipping was the MUNIN project. This project focussed on an autonomous bulk carrier that is monitored and, if required, operated, by a shore control station (Burmeister et al. 2014). The MUNIN project has focussed mostly on navigation. Additionally it mentions the importance of robust propulsion and the regulatory aspect of autonomous shipping (MUNIN 2016). A second major project of interest is the AAWA project. This project, spearheaded by Rolls Royce, has placed focus on four areas: situational awareness, legal implications, safety and security, and the business case (Poikonen et al. 2017). Within other research navigation (Lloyds Register, QinetiQ, and University of Southhampton 2017), collision avoidance (Beser and Yildrim 2018; Kuwata et al. 2014), general control (Zheng, Negenborn, and Lodewijks 2016; Haseltalab and Negenborn 2019), navigation through artificial intelligence (Chen et al. 2019) and (remote) communication (Jokioinen 2015; MacKinnon, Man, and Baldauf 2015) with an autonomous ship are also a common subjects. However, reliable propulsion, cargo handling and ship-to-ship communication have received far less attention (Kooij et al. 2018).

Most of the research presented in the previous paragraph focusses on one part of autonomous shipping, such as navigation, collision avoidance or propulsion. However, the impact of each of these solutions on the complete system of the ship has not been investigated. It is unknown how each of these single solutions will impact the required crew on a ship. Since the reduction of the size of the crew and the associated cost is one of the main drivers for ship owners to strive for increased autonomy and automation on their ships, this is an important knowledge gap that prevents a rational assessment of viable autonomous shipping concepts. In this paper, the extent to which increased automation and autonomy can indeed enable changes in crew size and composition is quantified using a purpose-built crew analysis algorithm. This algorithm is used to find the cheapest crew composition to perform all required tasks. This is done by analysing the tasks that the crew currently performs in order for the ship to function and by analysing the capabilities (i.e., skills) of each crew member with regards to these tasks.

Since the aim of this paper is to analyse the effects that added automation could have on the current manning situation, it is important to first model the current workload and the resulting current manning situation. From this current workload, automation can be simulated by removing tasks from the workload. For example, when using an automated mooring system, the crew no longer has to perform the mooring tasks. The algorithm can be used to determine the effects of automation, which in this article will be shown in two case studies, performed on a 750 TEU short sea container vessel. In the first case study, the effects of automated navigation tasks are investigated, in the second, both the navigation tasks and the mooring tasks are automated.

To summarise, this paper presents the following:

- A method to identify the effects of automating specific tasks on board of a short sea container vessel on the size and composition of the crew
- A detailed analysis of two case studies, one in which the navigation of the ship is automated and one in which the navigation and mooring are automated. These analysis provide new insights into the viability of autonomous shipping

2. Theory

Finding the optimal crew for a given set of tasks on board a ship is a typical 'assignment problem'. The tasks that the crew executes during a travel phase do not have strong interdependencies. In practice, this gives the crew members significant freedom in choosing when to execute a task. This simplifies the problem, as detailed scheduling is not required and all tasks are performed by a qualified crew member. This leads to a set of n tasks that need to be performed. A set of m agents (crew members) is available to perform these tasks. The goal is to find the cheapest set of crew members to perform the tasks.

2.1. Workload modelling

Modelling a workload to assess the optimal manning situation is commonplace in many different areas ranging from a labour force in a factory (Santos, Fukasawa, and Ricardez-Sandoval 2018) to an entire naval fleet (Bielli, Bielli, and Rossi 2011). In the maritime industry, most of the research on optimised manning has been performed for naval ships (e.g., Archer, Lewis, and Lockett 1996; van Diggelen, Janssen, and van den Tol 2016; Wetteland, O'Brien, and Spooner 2000). Alapetite and Kozine (2017) looked into the safe manning of merchant ships. Most of these studies apply a variation of network simulation modelling, and more specifically discrete event simulation (DES), to solve the problem. In addition to DES, there are several other methods that can be used. Heimerl and Kolisch (2009) mention several different approaches, ranging from a sequence of transportation problems to mixed-integer linear programming.

The benefit of DES is that it allows for the use of an inter-arrival time between different tasks, changes in the probability distribution of task length (Alapetite and Kozine 2017), and the use of time sensitive tasks that are dependent on each other (van Diggelen and Post 2016). However, while these attributes are applicable in highly time sensitive (military) procedures, they are less so on a merchant vessel. There, most tasks are less time sensitive and have fewer dependencies, especially if a voyage is subdivided into several phases, like normal sailing, arrival & departure and loading & unloading.

The problem can also be defined as a mixed integer linear programming problem, as is done in this paper. However, this is only possible if the planning (or task list) and the number of agents with a specific skill are known for each phase (Heimerl and Kolisch 2009). Approaching the problem in this way means that there are many different methods to solve the problem, ranging from heuristic methods to specific algorithms (Hillier and Lieberman 2001).

In this paper, the assignment problem is solved by using a greedy algorithm. A greedy algorithm is a heuristic method that is used in operations research to quickly find a solution to a problem. As the algorithm is based on logical choices made in each step the implementation time is relatively short. (Sharma 2019). This also means that the runtime of the algorithm is very short. This logic-based decision process is also the downside of a greedy algorithm. It looks for local optima in the hope of finding the global optimum, which it does not achieve for every problem (Sharma 2019). To reduce the possibility of the algorithm ending up in a local optimum, the tasks are sorted from most expensive to cheapest. Additionally, the problem is small enough to perform a manual check on the results to identify possible local optima. The following sections explains the crew analysis algorithm (CAA) that utilises this greedy algorithm.

3. Method: the crew analysis algorithm

The CAA consists of three main parts: the input, the algorithm, and the output. As stated, the goal of this algorithm is to find the cheapest crew, in terms of crew cost for the operator, that can perform a specific workload. To analyse the effect of adding automation, it is important to start with the current situation. For this research, the basis of the two input databases, discussed later on, is the current, conventional, situation. This means that the tasks that need to be performed and the skills the crew members have with regards to these skills is based on practice. Figure 1 shows a high-level overview of the Crew Analysis Algorithm consisting of the input, the algorithm, and finally the output. This algorithm was previously presented in detail in Kooij and Hekkenberg (2019).

As mentioned, the input for the algorithm consists of a database of tasks and a database of possible crew members. For each crew member, it has been determined which skill level they have for the execution of the various tasks. The different levels are explained in Table 1. Each crew member will have a maximum of 12 hours to work per day. However, it is possible that the travel phases do not span the full 12 hours. This number of hours is the same for all crew members. The specific ship and trade route investigated in this article, represent a relatively uncomplicated case. The ship does not require a pilot to enter or exit port, nor does it require stevedores to board the ship during loading and unloading.

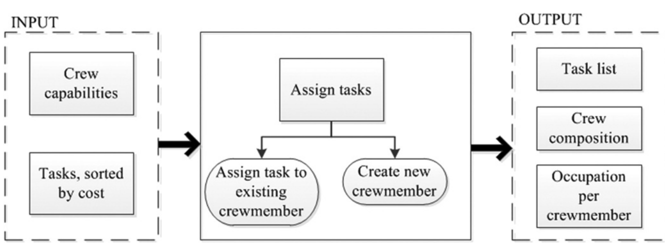

Figure 1. Basic overview of the crew analysis algortihm.

Table 1. Explanation of skill levels for the different crew members.

Level	Explanation
0	The crew member is not able to perform this task.
1	The crew member is able to perform the task under supervision (e.g., with some instruction all crew members would be capable of throwing a line to shore during the mooring process) or the crew member does not require training to perform the task.
2	The crew member is capable of performing this task without supervision

In order to avoid scheduling issues with tasks that take place at different moments throughout a single journey, the journey is split up into three travel phases. Each of these phases is governed by its own crewing requirements. The three travel phases are: arrival and departure, normal sailing, and loading and unloading.

3.1. The task and crew databases

AS mentioned above, the input for the algorithm is divided into two databases: a task database and a skills database. The input for these databases has been collected using a combination of observations and expert interviews. The task analysis is based on a functional breakdown analysis performed in earlier research (Kooij et al. 2018). The ship's main functions as well as their sub-functions are identified using a variation of Watson's approach (Watson 1998). These functions are then linked to a breakdown of the systems that are present on the ship. From these systems, the tasks of the crew that are required for the fulfilment of the ship's functions can be determined. This translates into a task list of all the tasks that need to be performed for the ship to operate smoothly.

The information gathered through the theoretical work has been validated using a two-tiered method. First the primary author performed a field study combined with exploratory expert interviews on the *MV Endurance*, a 750 TEU short sea container vessel crewed by 12 people. During the field study, the author shadowed the different members of the crew and conducted unstructured interviews regarding their work, tasks, and skills. In a second step these findings were corroborated with experts from industry and nautical education using systematizing expert interviews.

This method resulted in a list of tasks that need to be performed during the journey. Although a very large number of small subtasks have to be performed on board, many of these tasks can be clustered into larger tasks. For these larger tasks the workload and required man-hours can be estimated more reliably. For example; in the engine room the engineers perform planned maintenance as well as repairs on a wide variety of equipment. Instead planning these individual tasks in detail, the engineers perform a full day's work, in which they execute all of these tasks at the most suitable moment. This clustering of subtasks prevents an analysis of the effects of small automation measures for individual subtasks, but the selected aggregation level is suitable to assess the impact of larger automation options such as automated mooring or autonomous navigation.

3.1.1. Task database

For each task, several properties have been determined using the abovementioned method. These properties include: the required number of crew members, their required skill level, workload, and the travel phase in which the tasks are performed. In addition, it is determined if the tasks can be split between different crew members or not. Figure 2 shows how the task database looks and what information is included.

	Task properties						Relevant travel phase		
Task name	Split	Location	Number of crew	Total time in hrs	Simultaneous	Required skill level	Loading and unloading	Arrival and departure	normal sailing
Manoeuvring the ship during arrival and departure	0	1	1	1	0	2	0	1	0
Watch in engine room during arrival and departure	0	2	1	1	0	2	0	1	0
Prepare deck for arrival and departure	0	3	4	1	0	1	0	1	0
Supervise deck preparation for arrival and departure	0	3	3	1	0	2	0	1	0
Handling mooring lines	0	3	4	0	0	1	0	1	0
Clean up deck after arrival and departure	0	3	4	1	0	1	0	1	0

Figure 2. Excerpt of the task database.

3.1.2. Crew capability database

The capability database contains the skill of each of the crew ranks for each of the tasks. On the ship used for this article, 10 ranks have been identified, distributed over 3 departments. This distribution can be found in Table 2. Figure 3 shows an excerpt of the crew capabilities database.

The starting point for determining the capabilities of each of the crew members were their current tasks. In addition to giving them these skills, each of the crew members have also been assigned the skills of their subordinates. So, a captain can also perform the tasks of the chief officer and the second officer, even if he does not normally perform these tasks. This is done because it is assumed that people do not lose a skill just because they were promoted to a higher position.

3.2. The crew analysis algorithm

In this part the detailed workings of the CAA are discussed. Figure 4 shows the three main parts of the algorithm: data preparation (I), assignment of tasks that can be split (II), and finally assignment of tasks that cannot be split (III). These three parts will be discussed below.

3.2.1. Section I: data preparation

When the algorithm is initialised (Section I in Figure 4), tasks are first sorted by their execution cost (i.e., based on the cheapest crew member that can perform a task). This ensures that the crew composition that the program suggests is in fact the cheapest option (for a further explanation see Section II). The second input required is the list of potential crew members.

Starting with a crew of 0, the algorithm keeps track of all required crew members, their assigned tasks and how much time they have left in a workday to perform other tasks. This list, together with the requirements regarding the task such as skill level and required man hours allows the program to set up a list with crew members on board who can perform the selected task.

The remainder of the tasks, are subdivided in two categories by the algorithm. Tasks that can be split between multiple crew members end up in section II whereas the tasks that cannot be split over multiple crew members end up in section III. This means that for each task, either section II or section III is completed.

3.2.2. Section II: tasks that can be split

In section II, the tasks that can be split between crew members, are assigned. This section concerns tasks that can easily be transferred to another crew member before completion. The algorithm executes a loop in order to assign all hours of the task to a crew member. There are two options to assign the hours: Either there is a crew member on board that can perform the task or there is not. If

Table 2. Overview of the crew ranks implemented in the algorithm, sorted per department.

Bridge Department	Engineering Department	Deck Department
Captain	Chief Engineer	Bosun
Chief Officer	Second Engineer	Able Bodied Seaman (ABS)
Second Officer		Ordinary seaman (OS)
		Deck Boy

	Captain	Chief engineer	First officer	2nd Engineer	2nd officer	Bosun	Cook	ABS	OS	Deck boy
Port watch: Cargo supervision	2	0	2	0	2	1	0	1	1	1
Port watch: access control	0	0	0	0	0	2	0	2	1	1
Perform administrative duties: Loading and unloading	2	1	1	1	1	0	0	0	0	0
Perform administrative duties: Normal sailing	2	1	1	1	1	0	0	0	0	0
Prepare food and drink	1	1	1	1	1	1	2	1	1	1

Figure 3. Excerpt of the crew capabilities database showing the tasks in the first column and the skills of the different crew members in the corresponding rows.

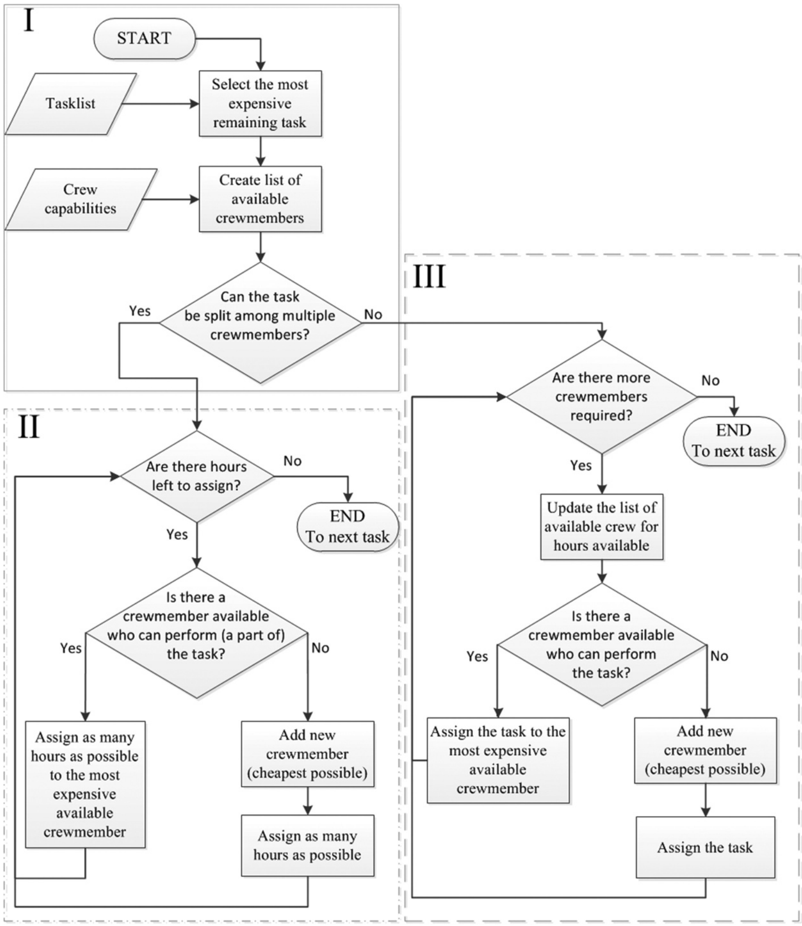

Figure 4. Simplified overview of the CAA.

one or more crew members on board can perform (a part of) the task as many hours as possible are assigned to the most expensive available crew member. If there are no more tasks that require this crew members specific skills, this crew member can now be assigned tasks that are below their paygrade. This ensures that the crew members have as full a workload as possible.

If there is no crew member on board that can perform the task, the algorithm creates the cheapest crew member capable of performing the task. Once again, due to the way the tasks are sorted in Section I, it is not possible that a more expensive crew member is required later on in the process. This means that the cheapest crew member possible is the most economical choice.

3.2.3. *Section III: tasks that cannot be split*

In section III tasks are assigned that cannot be split among multiple members of the crew. An example of a task that cannot be split is the manoeuvring of the ship during arrival and departure. Once a crew member has started this task, it is better that they finish the task and not hand it over halfway through. In general, the steps are very similar to the steps taken in section II. However, in this case, the loop does not run until all hours are assigned but until the required number of crew members are have this task assigned.

3.2.4. Communal tasks

There is a final distinction of tasks, that is not made in Figure 4. This is the difference between communal tasks and other tasks. Communal tasks are the tasks that require multiple specific crew members of different skill levels to perform the task, for example the task of work planning, which requires a chief engineer, a chief officer, and a bosun to perform the task together. These tasks are assigned prior to the other tasks. This ensures that the specific crew members required to perform these tasks have enough hours left to perform the task.

3.3. The output

After the algorithm has run through the three travel phases and all the tasks have been assigned, the CAA produces two important outputs: an overview of the crew members that are required in each travel phase, and a graph depicting the occupation rate of each crew member for each travel phase.

The list of crew members per travel phase can be used to quantify the effects of added automation. It shows which crew members are required per travel phase given a certain workload. By comparing this to the conventional situation, it is possible to identify the changes to the crew. Additionally, this list can be used to determine in which travel phase automation should be added to further decrease the crew size. Since the crew requirements are split between the three different travel phases it is possible to identify the crew requirement per travel phase. That way, it is also possible to identify the normative travel phase, which determines the total number of crew members. To lower the overall crew requirement, tasks in this travel phase need to be reduced.

By combining the outcome of the three travel phases, the minimal size of the crew can be determined. This can be a combination of the crew required for different travel phases, since not all types of crew members are required for all travel phases.

The graph that is used to depict the workload of each crew member is shown in Figure 5. The graph also shows which part of the work that the crew member performs is actually at their level and for which part of their job they are overqualified (denoted by the two colours of the bar graph).

This information can be used to identify ways to reduce the crew cost. An example of this is the bosun, who only performs around 10% of their workload at their own level, while the rest of it could also be done by a deck boy. If a way can be found to remove that 10% from the workload, het bosun could be replaced by a deck boy, thus leading to a reduction in crew cost.

In the graph, it can be seen that all the crew members are assigned a full workload, expect for the final deck boy. This follows logically from the way the tasks are assigned, i.e., that tasks are assigned to the most expensive crew member that still has time to do them.

4. Results: the case studies

In this paper, two case studies are performed, one which investigates the effects of automating the navigation tasks and a second focussed on the combined effects of automating the navigation tasks and the mooring tasks. These two groups of tasks consist of strongly interrelated tasks, which are likely to be grouped together in any possible solution. The reference vessel for these studies is the *MV Endurance*, a 750 TEU container vessel sailing a liner service between two European ports. Typically, a ship of this size has 10 to 12 crew members, dependent on the cargo type, route, and ship operator. The *Endurance* has a crew of 12. The size of the crew is relatively large since the crew can assist with loading and unloading of the cargo. This is not always allowed but can significantly reduce the cost for the operator as crew members can be significantly cheaper than the port's stevedores.

Not all travel phases require the same number of crew members. On the reference ship, the loading and unloading phase requires the most crew members, 12. This is due to the above-mentioned policy. The normal sailing phase requires 11 crew members and the arrival and departure phase requires 8 crew members.

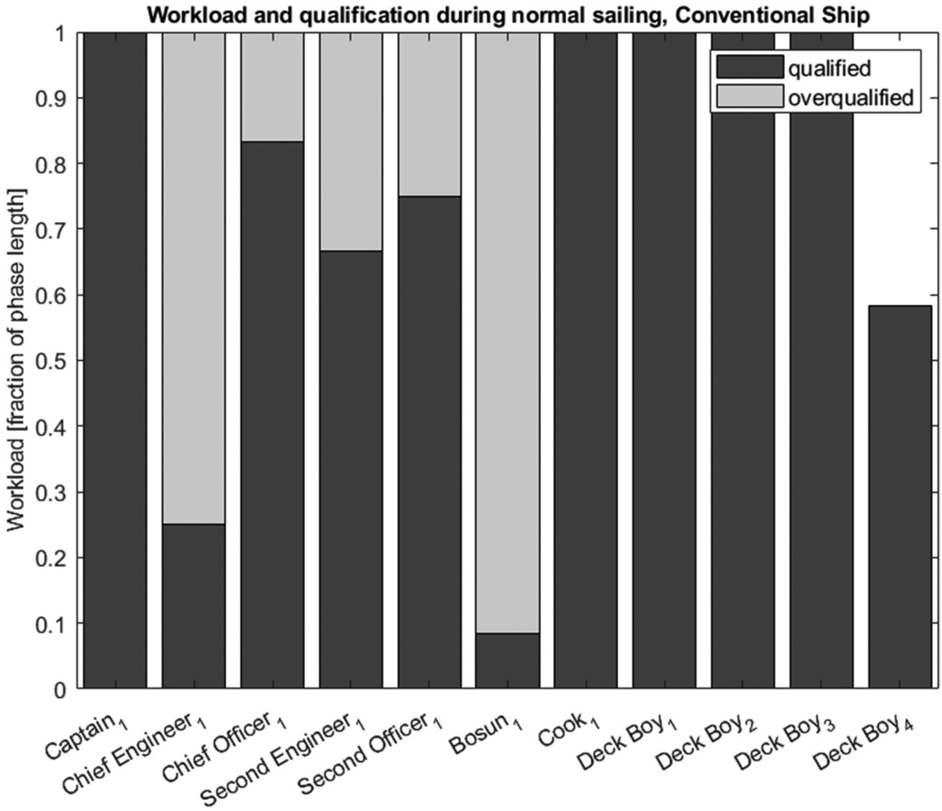

Figure 5. Example of an occupation graph, with the crew ordered from most expensive (left) to least expensive (right).

For the first case study, tasks are assigned to crew members in the traditional way, that means crew members will only perform tasks within their own department, even if they have the required skill to perform a task in another department.

4.1. Case study 1: automating the navigation tasks

This case study analyses the effects of full automation of the navigation tasks. The navigation tasks on the ship are manoeuvring the ship, keeping a night watch, and general watch keeping. Watch keeping, in turn, entails having situational awareness, route following and communicating with other ships. Removing these tasks can enable crew members to perform other tasks within their own department as defined in Table 2. The next sections explain the effects of automating these tasks on the size of the crew on the ship.

4.1.1. Normal sailing phase

The impact of the automation of the navigation tasks on the workload of the crew is significant during the normal sailing phase, especially for the bridge department. However, this reduction in workload does not result in any major reductions in the required crew, as can be seen in Figure 6. The size of the crew decreases by only one crew member, the second officer. However, this figure also shows that for a number of crew members, the workload decreases significantly. For example, the chief officer (denoted by the third bar) goes from a full workload to one where he is only assigned tasks for less than 20% of the time. Such a low workload is an inefficient use of resources as it leaves several crew members with only a very low workload. Furthermore, it only leads to an

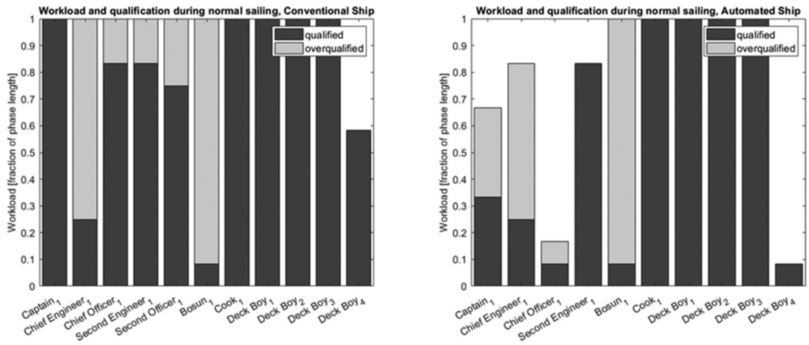

Figure 6. The required crew members and their workload for the conventional situation (left) and the automated situation (right).

absolute reduction of 1 crew member. If automating the navigation tasks is to have a more significant effect on the size of the crew of a ship, a radical change in task assignment is required.

4.1.2. Arrival and departure phase

During the arrival and departure phase, the impact of automating the navigation tasks is relatively small. This is mostly because this phase normally does not take very long which means that multiple crew members are not required to perform the navigation tasks. In this case, the required number of crew members is reduced from 9 to 8 crew members, as the second officer is no longer required on board. The tasks that the second officer performs in the conventional situation have been transferred to other crew members on the ship that also have the ability to perform that task. For example; the second officer performs a supervision task during the arrival and departure phase, which is now performed by the captain.

Figure 7 shows that both the captain and the chief engineer perform only tasks for which they are overqualified during this phase, as becomes clear from the two light grey bars. The reason these two crew members are still selected by the algorithm is because both of them perform a task called *ultimate responsibility*. The international regulations state that a captain must be responsible for the ship at all times and similarly a chief engineer must be responsible for the engine room (International Maritime Organisaton 2000). While other crew members may have responsibility of either the ship or the engine room during their watch, the ultimate responsibility lies with the captain and the chief engineer. These tasks do not require any time to be spent on them but cannot be assigned to another crew member.

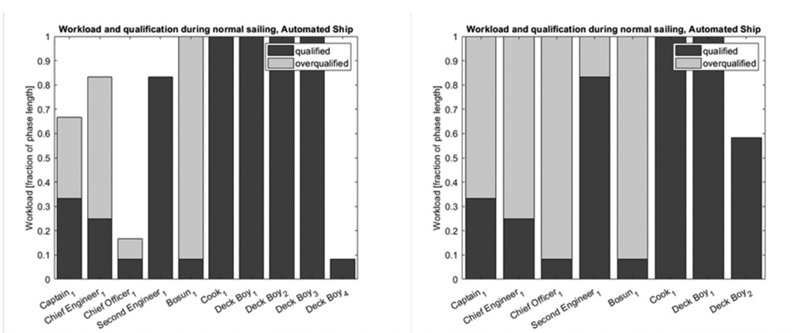

Figure 7. Workload and crew requirements for the arrival and departure phase in the conventional situation (left) and the automated situation (right).

4.1.3. Reconsidering the traditional task distribution

In the previous section, tasks were shifted between crew members in the same department, which did not result in significant changes in the required number of crew members. However, the results did show a significant decrease in the workload of specific crew members, something that is not economically beneficial for the ship owner. In the next study, this constraint is removed. This means that a crew member can now also perform tasks that are outside their department. However, a crew member must still have the required skill and skill level to perform a task.

Figure 8 shows that having crew members perform tasks from other departments allows for a further reduction of two crew members, two deck boys, and a full workload for most of the crew involved. However, it does also increase the amount of time that crew members perform tasks for which they are overqualified, specifically the chief officer. This could negatively influence the work enjoyment of these crew members.

Table 3 gives an overview of the number of crew members that are required in each travel phase. The table shows that not using the traditional task assignment causes a larger decrease in the required number of crew members in the normal sailing phase. The most important conclusion from this table is that in order to reach the full potential of automation, a thorough re-thinking of the way the ship and its crew operate is required. This means investigating changes in tasks for crew members, which in turn could mean a change in training. While this would require a radical change in the current culture, this case shows that it is crucial to achieve maximum benefit from automation of tasks.

4.2. Case study 2: automating the navigation tasks and the mooring tasks

In this second case study, the effects of automating the mooring tasks, in addition to the previously investigated navigation tasks is investigated. The task cluster ‘mooring’ requires the most crew members during the arrival and departure phase. The mooring task requires up to 7 crew members at the same time who prepare the deck for the mooring or unmooring procedure, handle the lines, supervise the process, and finally clean up after the ship has arrived or departed. Handling the lines is a physically hard job and accidents are not uncommon during the execution of this set of tasks.

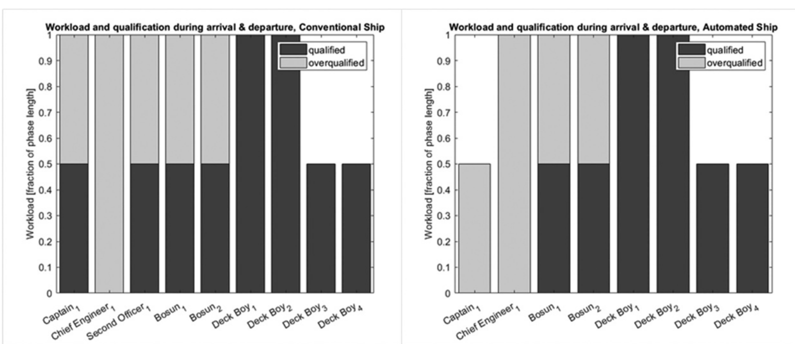

Figure 8. The difference in workload and crew composition during normal sailing between the automated situation with traditional task assignment (left) and without traditional task assignment.

Table 3. Summary of the required crew members per travel phase and situation.

Travel phase	Conventional situation	Automated situation—Traditional roles	Automated situation—non-traditional roles
Arrival and departure	9	8	8
Normal sailing	11	10	8

4.2.1. Arrival and departure phase

Figure 9 shows that the influence of this added automation during the arrival and departure phase is significant. The required crew reduces from 8 to only 2 crew members, a captain and a chief officer if both the navigation tasks and the mooring tasks are automated. The captain has no workload outside of the *ultimate responsibility* task which does not require man-hours. The chief engineer only performs the *ultimate responsibility* task at their own level. All other tasks could also be performed by other, cheaper, crew members. Regulations state that during sailing in shallow water, an engineer has to be present in the engine room at all times. This is to ensure that, should something go wrong, someone is available to quickly address the problem. This shows that at some point, it is important to not only look at the technical and economic feasibility of automation but to also investigate the potential regulations that could hinder progress.

4.2.2. Normal sailing phase

The normal sailing phase is not influenced by the additional automating of the mooring tasks. That means that in this phase the crew requirements are the same as were calculated in case study 1.

4.2.3. Loading and unloading phase

The loading and unloading phase does not involve any navigation or mooring tasks and therefore, there are no changes between the conventional and automated phases. However, due to the ports that the analysed ship services, it is the normative phase and requires the most crew members, 12. This phase also requires the most expensive crew of the three travel phases. Although the ship is not moving, the bridge department and engine room department have several tasks during loading and unloading (see Figure 10). In the engine room maintenance is performed that cannot be done while the engine is running or for which specialised equipment or personnel is required. Additionally, the engine room crew is responsible for the bunkering of fuel among other things. For the deck department the tasks consist of administrative tasks for the captain and a port watch for the chief and second officer. This means that they monitor the ship while it is in port. Additionally they supervise the loading and unloading process.

Although the arrival and departure phase only requires two crew members, the other two phases require a significantly higher number of crew members, as shown in Table 4. This means that, in addition to paying for an automatic mooring system, the ship operator is also required to still pay for the crew on board, who could also perform the mooring tasks. This shows that there is a balance between investing in new technology and requiring less crew to sail the ship. Focussing only on one travel phase or on a single technical solution, will ultimately not help significantly to reduce the size of the crew. A combination of solutions for various tasks is required to achieve the highest savings.

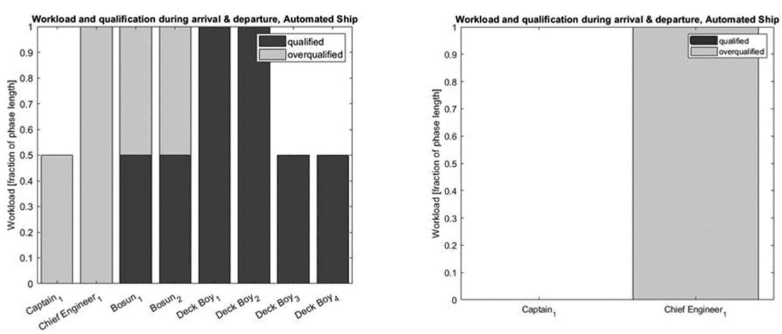

Figure 9. Decrease in the required number of crew members between a ship with automated navigation tasks (left) and a ship with automated navigation and mooring tasks.

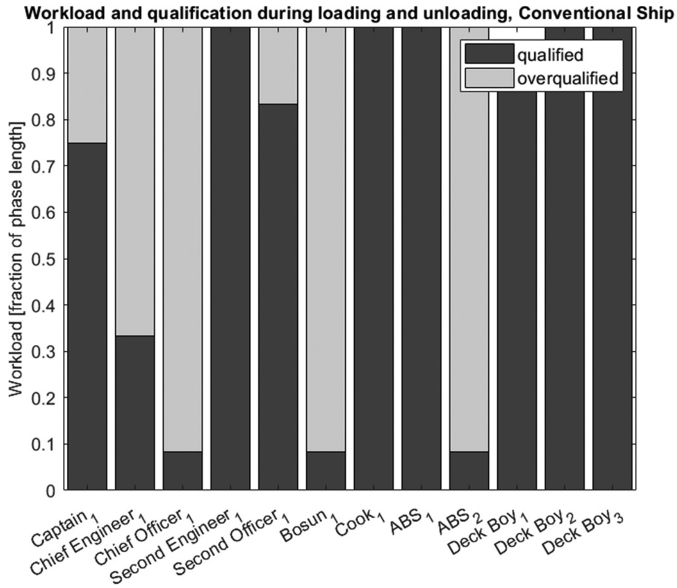

Figure 10. Workload and crew requirements for loading and unloading phase during both the conventional situation and the automated situation.

Table 4. Changes in crew requirements per travel phase.

Travel phase	Conventional situation	Automated situation—non-traditional roles
Arrival and departure	9	2
Normal sailing	11	8
Loading and unloading	12	12
Required crew (whole journey)	12	12

5. Discussion

The two examples in this paper show that reducing the crew through added automation is possible. However, there are several limitations to consider. Firstly, automation options typically address a single task or subtask. This means that the added automation does not address a reduction in crew size over the whole trip but in one or two travel phases. This only leads to an inefficient use of resources and not necessarily a significantly smaller crew.

The reduction in workload is a second limitation to consider. For the normal sailing the influence of automating navigation tasks on crew composition is small when tasks are only relocated to others within the same department. While the crew is reduced by one crew member, the main effect is the reduction of workload for specific crew members, in one case down to 10% of a full workday. This situation would not be preferable for a ship owner who aims to keep the costs low. However, a lower workload, if distributed properly, would not necessarily have only negative aspects. Many maritime accidents have been attributed to fatigue of the seafarers (Xhelilaj and Lapa 1996). If the decrease in workload due to automation could be distributed evenly between the crew members to reduce each of their workloads slightly, sailing could potentially be made safer and cheaper.

Third, the economic aspect is important. A solution must not only be technically feasible, but also economically viable. For example, there are options to reduce the crew size during the loading and unloading phase, but they are costly. Using an automated terminal, for example, could make a part of the crew redundant in this phase, just like using stevedores would. However, industry experts agree that both options would be significantly more expensive than hiring the additional crew members, especially for short sea vessels that call in port often. The high cost of the stevedores and automated terminals have driven ship owners to sail with larger crews than strictly necessary. This practice, combined with the findings of the case study regarding the loading and unloading phase, could form a significant obstacle towards low-manned and unmanned ships.

To find other potential obstacles, an economic analysis of different automation options should be performed. In future research, the cost of automation options should be compared to the benefits of a smaller crew. This way, it is possible to find promising combinations of automation which will lead to economically viable low-manned, and ultimately, unmanned ships.

Automating the navigation tasks only influences the crew size in two of the three travel phases. Since the loading and unloading phase requires the largest crew in the investigated case, the crew size will not decrease by only automating the navigation tasks. This means that a solution also has to be found to decrease the required crew in the loading and unloading phase. This shows that it is important to analyse the required crew in all travel phases and to reduce the crew in the phase that requires most crew members first. This will allow for a reduction in the crew size.

Letting go of the traditional task distribution significantly increases the effects of the automation of the navigation and mooring tasks on the required crew size. It shows that reducing the crew size is not just about automation, it is also about organisation. Only with a combination of these two factors can the maximum crew reduction be reached. However, adapting the tasks that a crew member works also increases the percentage of the time that this crew member spend working below their training level, which could decrease job performance and enjoyment. To combat this, the crew would need to be retrained to ensure that all crew members work at their own level. An experiment was performed with dual-educated crew members (so-called Marofs) that could perform both officer's duties and engineer's duties in the Dutch maritime industry (Serné 1998). This allowed ships to sail with a smaller crew since tasks that traditionally required two differently educated crew members could now be performed by one Marof. This shows that training crew members differently could reduce the crew size.

Automating both the navigation tasks and the mooring tasks can significantly reduce the number of crew members in the arrival and departure phase. If the navigation and mooring tasks are automated, only a captain and a chief officer are required during this phase. The captain only performs the task *ultimate responsibility* which does require any actual hours. The chief officer performs a watch keeping task in the engine room as well as the *ultimate responsibility* task. All these tasks are governed by regulations to ensure the safety of the ship. In the event of a problem, the responsibility for the ship and the engine room has to be clearly defined. Additionally, in shallow water like during arrival and departure, it is important to have a crew member on standby to assist in the engine room quickly, in Figure 8, this is the chief engineer. This shows that the governing rules will have a great influence on crew reduction on a ship. It is of the utmost importance that the governing rules are evaluated to allow for changes that enable unmanned and autonomous shipping to become a reality. A goal-based approach with regards to the rules could ensure that the aim of the rules is honoured but would also allow designers and operators the freedom to attempt different designs.

Finally, an observation can be made regarding the method used. In the beginning of the paper, it was mentioned that in this case, the scheduling is left out of the algorithm. This is possible due to the nature of the tasks on board of a merchant ship. These tasks are not time sensitive, nor are they very complex, in the sense that they do not need many people performing subtasks at the same time. Therefore the algorithm is capable of finding a feasible solution without scheduling tasks within a travel phase. However, this method is not suitable to be used on board of ships that do have these complicated tasks, such as working vessels or navy ships. For these types of ships, discrete event simulation is more suitable.

6. Conclusions

In this article, a crew analysis algorithm, which heuristically solves and task assignment problem using a greedy algorithm, is used to analyse the effects of added automation on the size and composition of the crew.

The crew analysis algorithm can be used to estimate the changes in crew composition that increased automation on the ship can cause. Industry experts have verified both the starting point of the algorithm, the current manning situation, and the crew that the algorithm determined. This verification shows that the CAA can be used to analyse and evaluate the effects of added automation on the crew of a ship. The analysis method presented in this paper aids in the determination of the effects of automation options or procedural changes. The output that it provides is important for future economic viability analyses.

As shown by the two automation cases discussed in this paper, adding automation does not immediately influence the size of the crew of the whole trip. This means that it is important to investigate which automation options are possible and what the effects are. Automating for the sake of automating will not lead to cost savings on the ship. It might even lead to a higher operational cost due to the operating and maintenance cost of the systems in addition to the cost of a full crew. Adding automation might be accompanied to by a change in responsibilities for the various crew members or different training cost. However, a change in the task assignment and the training of crew members might reduce the workload of each (or some) of the crew members. This could reduce fatigue under maritime professionals and thus increase the safety of shipping in general and the ship in particular.

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