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Optimizing inspection plans for multiple oil and gas equipment under resource constraints

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Safety is critical for many industries where a failure may impact the environment and human lives, such as in the oil and gas sector. Risk-based inspection has been used for years to identify risk levels in operations and to design inspection and maintenance programs to evaluate the most critical failure modes of the equipment. These programs usually are designed considering two main and clearly conflicting objectives, which are to maintain operations at acceptable risk levels while struggling to keep the costs associated with inspections manageable. Therefore, studies have handled this issue as a multiobjective problem and used heuristics to optimize equipment inspection programs in terms of risk and cost. However, in real-world applications, material and human resources restrictions proved to be crucial factors when creating inspection plans for a set of equipment. This paper presents an early stage methodology for optimizing inspection plans for multiple equipment in light of resources availability over time. The proposed methodology considers the appropriateness of inspection methods for this industry and their frequency of use to achieve acceptable risk levels while optimizing resources, reducing costs. The methodology is evaluated using a set of ten Christmas Trees subject to a limited number of offshore support rigs for inspections. The Pareto fronts for different constraint values showed a patent risk and cost improvement compared to a standard inspection plan using fewer rigs.

Keywords: RBI, optimization, offshore, inspections, multi-equipment, multiobjective, NSGA-II.

1. Introduction

While petroleum products have been increasingly consumed worldwide, the production growth has only been possible due to the innovative nature of this sector. This includes the extraction of a significant amount of oil and gas on offshore installations, despite the enormous challenges involved in this operation. Amongst them is the reliability of the whole system, maintaining safety and regulatory compliance. Despite significant progress, competitiveness has continuously pushed this industry towards more efficient operations.

A failure on offshore installations can lead to natural disasters and endanger human lives. Therefore, inspections and maintenance programs are crucial. Risk-based inspection (RBI) methodology can be used as a basis for creating equipment inspection plans by combining both the likelihood and the consequence of a failure. As more inspections are performed, more information regarding the equipment state is known, contributing to reduce system failures and consequently maximize asset availability. Therefore, a well-conceived inspection plan can be useful for minimizing the risks involved in oil and gas platforms and allows preventive maintenance actions to be taken. On the other hand, the greater the number of inspections, the greater the cost of the operation.

The problem of planning inspections is commonly modeled in the literature as a multiobjective optimization problem most considering both risk and cost as objectives. Although it has been extensively studied, there is a clear need for additional research that incorporate constraints when allocating inspection resources. Ideally, this would allow individual adjustment of resource allocation to improve overall efficiency (George et al., 2022). This gap in the literature is mainly due to the fact that previous work handled the problem of optimizing inspection plans considering only one equipment. Therefore, all inspection resources would be available for utilization. However, in real-world scenarios, multiple equipment installations compete for limited resources, making optimal resource allocation a challenging problem.

In this paper we present the early stages of a methodology for designing inspection plans for multiple petroleum equipment installations aiming to minimize the risk of failures and the cost of inspections while taking into account the availability of resources over time. To assess the risk of failure for each equipment over time, the methodology proposed by Maturana et al. (2022) was used. 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 a support rig. Here, this multiobjective optimization problem (MOP) is handled by using the Non-dominated Sorting Genetic Algorithm II (NSGA-II) (Deb et al., 2002) subjected to the availability of offshore support rigs.

2. Literature review

This section focuses on two main topics for the literature review: algorithms for solving multiobjective optimization problems (MOP), and resource allocation.

2.1. *Multiobjective optimization algorithms*

Solving MOP is generally a more complex task than solving single optimization problems (SOP). In order to avoid some intrinsic difficulties, some authors adopt a strategy of transforming a MOP into a SOP, as performed by Martorell et al. (2009) and Su and Liu (2020). This simplification allows the use of algorithms developed to solve SOP. In this strategy, all objectives are combined into a single meticulously constrained function. Common methods of adaptation are the use weighting objectives method and the global criterion method (Miettinen, 1998; Oliveira, 2005).

However, as these simplifications are user-dependent, they can introduce uncertainties if the parameters are not properly selected, such as the assignment of weights. On the other hand, adapted MOP algorithm solvers based in methods such as Genetic Algorithms (GA) and Particle Swarm Optimization (PSO) are found in the literature. One of the most used variants of GA is the NSGA-II (Su and Liu, 2020; Zhang and Yang, 2021; Gong and Zhou, 2018; Dabagh et al., 2022).

According to Zhou et al. (2011), the majority of Multiobjective Evolutionary Algorithms (MOEAs) such as the NSGA, share a similar structure: a selection operator based on the Pareto dominance and the reproduction and mutation operators, applied iteratively. The main idea of NSGA is the selection process, used to sort the dominated and non-dominated solutions, and a method to create clusters, called crowding distance, with the objective of maintaining the diversity of the population (Castro, 2001). As mentioned by Meng et al. (2023), the NSGA-III is suitable for most MOP problems and, especially for solving complex and nonlinear issues with three or more objectives.

Like MOEAs, the Multiobjective Particle Swarm Optimization (MOPSO) algorithm, introduced by Coello Coello and Lechuga (2002), relies on a population, or in this case a swarm. The particles benefit from their previous experiences and experiences from the other particles of the swarm. In MOPSO, it is proposed the use of an external archive to save the history of non-dominated solutions, a mutation operator, and a restriction mechanism. As a result, a Pareto Front can be formed (Coello Coello and Lechuga, 2002). An improved MOPSO algorithm is proposed by Kong et al. (2021) mainly to reduce the disadvantage of the premature convergence of this algorithm due to its ease of falling into local optimum. Three modifications are carried out: new learning strategies, a search strategy based on simulated binary crossover (SBX) and polynomial mutation (PM), and a dynamic archive maintenance strategy. MOPSO is also used for risk-based inspection planning in Petrochemical industry (Dabagh et al., 2022) and preventive maintenance of offshore safety critical equipment considering risk and maintenance cost (Han et al., 2022).

2.2. *Resource constraints*

While single equipment MOP is satisfactory in some applications, it may be inadequate in a more realistic multiple equipment scenario. To solve this problem, Oyarbide-Zubillaga et al. (2008) conceived a preventive maintenance optimization model using Discrete Event Simulation (DES). Within this method, the behavior of the equipment is described by an analytical model, which also includes the deterioration and failure processes independently, while the stochastic nature of real models is preserved. Goti et al. (2019) extended this model by considering the condition-based maintenance of equipment. Both models were applied to a hubcap production system, but the study did not take into consideration the constraints on resources that are often present in larger installations.

Resource management can be modeled in different ways in multiobjective optimization problems. Mostly, the main resource constraint is the available budget, but many studies have included human or material resource limitation in the objective formulation. In Martorell et al. (2009), maintainability is a function of the personnel and material availability, where different solutions can be obtained using different resource parameters. Some works handle resource limitations in a post-processing routine, as in Su and Liu (2020). Others use a penalty on the individuals of the evolutionary algorithm which exceeds a threshold to induce feasibility (Gong and Zhou, 2018).

However, the most common strategy is to model resource availability as constraints, which is a fundamental concept in the optimization formulation, and their implementation varies according to the problem. For the maintenance planning of adjacent wind farms, Zhang and Yang (2021) proposed a model to minimize costs and resources, subject to resource availability constraints, among others. The model uses an incidence matrix between maintenance tasks and maintenance resources, each of them requiring specific maintenance resources. In the pavement maintenance and rehabilitation (MR) problem, the segment grouping is a common practice employed to reduce costs. However, aiming to avoid resource wastage and the inefficiency found in this strategy, Meng et al. (2023) considered the optimization problem subject to the constraints of annual budgets, individual and network pavement performance, and the minimal and maximal length required for a MR project. including a range of constraints into their model. These included maximum battery capacity and operational limits for generators, as well as a time-varying resource, environment-dependent renewable energy sources, such as solar and wind power.

As shown in the review conducted by George et al. (2022), there is potential for further research concerning the resource allocation on the offshore environment, where specific limitations are found, such as the accommodation space and the tight schedule for accomplishing the tasks. In addition, a dynamic resource allocation that allows each maintenance item to independently adjust its resource allocation based on the time required to complete the activity would help to improve resource utilization.

3. Methodology

The methodology proposed in this article aiming to design inspection plans of multiple offshore equipment by optimizing the risk of failures and the operational cost constrained by resources availability is presented in this section. As a case study, a set of ten Wet Christmas Trees of 600 meters depth (XT-600m) is considered.

Here, an inspection plan is conceived as a sequence of windows of opportunity (a unit of time) for performing equipment inspections. For each window there are two possibilities: i) perform an inspection using one or a combination of methods; ii) perform no inspection.

In the case study, a window of opportunity x represents one month and the inspection plans are designed for five years. Although it is a short time horizon considering equipment lifespan, this is only a preliminary experiment to evaluate the proposed methodology.

Let x_i be the i-th inspection window of opportunity (time unit), with $i \in \{1, .., K\}$, and j be an inspection method, with $j \in \{0, \ldots, M\}$, where M is the number of inspection methods and their combination and $j = 0$ represents no inspection. Thus, $x_{12} = 7$ represents that the 7-th method (or combination) will be used in the 12-th month to inspect one equipment. In the case study, $K = 60$ (five years) and a method (or combination) can be chosen from $M = 29$ available for each opportunity.

To establish a baseline for comparison with the optimized solutions, a standard optimization designed by operator experts is employed here, which performs a visual inspection at the 36th month and functional tests every six months. This baseline inspection plan was designed considering guidelines from regulatory bodies, such as the Brazilian National Agency for Petroleum, Natural Gas and Biofuels (ANP), and international guidelines such as the American Petroleum Institute (API) and NORSOK.

3.1. *Risk and Cost Evaluation*

Although information regarding failure modes has been obtained from the equipment by the Failure Mode Effects and Criticality Analysis (FMECA), the risk indices in the present paper were calculated using the methodology proposed by Maturana et al. (2022), which is better suited for the purpose of this study as it incorporate the impact of inspections. This methodology is based on the different states (fault, degraded and operational) of an equipment, and assumes that any failure or degradation identified during inspections triggers repair actions that restore the equipment to the operational state.

When a multi-equipment scenario is considered, the risk is determined as the highest one among them over time. This is the adopted to maintain the integrity of all equipment at a maximum acceptable risk. Therefore, let r_i be the risk index of an equipment e at time i, the maximum risk of this equipment is given by $max_e(r_i)$ for $i \in \{1, ..., K\}$ and $e \in \{1, ...E\}$, where E is the number of equipment. Considering a set of equipment the risk is given by $\phi = max(max_e(r_i))$.

In a complementary way, the work developed by Cuba et al. (2022) defines the failure detection probabilities once each inspection method is used and, therefore, the assessment of its quantitative impact on the risk. These probabilities are employed in the model to evaluate the risk indexes according to the inspection method adopted and the moment of its application. Many inspection methods investigated there and their probabilities of detecting a failure are used here.

Regarding the cost of the inspection process, it is defined in terms of the estimated average daily use of rigs required to employ an inspection method and the costs of their navigation time. The total cost calculated for each inspection plan is the sum of these individual costs.

3.2. *Constraints*

One of the main objective of the present paper is to introduce constraints in the optimization problem to address the multi-equipment approach. Therefore, the availability of rigs is considered here. It is adopted that for each inspection method employed in a unit of time, a rig will be allocated full-time to it. Thus, this dynamic gives rise to a resource constraint approach that must be imposed on the generated inspection plans. Here, the availability of rigs is adopted as a case study because it was indicated as the most important resource by experts, as well as through analysis of maintenance, incidents and accidents reports. However, many other constraints are valuable for the inspections of oil and gas equipment. For instance, the cost of navigating the ROVs between different wells for electrochemical potential measurement may be a constraint, even when these ROVs are available. Another example are the human resources available.

3.3. *NSGA-II*

In this work, the NSGA-II is used to address the MOP of designing inspection plans and its Python library *pymoo* is employed for the experiments (Blank and Deb, 2020). Other multiobjective optimization algorithms could be employed, but the NSGA-II was chosen due to its success in similar problems (see Sec. 2.1).

An individual of NSGA-II represents a multi-equipment inspection plan. For this reason, each individual's gene represents a window of opportunity to inspect an equipment. Table 1 shows an example of the representation of part of a single individual for six months, where the internal integer values reference its inspection method. In this excerpt, the inspection methods are coded as follows: 0 - no-inspection, 1 - visual inspection, 2 - electrochemical potential measurement, 3 - ultrasonics.

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

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

Knowing this structure and aiming to simplify computational processing, as well as satisfy the algorithm's inputs within the software, the individual takes the form of a one-dimensional array of size $K \cdot E$. Thus, it is possible to handle risk and cost calculations for each equipment (and consequently for the set) considering that the sequence referring to the e-th equipment is the interval that starts at position $(e-1) \cdot K$ and ends at $(eK-1)$. This encoding strategy can be seen in Figure 1.

1st Equipment				2nd Equipment				...	Eth Equipment			
0	1	...	K - 1	K	K + 1	...	2K - 1	...	(E - 1)K	(E - 1)K + 1	...	EK - 1
12	29	...	13	15	29	...	23	...	15	29	...	13

Fig. 1. One-dimensional representation of multi-equipment.

Given the individual encoding, it is necessary to define the genetic operators and other parameters for the algorithm to be able to create, process and classify individuals in new generations.

3.3.1. *Genetic Operators*

The crossover operator combines characteristics from two parent individuals in order to generate a fitter offspring individual. The mutation operator is also crucial for genetic diversification within a population. When combined, genetic operators improve the algorithm's search space, escaping from a possible premature convergence to a local optimum. As in Morais et al. (2022), the SBX crossover operator is used here with crossover probability of 0.9 and the polynomial mutation operator with a probability of 0.02 (Deb and Tiwari, 2008).

3.3.2. *Algorithm Constraints*

Constraints can be handled using different strategies. By default, in the Python library *pymoo*, multiobjective algorithms follow the feasibility-first strategy, which ranks feasible solutions as superior to unfeasible ones throughout the generations, regardless of the relative rank of their respective objective functions (cost and risk evaluation).

The resource constraint was modeled considering that for each unit of time, the maximum number of inspections can not exceed the number of available rigs. This occurs because we considered that a rigs is always necessary to perform an inspection, independent of the method employed. For this purpose, the algorithm checks if a maximum of P rigs is used for each window of opportunity i (month). Considering the number of equipment installations E and available rigs P, a solution (inspection plan) is feasible if the sum of inspections performed at any window is less than P. Thus, $E - P$ equipment can not perform any inspection for the same window (time) i for the solution to be considered feasible.

Therefore, in the feasibility check, it is enforced that any solution that exceeds the maximum amount of rigs used becomes unfeasible. This is done assigning a high value to its risk and cost evaluations, exceeding the maximum limits. It is noteworthy that in this implementation, the algorithm ends up spending time processing costs and risks of solutions that are later evaluated as unfeasible, but the modeling has proven effective in identifying feasibility.

Furthermore, the feasibility-first approach of NSGA-II acts in the individual selection process, but does not exclude unfeasible solutions, only deprioritizes them for reproduction of the next generation. Thus, it is necessary to distinguish the degree to which a solution violates constraints. Thus, a factor $b \cdot C$ was added to the cost and risk of these solutions, where b is the number of opportunity windows that the evaluated solution breaks the resource constraint and C is a constant. This allows the algorithm to also select the best unfeasible solutions over the generations, contributing to their convergence.

Since the GA is a stochastic method, ten repetitions were performed for each rigs constraint. The algorithm parameters are shown in Table 2:

Table 2. Parameter values used in the case study.

Parameter	**Value**
Months (windows of opportunity)	60
Inspection methods (amount)	29
Population size	50
Individual size (Genes)	600
Number of NSGA-II iterations	250
Crossover Probability	0.9
Mutation Probability	0.02
Number of equipment	10
Rigs (maximum) - constraint	{1,5,9}
Repetitions for each rigs constraint	10

4. Results and Discussion

The amount of unfeasible solutions for 1, 5 and 9 rigs is shown in Figure 2. It is possible to observe a difference in the trend of the curves for each constraint value. In a more restrictive environment, there is a downward trend at the beginning of the generations followed by an increase in the number of unfeasible solutions. This is indicative of the difficulty found by the optimization in generating feasible solutions in a very restrictive scenario. On the other hand, with nine rigs, the number of unfeasible solutions remains very close to zero.

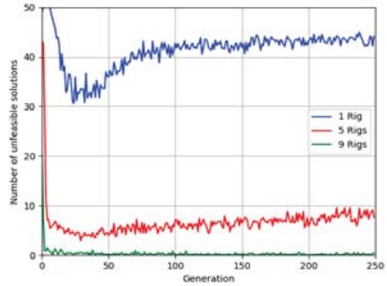

Fig. 2. Number of unfeasible solutions per generation for different constraint values (number of rigs).

The difficulty of generating feasible solutions observed here corroborates the behavior observed in Figure 3. The graphs show the evolution of solutions over generations for a repetition of each rigs constraint.

These graphs show that the GA explored a broader search space when a larger number of rigs are available. This was the expected behavior since the algorithm has greater freedom to explore this space. Additionally, it is possible to observe the convergence of GA towards the Pareto front. It is also evident the convergence to feasible solutions over the generations using the feasible-first strategy to rank the best solutions by NSGA-II.

One-rigs constrained optimization has difficulty generating better feasible solutions over generations, thus, the points in the one-rigs constrained graph are concentrated in low-cost regions, where there is lower resource utilization but higher risk involved.

To analyze how the non-dominated solutions for $\{1,5,9\}$ rigs cover the search space, Figure 4 shows the Pareto fronts. In this figure, only the feasible solutions were considered, where each solution represents an inspection plan constrained to the number of rigs available for each unit of time. This graph shows the difficult of the optimization algorithm to generate feasible solutions in more constrained environments. Although the experiment using only one rigs faced difficulty in exploring some regions, it managed to generate solutions as good as the cases less constrained when the cost is less than 0.1×10^7.

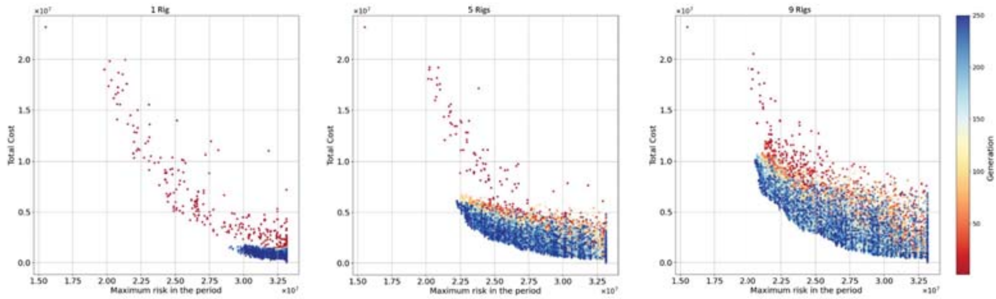

Fig. 3. NSGA-II convergence for each constrained optimization.

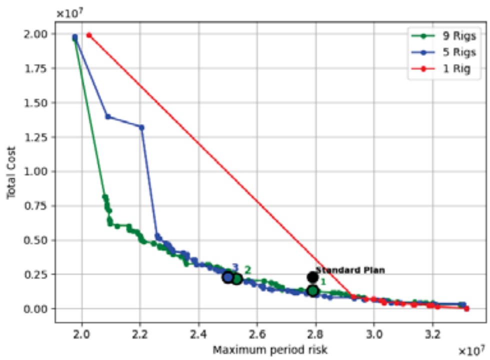

Fig. 4. Pareto front for one, five and nine rigs.

Comparing the cost and the maximum risk of the inspection plans found by the NSGA-II with the standard plan, it is possible to note that the algorithm achieved better results for five and nine rigs (Figure 4). It is worth mentioning that the standard plan is unconstrained, i.e., since inspection plans are designed for ten equipment, an amount of ten rigs is considered. Thus, the algorithm found better solutions for both objectives, cost and risk, using fewer resources than the standard plan.

The experiments constrained to five and nine rigs achieved better solutions compared to the standard plan, both in terms of risk and cost. Table 3 shows the comparison between three inspection plans with cost or risk similar to the standard plan. These solutions are identified in Figure 4. For the solution 1, the optimization with nine rigs has very similar risk but a cost reduction of about 40%. In terms of risk, the optimization process was able to find two solutions with about 10% lower risk and slightly lower cost.

Table 3. Comparison of optimized solutions with similar risk or cost to the standard plan.

Solution	Number of rigs	Risk (Δ %)	Cost (Δ %)
1	9	0.03	-40.95
2	9	-9.42	-3.98
3	5	-10.23	-0.94

5. Conclusion

In this paper, an initial methodology is presented to address the problem of optimizing inspection plans for multiple oil and gas equipment while taking into account resource availability. Aiming to simultaneously minimize the risk of equipment failure and inspection costs, the NSGA-II algorithm was applied to solve this multiobjective optimization problem.

The experimental results showed that the algorithm is capable of converging towards regions of the search space that yield better solutions, that is, inspection plans with lower risks and costs. In addition, considering five or nine rigs, the NSGA-II was able to achieve better solutions than a standard inspection plan for a set of ten Wet Christmas Trees of 600 meters depth. This implied a risk reduction of approximately 10% and 40% of cost savings.

When the optimization was performed using only one rigs, no solutions that surpassed the standard plan were obtained. In fact, the algorithm was unable to explore regions of the search space related to performing many inspections, that is, regions that result in high costs.

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