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Optimization of Daily Operations in the Marine Industry Using Ant Colony Optimization (ACO)-An Artificial Intelligence (AI) Approach

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ABSTRACT: The maritime industry plays a crucial role in the global economy, with roughly 90% of world trade being conducted through the use of merchant ships and more than a million seafarers. Despite recent efforts to improve reliability and ship structure, the heavy dependence on human performance has led to a high number of casualties in the industry. Decision errors are the primary cause of maritime accidents, with factors such as lack of situational awareness and attention deficit contributing to these errors. To address this issue, the study proposes an Ant Colony Optimization (ACO) based algorithm to design and validate a verified set of instructions for performing each daily operational task in a standardised manner. This AI-based approach can optimise the path for complex tasks, provide clear and sequential instructions, improve efficiency, and reduce the likelihood of human error by minimising personal preference and false assumptions. The proposed solution can be transformed into a globally accessible, standardised instructions manual, which can significantly contribute to minimising human error during daily operational tasks on ships.

1 INTRODUCTION

Approximately, 90% of the world trade is captured by the maritime industry, comprising more than 60,000 merchant ships and over a million seafarers [1]. In recent years, the maritime industry has strived to improve reliability and ship structure to minimise the risk of casualties and improve performance. However, the casualties are still high. One of the key reasons is the heavy dependence of the system on human performance, which leads to human error and thus losses [2]. Any act or lack of action that results in or contributes to a casualty or near-casualty is considered a human error by the Maritime Transportation Research Board [3].

An analysis of 39 collisions reveals that most maritime accidents are caused by decision errors [4]. A few contributing factors at the preconditional level included an operator's lack of situational awareness, attention deficit, and inefficient inter-ship communication. There was often inadequate operational planning at the leadership level [5]. Human error and/or violations are estimated to be responsible for 75% to 96% of maritime accidents [1].

Several studies are being conducted that examine near-miss errors that could occur in the daily operations of machinery spaces. These tasks are often performed by marine engineers based on their experience rather than following rules. The Australian Safety Bureau reports that most oil spills are caused by errors during the critical task of transferring oil between tanks [6]. Numerous studies have been conducted on techniques for preventing maritime accidents. Research has evolved over the last half-century from focusing on naval architecture to examining human error. It is likely to continue exploring the socioeconomic factors involved in maritime accidents [7].

Recently, the maritime industry has taken initiatives to globalize standards to ensure safety on the vessels. The International Convention for the Safety of Life at Sea (SOLAS) is considered to be the most widely accepted treaty for the safety of merchant ships. In 1994, the International Maritime Organization (IMO) added International Safety Management Code (ISM) to SOLAS, to improve management, operations, and preventive measure for pollution on ships. Regulations for maritime safety are developed using a Formal Safety Assessment (FSA). Human variables, technical variables, and organizational variables are all considered by FSA. However, it does have its limitations. Relying on the expert's quantitative risk assessment puts the FSA in the realm of human error [8]. Human-technology interaction has been optimised through the development of novel techniques for enhanced automation monitoring and appropriate risk assessment [9].

With the advent of technology and its implementation to improve engineering systems, artificial intelligence (AI) has been used to optimise, improve, and implement the best strategies to cope with problems on vessels. However, the focus has been restricted to emergency situations only, whereas human error equally contributes to daily operational tasks. Our research aims at providing a potential solution to reduce the risk of human error during the daily operational tasks on vessels. We propose the use of an Ant Colony Optimization (ACO) based algorithm to design and validate a verified set of instructions for performing each operational task that is integrated, globally accessible, and standardised. Following an AI-based approach would help us optimise the path for complex tasks, provide a clear set of sequential instructions, improve efficiency, and reduce the likelihood of human error by minimising personal preference and false assumptions. Moreover, these are meant to be created once and for all, applicable to all operational tasks, and applicable to all types of ships.

Originally developed in 1992 by Marco Dorigo to solve the Travelling Salesman Problem (TSP), the ACO has proven to be beneficial [10]. Its aim was to find the shortest Hamiltonian cycle track between two cities and back. Ant Colony Optimization (ACO) is a metaheuristic algorithm inspired by the natural behaviour of ants to figure out the best path from one point to another. It is an artificial intelligence (AI) based technique, which simulates ant behaviour based on their trail of pheromones. It explores different paths using pheromone trails and then finds the best solution using this process. In the maritime industry, ACO can be implemented to optimise engine operations by searching for the best parameters and procedures to carry out a task. For instance, optimization of fuel consumption [11], managing engine emissions [12], engine maintenance and repair [13], navigation, and weather routing [14], are some of the areas where it can be implemented. Path planning problems can be solved using the ACO algorithm in the maritime industry, to avoid collisions [15]. Maritime applied the same algorithm to optimise group project management, including efficient and effective scheduling of funds, manpower, equipment, and materials [16]. The algorithm can consider various factors simultaneously. Despite the fact that the ACO algorithm is a heuristic method and doesn't guarantee global optimality, it is able to provide a reliable result within a reasonable time frame. A variety of problems related to combinatorial optimization can be handled using the algorithm [17].

2 METHODOLOGY

The oil transfer pump is a crucial component found on all ships. Its main purpose is to transfer oil, which is not only necessary for reaching a vessel's destination but also poses a significant risk if mishandled [18]. Therefore, it is imperative to ensure that marine oil transfer pumps are reliable and efficient. In most cases, ships utilise heavy fuel oil (HFO) to power their engines, which is first stored in bunker tanks located in the double bottom, after being received from the port or bunker barge. The oil transfer pump then transfers the HFO to the settling tank in the engine room, which is its primary function.

The marine industry heavily relies on oil transfer pumps for various purposes, including returning excess oil from the overflow tank to the storage tank and transferring diesel oil from one tank to another. The importance of having reliable oil transfer operations cannot be overstated since even the slightest error can result in hazardous situations, such as oil spills. Therefore, it is crucial to prioritise the maintenance and proper functioning of these pumps in the marine industry.

Oil transfer is a crucial task onboard ships, but it also poses significant hazards. To ensure safety, automatic alarms, and switches should be in place. Each tank, including the settling and service tanks, should have low and high alarms. The low alarm signals the need for more oil, while the high alarm and switch alert the crew when the tank is close to overflowing. In such a situation, the oil transfer pump should automatically switch off. If not, an alarm will sound, and engineers must manually shut the pump off as excess oil flows into the overflow tank. Although automatic switches are necessary, it is also vital to have manual controls and an emergency switch located outside of the engine spaces. This allows for quick response in case of a dangerous situation, such as an oil spill or fire, and allows crew members to stop the oil flow from a safe location.

Several research studies have investigated near-miss errors that may occur during daily operational tasks in machinery spaces, which can potentially lead to accidents. In many cases, marine engineers rely on their experience rather than following a set of established rules when performing these tasks [19]. The Australian Transport Safety Bureau (ATSB) reports that the majority of oil spills result from errors during the critical task of transferring oil from one tank to another. These findings highlight the need for effective guidelines and training to prevent accidents and ensure safe practices in the maritime industry [20].

Our study suggests a solution to reduce the occurrence of human errors in ship operations. We recommend the creation of a standardized instruction manual, which would be globally accessible and fully integrated. This manual would provide a verified set of instructions for each operational task and following it would reduce the likelihood of human error. To develop and verify these instructions, we propose the use of an Ant Colony Optimization (ACO) based algorithm.

3 ANT COLONY OPTIMIZATION – THE CONCEPT

The basic idea of ant colony optimization (ACO) is to simulate the behaviour of ants searching for food in order to find an optimal solution to an optimization problem. The algorithm works by constructing solutions iteratively, with each iteration consisting of a set of ants building a solution by moving through the problem space. The conceptual representation of ACO for path optimization is shown in Figure 1.

To do this, ACO uses a graph representation of the problem, where the nodes represent the decision variables, and the edges represent the possible solutions or connections between those variables. The ants move through this graph, leaving pheromone trails on the edges they traverse. These trails represent the cumulative experience of the colony and influence the probability that other ants will follow the same path in the future.

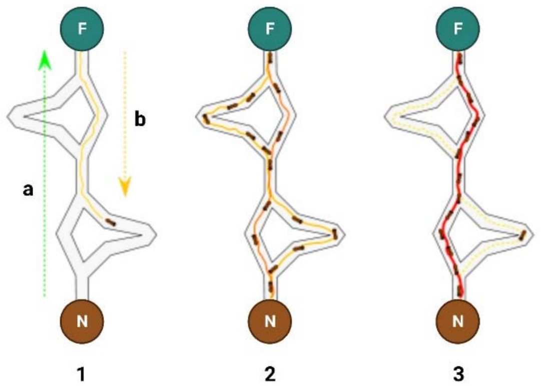

Figure 1. Concept diagram of Ant Colony Optimization (ACO) Algorithm. Where N and F denote Nest and Food, a is the ongoing direction and b is returning direction. Part 1: shows the early process where ants start finding a path between nest and food and lay pheromone. Part 2: shows the intermediate process where ants went through all possible paths. Part 3: shows the most adopted path with the highest pheromone level.

Here are some of the key equations used in the ACO algorithm:

Pheromone trail update equation:

$$\tau_{ij} \leftarrow (1-p)\tau_{ij} + \rho\Delta\tau_{ij} \tag{1}$$

where τ_{ij} is the amount of pheromone on the edge connecting nodes i and j, ρ is the pheromone evaporation rate, and $\Delta\tau_{ij}$ is the amount of pheromone deposited on the edge by the ants that found a solution using that edge.

Probabilistic solution construction equation:

$$p_{ij}(t) = \frac{\tau_{ij}(t)^{\alpha}\,\eta_{ij}(t)^{\beta}}{\sum \tau_{kl}(t)^{\alpha}\,\eta_{kl}(t)^{\beta}} \tag{2}$$

where $p_{ij}(t)$ is the probability of an ant choosing the edge connecting nodes i and j at time t, $\tau_{ij}(t)$ is the amount of pheromone on the edge at time t, $\eta_{ij}(t)$ is the heuristic value of the edge at time t, α and β are parameters that control the influence of the pheromone and heuristic information, and the sum is taken over all possible edges k and l at the ant's current location.

Local pheromone update equation:

$$\tau_{ij} \leftarrow (1-\alpha)\tau_{ij} + \alpha\tau_0 \tag{3}$$

where τ_0 is a constant value representing the initial amount of pheromone on the edges, and α is a parameter that controls the influence of local pheromone updates. This equation is used to update the pheromone trail on the edge immediately after an ant has used it to construct a solution.

Global pheromone update equation:

$$\tau_{ij} \leftarrow (1-\rho)\tau_{ij} + \rho\Delta\tau_{best} \tag{4}$$

where $\Delta\tau_{best}$ is the amount of pheromone deposited on the edge by the best ant in the current iteration. This equation is used to update the pheromone trail on all edges after each iteration.

Objective function:

f(x) = objective function value for solution x (5)

The objective function is used to evaluate the quality of the solutions found by the ants.

The goal of the optimization problem is to find a solution that maximises or minimises this function. Overall, the ACO algorithm is a powerful optimization technique that has been used to solve a wide range of complex problems in fields such as transportation, logistics, and telecommunications. The key to its success is the combination of probabilistic solution construction, pheromone trail updates, and heuristic information to guide the search process.

4 CASE STUDY

Title: Optimization of Diesel Oil (DO) Transfer Process in Maritime Using Ant Colony Optimization

Introduction: The purification of diesel oil is a critical process in the maritime industry, as it ensures the safe and efficient operation of marine engines. The process involves removing impurities such as water, sediment, and other contaminants from the fuel. Figure 2 presents the components involved in the initiation of the DO transferring process from a storage tank to a service tank. There are several multi-step complex daily operational tasks involved to complete the DO purification process. The person interacting with these operations certainly knows how to carry an individual task but the sequence and distance are not optimised and are either based on human preference or subjected to random choice. Optimization of such complex processes using AI could reduce the overall time of carrying out the process and would make it more efficient. In this case study, we will use ant colony optimization to optimise the purification process for a marine vessel, with the goal of maximising the efficiency of the process and minimising the time required for purification.

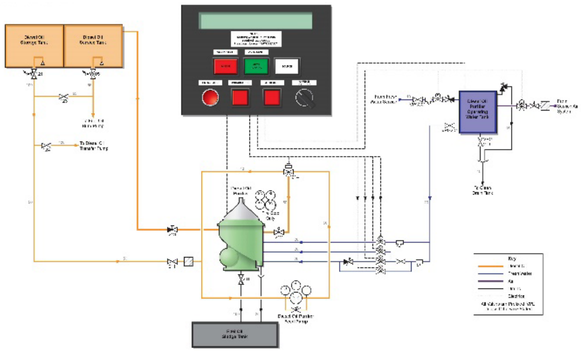

Figure 2. Diesel oil purification piping diagram of M.T FERU.

Problem Statement: The diesel oil purification process on a marine vessel involves passing the fuel through a series of filters and separators to remove impurities. The process requires the regulation of several components. The goal of the optimization process is to find the optimised path to complete the process to ensure efficiency.

Preliminary Analysis: To conduct an evaluation, a cohort of 15 engineers possessing a minimum of three years of relevant experience was selectively recruited. These engineers were assigned the designated task of transferring DO from the storage tank to the service tank in a simulator, involving steps as depicted in Figure 3. Prior to the evaluation, the engineers had received comprehensive training in operating the simulator. Each engineer was instructed to perform the task utilising their own heuristic approach, thereby implementing a unique method deemed optimal by the individual. It was observed that the sequence of steps and total distance to accomplish this task by each engineer, varied greatly, validating our hypothesis that daily operational tasks rely heavily on human preference and are prone to error. Therefore, we need a globally standardised method to optimise these complex operations, thereby reducing the error risk and increasing the process efficiency.

Solution Approach: We will use ant colony optimization to optimise the diesel oil purification process. ACO is a powerful optimization technique that is well-suited to problems with multiple steps and complex interactions between them. The algorithm works by simulating the behaviour of ants searching for food, with the goal of finding the shortest path to the food source. In our case, we will use ACO to search for the optimal pathway of daily operational tasks to accomplish the purification process. One such task is transferring DO from the storage tank to the service tank. In order to transfer the DO, the engineer officer on watch must transfer fuel from the bottom tank to the Settling tank; this transfer requires 10 tasks to be completed successfully. The tasks are mentioned in Figure 3.

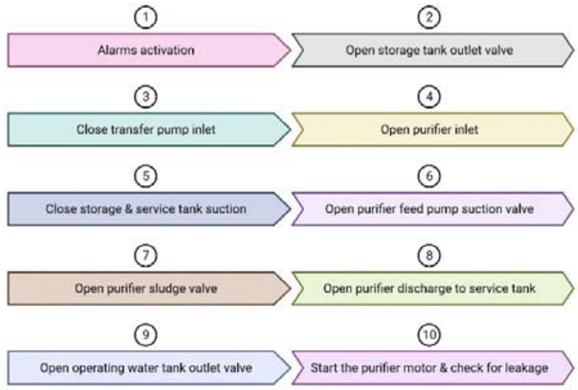

Figure 3. Steps involved in the transfer of diesel oil from the storage tank to the service tank.

Solution Methodology: The steps involved in ACO optimization are represented in the algorithm flowchart in Figure 4. The first step in applying ACO to the diesel oil purification process is to define the problem parameters and objective function. The objective function for this Ant Colony Optimization algorithm is the fitness function, which calculates the total distance of the tour for a given ant. In mathematical notation, this can be represented as:

$$\text{Fitness} = \sum(i=1 \text{ to } n-1)\ \text{dist}(\text{tour}(i), \text{tour}(i+1)) \qquad (6)$$

where dist. is the distance function between two nodes and tour is the sequence of nodes visited by an ant. The goal of the algorithm is to minimize this fitness function by finding the shortest tour possible.

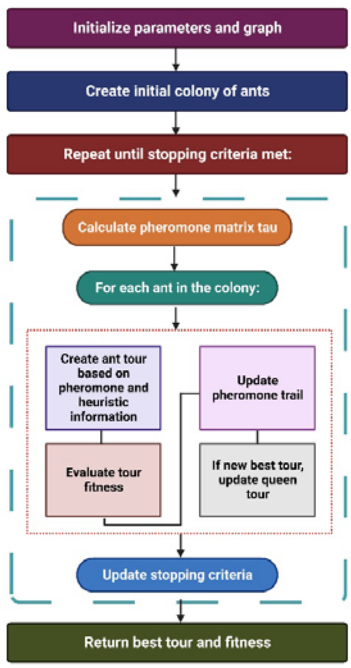

Figure 4. Pseudocode for MATLAB implementation of ACO optimization algorithm.

In this case, the problem parameters are distance, and the objective function is the efficiency of the purification process. Next, we will initialize the ACO algorithm by defining the number of ants, the pheromone trail, and the heuristic information. The pheromone trail represents the cumulative experience of the ants, while the heuristic information represents the domain-specific knowledge of the problem. We will use the local and global pheromone update equations to update the pheromone trail as the ants search for the optimal solution. Once the ACO algorithm is initialised, we will run it for a specified number of iterations, with each iteration representing a complete search cycle by the ants. At each iteration, the ants will construct a solution by selecting values for each task, based on the pheromone trail and heuristic information. The quality of the solution will be evaluated using the objective function, and the best solution found by any ant in the iteration will be used to update the pheromone trail using the global pheromone update equation. The ACO algorithm will continue to search for the optimal solution until a stopping criterion is met, such as a maximum number of iterations or a convergence of the solution quality.

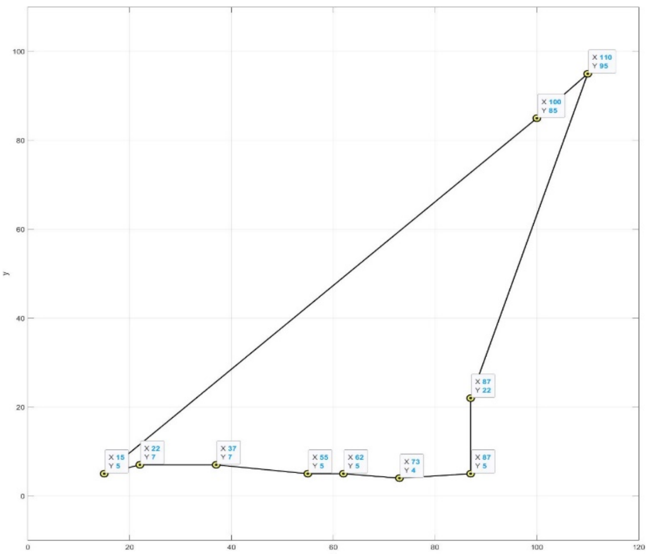

Figure 5. Results of ACO optimization to find out the best possible path to complete the tasks involved in diesel oil purification, where the x and y axis presents the distances between each component.

Results: The application of ACO to the diesel oil purification process on a marine vessel resulted in significant improvements in the efficiency of the process by optimising the best-suited path for the complex daily operation of the diesel oil purification process as shown in Figure 5. By optimising the distance and prioritising the sequence of steps, the daily operational tasks related to purification can be performed more effectively and in less time. It is important to note that other optimization techniques, such as Monte Carlo simulations, can be used to find optimal solutions. However, ACO was chosen for this study due to its effectiveness in solving complex problems with large search spaces and finding global optima more efficiently. This is especially important in the context of optimizing daily operations in the marine industry, where the search space can be vast and the optimal solution may not be easily apparent. Therefore, while other optimization techniques may have potential to be used in this context, the selection of ACO in this study was based on its ability to efficiently explore the search space and find the optimal solution. The use of ACO allowed us to explore the solution space more thoroughly and find the optimal solution, which would have been difficult or impossible using other optimization techniques. In conclusion, the use of ant colony optimization for the optimization of the diesel oil purification process in the maritime is a powerful tool that can lead to significant improvements in the efficiency of the process. We can extend the use of AI to optimize multi-parameter processes. Furthermore, the technique can be applied to other optimization problems in the maritime industry, as well as other industries with similar problems.

5 DISCUSSION AND CONCLUSION

The maritime industry is considered a driving factor in the global economy. The high dependence on human performance in the maritime industry often leads to a high number of casualties, and decision errors are the primary cause of maritime accidents. Previous studies have addressed this issue by implementing various approaches such as decision support systems [21, 22], fuzzy logic [23, 24], and genetic algorithms [25, 26]. However, this study proposes an Ant Colony Optimization (ACO) based algorithm to optimize the path for complex tasks and provide clear and sequential instructions for daily operational tasks. This algorithm has been previously applied in various fields, including logistics [27, 28], transportation [29, 30], and communication networks [29, 31], and has shown promising results. There are several advantages to using ACO for the optimization of complex problems such as the diesel oil purification process in the maritime. First, ACO is able to handle problems with multiple parameters and complex interactions between them. Second, ACO is able to explore the solution space more thoroughly and find the global optimum solution, rather than getting stuck in local optima. Finally, ACO is able to adapt to changes in the problem environment. The use of ACO for the optimization of the diesel oil purification process in the maritime is a powerful tool that can lead to significant improvements in the efficiency of the process.

In our research, we have applied the ACO algorithm to daily operational tasks in the maritime industry, such as transferring fuel from storage tanks to service tanks. The proposed solution provides a set of verified instructions for performing each task in a standardised manner, thus minimising personal preference and false assumptions. The proposed solution has numerous advantages, such as improving efficiency, reducing the likelihood of human error, and providing a globally accessible standardized instructions manual. This solution can have a significant impact on the maritime industry by reducing the number of casualties and improving the overall safety of operations. In conclusion, our research article proposes an innovative approach to optimise daily operational tasks in the maritime industry using AI-based techniques. The study builds on previous research and provides a comprehensive discussion of the proposed solution's advantages and potential impact on the industry. Overall, this research has the potential to contribute to the safety and efficiency of the maritime industry. In future, this technique can be applied to other optimization problems in the maritime industry, as well as other industries with similar problems, such as transportation, logistics, and telecommunications. Moreover, multi-factor complex studies can be conducted using this model to evaluate large-scale implementation and validate its use for process optimization.

Table 1. ACO Optimised the sequence of steps involved in the process of diesel oil transfer from the storage tank to the service tank.

Process	No.	Steps	Normal in-service condition	Transfer condition	Valve Position	Location (X, Y Coordinates)
Transfer of diesel oil from storage to service tank	1	Confirm DO Service Tank High-Level alarm is operational by activating the float switch	-	-	-	(100, 85)
	2	DO Storage Tank Outlet Valve	Shut	Open	(V-PL121)	(15, 5)
	3	DO storage & service tank common suction	Shut	Shut	(V-PL123)	(22, 7)
	4	DO transfer pump inlet	Shut	Shut	(V-PL124)	(37, 7)
	5	Purifier feed pump suction valve	Shut	Open	(V-PL211)	(55, 5)
	6	Purifier inlet V/V	Shut	Open	(V-PL212)	(62, 5)
	7	Open Purifier discharge to the DO Service Tank	Shut	Open	(V-PL213)	(73, 4)
	8	Open Purifier Sludge Valve	Shut	Open	(V-PL291)	(87, 5)
	9	Open the Operating Water Tank outlet valve	Shut	Open	(V-PG204)	(87, 22)
	10	Start the DO Purifier motor and allow it to run up to speed. Start the DO purifier Feed pump, select 'START' on the Purifier Control Panel. Check for any leakage including bowl leakage	-	-	-	(110, 95)

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