Advances in Reliability, Safety and Security, Part 6 – Kołowrocki, Magryta-Mut (eds.)
© 2024 Polish Safety and Reliability Association, Gdynia, ISBN 978-83-68136-18-0 (printed), ISBN 978-83-68136-05-0 (electronic)

Advances in Reliability, Safety and Security

ESREL 2024
Monograph Book Series

Integrated Inspection Planning Optimization And Routing Inspection Vessels For Multiple Petroleum Offshore Equipment

André L. D. Rossi[a], Rodrigo M. Tamasi[a], Gabriel S. Malta[b], Adriana M. Schleder[b], Leonardo O. de Barros[c], Rene Thiago C. Orlowski[c], Marcelo R. Martins[b]

[a]*Institute of Sciences and Engineering (ICE), São Paulo State University (Unesp), Brazil*
[b]*Analysis, Evaluation and Risk Management Laboratory – LabRisco, Naval Architecture and Ocean Engineering Department, University of São Paulo, Brazil*
[c]*Research and Development Center of Petrobras – CENPES, Petrobras, Brazil*

Abstract

Safety measures are fundamental for the operation of industries where a potential failure can impact human lives and have serious consequences for the environment. In the case of the oil and gas sector, the use of risk-based inspection is very common for creating plans that outline a routine of equipment inspections aiming to satisfy two main objectives: keep the risk at acceptance levels along with minimizing the operational cost of inspections. Most of these plans are created without taking into account a set of equipment and resource restrictions. This paper presents a methodology for designing inspection plans for multiple offshore oil and gas equipment while routing the inspection vessels. This method employs the NSGA-II aiming to minimize both risk and operational cost, which is mainly impacted by the inspection method used and the navigation cost. The K-means and the Ant Colony Optimization (ACO) algorithms were applied to create a divide-and-conquer approach. Experimental results with Wet Christmas Trees showed the need to integrate the routing of support vessels when planning the inspections of a set of equipment. This is more patent when a limited number of resources (vessels) are available and there are many inspections to be performed. Thus, it is possible to bring the real-world necessity of an oil well field subject to the need for frequent inspections.

Keywords: inspection plan optimization, routing, risk-based inspection, multi-equipment, offshore

1. Introduction

Despite the slowdown in fossil fuel consumption in recent years, many challenges have been posed to the oil and gas industry due to the increasing consumption of petroleum derived products in the last decades (Agency, 2023). One of these challenges is related to ensure the reliability of the offshore platforms and equipment while upholding safety and regulatory standards. Despite notable advancements, the relentless drive for competitiveness has consistently compelled the industry to adopt more streamlined and effective operational approaches. Even more that the occurrence of a malfunction in offshore installations has the potential to result in natural disasters and pose a threat to human lives. Consequently, the implementation of inspections and maintenance programs becomes imperative (Necci et al., 2019).

Inspection activities contribute to a better understanding of the equipment's condition, thereby contributing to reduce system failures and optimizing asset availability. Hence, a well-designed inspection plan proves valuable in mitigating risks associated with oil and gas platforms and facilitates the implementation of proactive maintenance measures. Nevertheless, it is essential to acknowledge that a higher frequency of inspections corresponds to increased operational costs.

In the literature, the challenge of devising inspection plans is frequently depicted as a multiobjective optimization problem (MOP), primarily taking into account risk and cost as key objectives (das Chagas Moura et al., 2015). However, there is an evident requirement for further research to integrate real-world limitations into the allocation of inspection resources. The ideal scenario involves the individual customization of resource allocation to enhance overall efficiency, as highlighted by George et al. (2022). However, prior research predominantly focused on optimizing inspection plans for a single piece of equipment, therefore, the availability of inspection resources is not a limiting factor. In addition, the cost of the inspections is significantly influenced by the route that inspection, maintenance and repair (IMR) vessels need to take to execute the inspection plan.

This paper presents an approach for integrating the optimization of inspection plans and vessels routing for multiple offshore oil and gas equipment considering both the risk over time and inspection costs. The underlying hypothesis guiding our proposal is that incorporating the routing of inspection vessels into the optimization process yield superior solutions in terms of costs. In this study, the Nondominated Sorting Genetic Algorithm II (NSGA-II) (Deb et al., 2002) is employed to deal with this multiobjective optimization problem (MOP). The routing problem is tackled using a machine learning algorithm to cluster the offshore equipment by their distance and the Ant Colony Optimization (ACO) to route a vessel within each cluster. The methodology proposed by Maturana et al. (2022) is used here to estimate the risk related to each equipment over time. In addition, the total cost of an inspection plan is estimated by considering the cost of each inspection method as well as the cost of mobilizing the vessels to perform the inspection methods.

2. Literature review

Effective risk management is crucial for organizations to enhance overall safety and attain optimal configurations for investment, repairs, and maintenance, thereby minimizing overall expenses. The Risk-Based Inspection (RBI) is a framework grounded in defining the acceptance level of risk concerning personnel, environment, and material consequences and is largely used to guide the design of inspection plans. Besides the risk, this plan should consider the costs of the inspections, mainly for offshore oil and gas installations, which are very expensive. Therefore, most of the studies tackle MOP using metaheuristics, such as evolutionary algorithms (Jones et al., 2002).

2.1. Multiobjective optimization algorithms

According to Zhou et al. (2011), most Multiobjective Evolutionary Algorithms (MOEAs), including the NSGA, share a common structure: an operator for selection based on Pareto dominance, along with reproduction and mutation operators that are applied iteratively. The primary concept behind NSGA is its selection process, employed to organize dominated and non-dominated solutions, coupled with a method for generating clusters known as crowding distance. This aims to uphold the diversity within the population (Castro, 2001).

Similar to MOEAs, the Multiobjective Particle Swarm Optimization (MOPSO) algorithm, introduced by Coello Coello and Lechuga (2002), depends on a population, or in this context, a swarm. The particles draw insights from their past experiences and those of other particles within the swarm. In MOPSO, it is suggested to employ an external archive for storing the history of non-dominated solutions, along with a mutation operator and a restriction mechanism. Consequently, this facilitates the formation of a Pareto Front (Coello Coello and Lechuga, 2002).

The research by Dabagh et al. (2022) highlights the importance of inspection plans that align with the cost and risk levels associated with equipment in the petrochemical industry. To address this, the study employs two metaheuristic algorithms, NSGAII and MOPSO, with the aim of optimizing the creation of these plans while taking into account limitations in human resources. A comparison between the algorithms indicates that, for large-scale problems, MOPSO proves more efficient than NSGAII. Despite focusing on a single piece of equipment, the approach tackles an NP-hard problem, showcasing the effectiveness of evolutionary algorithms.

In the investigations conducted by das Chagas Moura et al. (2015), a lack of clear guidance on inspection planning, including technique selection, was observed. Decision-makers may encounter challenges in determining whether to combine multiple low-cost/low-effective inspections or opt for fewer, more expensive inspections with higher effectiveness in detecting failures. The RBI+MOGA approach proposed by them removes the need for a user-defined risk target and offers insights into when and which inspection technique should be employed. It is crucial to note, however, that this study concentrated on the inspection plan for a single piece of equipment without addressing concerns or limitations related to inspection resources.

When devising inspection plans for offshore oil and gas installations, decisionmakers are accountable for numerous pieces of equipment within an oil production facility. Consequently, assuming unlimited inspection resources is unrealistic, emphasizing the need to schedule these resources (Goti et al., 2019). Determining the optimal allocation of inspection or maintenance resources presents a significant challenge, particularly when assets are geographically dispersed, requiring consideration of routing and travel time. The integration of process planning and scheduling (IPPS) is a widely explored concept aimed at enhancing the profitability of product manufacturing (Rakesh Kumar Phanden and Verma, 2011; Zhang and Wong, 2016).

2.2. IPPS

Traditionally, the conventional approach within a manufacturing system involved a sequential execution of process planning and scheduling for parts, with scheduling occurring subsequent to the generation of process plans. Recognizing the inherent complementarity of these two functions, it becomes imperative to integrate them more closely. This integration is essential for significantly enhancing the performance of a manufacturing system, as shown in Memarzadeh and Pozzi (2016), that uses a variety of integrated infrastructure systems.

Based on this concept, this paper adapts the planning and scheduling flow to establish integration between vessels available for inspection methods and their assignment generated by the inspection plan. Therefore, it is possible for the implemented inspection plan generation methodology to be subject to the availabilities imposed by the limited resources, which is analogous to the scheduling step.

A concept similar to that is proposed by Demir and Erden (2020), where the goal is to address the IPPS problem by seeking combinations that maximize job availability, comparing the use of two commonly employed algorithms. As one of the outcomes, the authors conclude the importance of an integrated approach to this type of problem, demonstrating greater effectiveness than individual approaches to planning and scheduling problems. Furthermore, Shao et al. (2009) presents an integration approach closely built upon the concept of genetic algorithms, highlighting the necessity for the planning process to impact scheduling and vice versa.

As a result of the analysis of the IPPS flow, it is evident that both the planning and scheduling problems are interdependent; in other words, even though they generate different responses, the process of one affects the other. Considering this and bringing it into the context of the RBI approach, along with the scenario of limited resources and geographically separated infrastructure, as is the case in the present study, it becomes necessary to control the logistics of these resources. Their assignment, consistent with the generated inspection plan, is crucial for assessing the feasibility of the solution and for a plausible calculation of the total costs involved in the plan.

Rashidnejad et al. (2018) make progress towards this problem proposing a biobjective model for preventive maintenance planning with the total maintenance cost and the availability of resources as the objectives to be achieved. Their model integrates the maintenance scheduling and the vehicle routing problems and used an adapted NSGA-II to find near-optimal Pareto front solutions.

Therefore, the need arises to address the inspection vessels assignment problem, which turns out to be a scheduling problem, so it can align with the guideline of planning phase. In this article, the control and optimization of the routing of vessels are proposed, as they are responsible for transporting inspection resources to each selected equipment.

2.3. Routing

With a network of geographically separated equipment and limited resources for operationalizing inspections, taking into account the travel time of these resources between the equipment is a requirement for modeling the total operation cost values, as stated in Camci (2015). Therefore, in the context of underwater equipment distributed across multiple oil wells, it is necessary to consider the routings that each inspection vessel must undergo for the entire inspection plan to be fulfilled.

Rashidnejad et al. (2018) addresses the integration problem of maintenance scheduling and vehicle routing, aiming to solve a multi-objective model that minimizes costs and maximizes the availability of resources used. The article adopts NSGA-II as the metaheuristic algorithm for the problem. In this case, the authors also propose a methodology for creating feasible initial solutions concerning resource utilization.

Ulsrud et al. (2022) investigated the problem of routing platform supply vessels (PSV) for offshore oil and gas installations aiming to minimize the cost, which is mainly impacted by fuel consumption of the PSVs. In this process, the authors considered sailing speeds and weather conditions. The solution proposed employes an Adaptive Large Neighborhood Search (ALNS) heuristic with a local serach and a set partitioning model. This model combines voyages generated in ALNS into new and likely more cost-effective solutions.

Another approach to addressing the routing problem is proposed by Tusar and Sarker (2023). In modeling the vessel fleet problem (VF) for transporting maintenance resources to offshore windmill farms (OWF), the authors tackle a multi-source and multi-destination (MSMD) problem. In this context, the VF problem necessitates routing that covers the entire maintenance route, ensuring that, considering all routes of all vessels, the cost effects associated with fleet movement are minimized. The computational tool employed to solve the problem was the IBM ILOG CPLEX, commonly used for solving the VF problem (Tusar and Sarker (2023)).

Additionally, Bektas (2006) compiles a set of real-world applications that reflect the MSMD scenario and, because of that, are modeled by the Multiple Traveling Salesman Problem (MTSP), a generalization of the traveling salesman problem (TSP), where there are multiple nodes to be visited by multiple salesmen. The work provides a survey of heuristics and exact methods utilized in the literature to solve the MTSP, such as the cutting planes algorithm and genetic algorithms, for example. Kencana et al. (2017) also evaluates the performance of the Ant Colony Optimization (ACO) algorithm for the MTSP and concludes that with a progressive increase in nodes to be traversed, the algorithm experiences an increase in processing time. Moreover, they conclude that there are no guarantees that an increase in the number of ants will reduce the minimum distance traveled in this case.

3. Literature review

The proposed approach focuses on Integrating the Inspection Plan Optimization and Vessels Routing (IIPOVR) considering the failure risk of multiple offshore equipment and the operational cost. Therefore, the IIPOVR includes the routing of the inspection vessels, accounting for the distances required to move them among different equipment locations. This approach aims to optimize the inspection schedules while also improving the logistical efficiency, implying directly in the operational costs.

The concept of an inspection plan in this context is defined as a series of time windows opportunities for conducting inspections. In each time window, there are two options: i) carry out an inspection with one or several techniques; ii) opt not to conduct any inspection.

In this study, a time window is equivalent to one month, and the inspection plans are structured for a duration of 60 months (five years). While this represents a relatively brief period in the context of the equipment's overall lifespan, it serves as an initial test to assess the effectiveness of the proposed methodology. Consider $x_{i,j}$ as the inspection performed in the i-th inspection time window at the j-th equipment, where i ranges from 1 to K and j from 1 to E. Additionally, the response variable x can take the value of 0, where $x_{i',j'} = 0$ signifies no inspection, up to M, which represents the amount of inspection methods and their combinations. For example, $x_{12,1} = 7$ implies that the 7th method (or its combination) will be employed in the 12th month for inspecting the first equipment. In this case study, the number of pieces of equipment E is equal to 10, to illustrate a set of 10 equipment, and for each inspection window, a choice can be made from 29 different methods or their combinations, denoted as $M = 29$.

To comprehensively assess the IIPOVR suitability, we contrasted it with the approach presented in ROSSI et al. (2023). In that study, the optimization process for inspection plans involving multiple oil and gas equipment neglects the routing costs for inspection vessels. Consequently, we denote that approach as IPO, an acronym for Inspection Plan Optimization. By comparing these two approaches the present study aims to elucidate the impact of vessels routing on the overall efficiency and cost-effectiveness of designing inspection plans for offshore equipment.

3.1. Risk and Cost Evaluation

The research presented in this paper employs the risk assessment methodology proposed by Maturana et al. (2022), which is distinctively advantageous for our study's objectives. This methodology, which differs from traditional methods used to obtain information on equipment failure modes, notably incorporates the impact of inspections. It fundamentally operates on the premise that equipment can exist in three states - operational, degraded, or faulty - and posits that any identified failure or degradation, detected through inspections, prompts repair actions that return the equipment to its operational state (assuming the condition "as good as new").

When analyzing scenarios involving multiple pieces of equipment, the risk is quantified as the highest individual risk observed across all equipment over time. This approach is essential to ensure that the integrity of all equipment is maintained within an acceptable risk threshold. Thus, for a given piece of equipment e, and at a specific time i, the risk index is denoted as r_i. The maximum risk for this equipment across the period is represented as $max_e(r_i)$, where i ranges from 1 to K, and e ranges from 1 to E, with E being the total amount of equipment. Thus, the risk considered during the optimization is then calculated as $\phi = max(max_e(r_i))$.

Furthermore, the study incorporates insights from the work of Cuba et al. (2022), which focuses on defining the probabilities of failure detection for various inspection methods. These probabilities are critical in quantifying the impact of different inspection methods on the overall risk assessment. By integrating these probabilities into the risk model, it becomes feasible to evaluate risk indexes in relation to both the inspection method employed and the timing of its application.

Lastly, the cost implications of the inspection process are addressed. These costs are primarily based on the average daily usage of inspection vessels and the time costs associated with their navigation, coupled with the operational costs associated with the usage of a specific inspection method. The overall expense of each inspection plan is calculated by summing these individual cost components, providing a comprehensive understanding of the financial aspects involved in the inspection process. For each routing process (monthly), we assumed the vessels start from a port.

3.2. NSGA-II

The core of this study involves utilizing the NSGA-II algorithm to formulate and solve the MOP of designing inspection plans. While other multiobjective optimization algorithms are viable options, NSGA-II is selected based on its demonstrated efficacy in similar problem scenarios as detailed in Section 2.1.

In the context of this research, an NSGA-II individual is conceptualized as a multi-equipment inspection plan. This translates to each gene within an individual representing a specific time window designated for the inspection of a piece of equipment. An illustrative example of how a single individual's inspection plan is represented over a six-month period is presented in Table 1. Here, different inspection methods are encoded as integer values - 0 for no inspection, 1 for visual inspection, 2 for electrochemical potential measurement, and 3 for ultrasonic inspection.

Table 1. Example of an inspection method plan for one equipment.

Month	1	2	3	4	5	6
Inspection Method	0	2	0	0	1	3

To streamline computational processing and align with the software's algorithmic requirements, each individual in the NSGA-II is structured as a one-dimensional array. The size of this array is determined by the product of K (the number of time periods) and E (the number of equipment). This configuration facilitates the simultaneous management of risk and cost evaluations for each piece of equipment, and by extension, for the entire equipment set. The encoding strategy of this one-dimensional array, showing the sequence for the e-th equipment, is visualized in Figure 1.

Equipment 1				Equipment 2				...	Equipment E			
1	2	...	K - 1	K	K + 1	...	2K - 1	...	(E - 1)K	(E - 1)K + 1	...	EK + 1
5	10	...	29	2	18	...	29	...	19	13	...	23

Fig. 1. One-dimensional representation of an individual for multi-equipment problem.

With the individual encoding established, it becomes crucial to define the genetic operators and additional parameters. These are imperative for the algorithm's ability to generate, process, and classify individuals across successive generations, thereby driving the optimization process forward. In alignment with the methodology presented in Morais et al. (2022), this study employs the Simulated Binary Crossover (SBX) and the polynomial mutation operator for the NSGA-II.

3.3. Integrated Routing Optimization

In the proposed approach, the routing of the inspection vessels is performed for each gene (month) of each individual within the NSGA-II. This is achieved through a twostep process. Initially, the K-means algorithm (Hubert and Arabie, 1985) is applied to group the equipment to be inspected in that month according to their distance, forming clusters that allow for more efficient route planning. This serves as a preliminary step to organize and simplify the routing problem by reducing the complexity of the decision-making process.

Following the clustering, the Ant Colony Optimization (ACO) algorithm is employed to tackle the Traveling Salesman Problem (TSP) within each cluster (Dorigo and Gambardella, 1997). The ACO algorithm, inspired by the foraging behavior of ants, is well-suited for finding optimal routes in complex scenarios. It simulates the pheromone trail-laying and following behavior of ants to iteratively improve the routing solutions. In each iteration, the algorithm explores various paths and evaluates them based on their efficiency, gradually honing on the most effective route.

By integrating K-means clustering with ACO for solving the TSP, the process efficiently manages the routing challenge for each individual in the genetic algorithm. The combination of these techniques ensures that the routes are not only optimized for distance and time but are also feasible and practical in real-world scenarios. This integrated approach significantly enhances the overall efficiency and effectiveness of the routing process, making it a robust solution in the context of complex logistical and operational challenges.

3.4. Experimental Setup

The experimental setup to assess IIPOVR and IPO performance include the number of inspection opportunities (in months), the number of different inspection methods (and their combination), number of pieces of equipment, among others. Wet Christmas Trees at a depth of 600 meters (XT-600m) were considered here. All the general parameter values and those specific of the algorithms employed here are detailed in Table 2. For conducting our experiments, we rely on the Python programming language. This experimental setup underscores the careful planning and attention to detail that characterizes the optimization process, ensuring comprehensive, reliable, and comparative outcomes.

In the NSGA-II, the parameter values have been selected to enhance the balance between exploration and exploitation in the genetic search process, ultimately leading to more effective and efficient optimization outcomes. The algorithm deployed in the *pymoo* library was used here (Blank and Deb, 2020). In the routing process, the K-means algorithm was used from the *scikit-learn* library (Pedregosa et al., 2011) and the only parameter set was the number of clusters ***k***. The ACO algorithm was developed by the authors and the parameters were defined empirically. The α and β parameters control the relative importance of pheromone and the local heuristic factor, respectively.

Recognizing the inherent stochastic nature of Genetic Algorithms (GAs), this study undertakes ten repetitions for each rigs constraint scenario to ensure robustness in the results.

Table 2. Parameter values used in the case study.

Context	Parameter	Value
General	Months (opportunities)	60
	Inspection methods (amount)	29
	Number of equipment	10
	Number of inspection vessels	2
NSGA-II	Population size	50
	Individual size (Genes)	600
	Number of iterations	250
	Crossover Probability	0.9
	Mutation Probability	0.02
ACO	Number of ants	50
	Number of iterations	100
	α	1
	β	2
	Evaporation rate	0.2
	Pheromone deposit	1
K-means	Number of clusters	2

4. Results and Discussion

The overall results comparing IIPOVR and IPO approaches are presented in Figure 2. This graph shows the risk index (x-axis) and cost (y-axis) of the solutions achieved by the NSGA-II lying on the Pareto frontier. The analysis of this graph allows a comparative perspective on the outcomes of two optimization strategies: one that incorporates routing during the optimization process and another that proceeds without it. To ensure an equitable comparison between the two approaches, a post-processing adjustment was made on IPO to include the cost of the routing the inspection vessels to the cost of the inspection method.

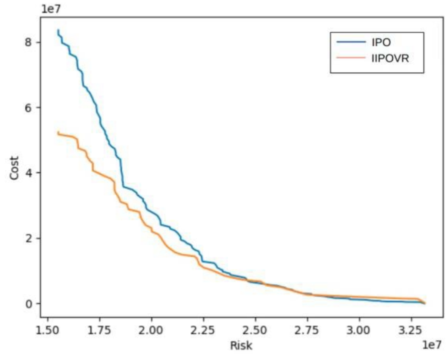

Fig. 2. Comparison of the Pareto Frontier between IPO and IPOVR approaches including the cost of routing.

The graph in Figure 2 indicate that the inclusion of routing generally yields a better risk vs cost profile. This means that IIPOVR achieves lower cost than IPO at the same risk index for most of the solutions in the pareto frontier. This improvement of integrating routing during the optimization process is highlighted when many inspections were planned. Such behavior of the approaches was expected since routing the vessels would have not a high influence when few pieces of equipment have to be inspected at each month.

Therefore, the superior outcomes of IIPOVR are likely attributed to the fact that routing steers solutions closer to an operational reality. By simulating conditions that more accurately mirror real-world logistics, routing enables the optimization algorithm to navigate a solution space that is inherently more reflective of practical constraints and efficiencies. This adherence to realistic operational parameters is presumed to be the driving factor behind the enhanced results, as it aligns the theoretical optimization closer to tangible, executable strategies.

Despite the optimization incorporating routing demonstrating improved results, an examination of the scatter plot shown in Figure 3 reveals that IIPOVR (right) have more difficult than IPO (left) in converging. This is evident because the individuals (points) of the former are widely dispersed throughout the search space. In contrast, the optimization that showed inferior performance (without routing) experienced a more gradual convergence over the generations. Given the complexity of the problem, it seems that IPO underwent more gradual improvements, yet it may have been constrained to local optima. On the other hand, these graphs show that there is room for improvement of both approaches, but mainly for the IIPOVR. This will demand a deep investigation aiming to improve the NSGA-II convergence considering the routing scenario, where there is a huge universe of potential solutions.

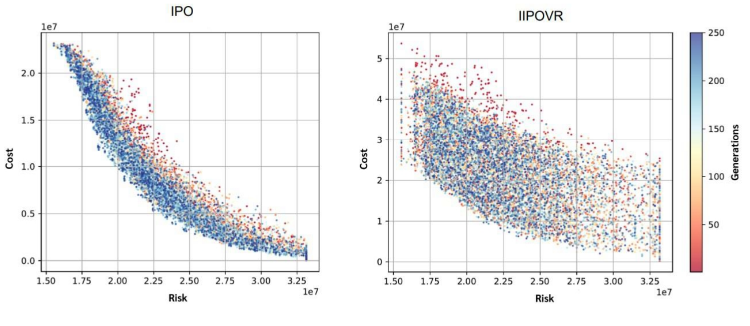

Fig. 3. The convergence of the individuals of IPO (left) and IIPOVR (right) over 250 generations.

The post-processing performed in the results achieved by IPO was necessary to compare it with IIPOVR (Figure 2). However, in order to analyze the impact of the routing cost in the total cost, we plotted both curves in Figure 4. The solid curve includes the routing cost of the solutions found by IPO whereas the dashed shows the relation between risk and cost considering only the cost of the inspection method itself. The blue area between both curves highlights the cost variations brought by the inclusion or exclusion of routing costs. It evidences that the routing process can be advantageous mainly when more inspections are performed, represented by smaller risks and higher costs.

The impact of the vessels routing cost on the Pareto frontier results is represented in Figure 4. It is clear that the most expensive inspection plans are disproportionately affected by this cost, as they involve numerous inspections of a variety of equipment. This observation highlights the importance of routing costs in defining the overall efficiency and viability of these operational plans.

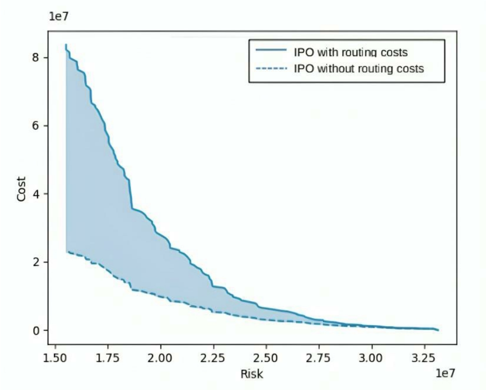

Fig. 4. The pareto frontier achieved by IPO after post-processing (solid curve) to include the routing costs and without this post-processing step (dashed line).

5. Conclusion

This study proposed an approach to integrate the inspection plan optimization and the vessels routing (IIPOVR) that operate these inspections on multiple offshore oil and gas equipment. The NSGA-II was used to the general optimization process with risk of failure and cost as the objective functions. In this process, the K-Means is employed to cluster the pieces of equipment considering their distance and an ACO algorithm traces the route to be done by the vessels. The effectiveness of the approach is assessed experimentally for ten Wet Christmas Trees and compared to ROSSI et al. (2023) (IPO), which does not support the vessels routing process.

The findings reveal that the inclusion of routing during the optimization task offers a better risk profile, mainly when many inspections are planned at withing a month. This occurs because vessels have to optimize their route to reduce navigation cost. This suggests an untapped potential of routing as an operational strategy to enhance optimization outcomes. Notably, this improvement points to the efficacy of routing in aligning theoretical optimization more closely with executable strategies in practice. On the other hand, the vessels routing process integrated in the inspection plan designing is very computationally expensive.

In addition, the IPPOVR found a more pronounced challenge in achieving convergence. This contrasted with the more streamlined and gradual convergence observed in the optimization excluding routing (IPO), despite its relatively inferior performance. This pattern reflects the complexity and nuanced nature of optimization challenges, especially when incorporating elements that mimic real-world operational conditions.

Acknowledgements

This paper reports part of the overall results obtained from Petrobras-sponsored research and development project number 0050.0121077.22.9, whose support the authors gratefully wish to acknowledge. Prof. Marcelo Martins also acknowledges his support from the Brazilian National Council for Scientific and Technological Development (CNPq) through grant 303908/2022-0.

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