

Article

Optimising Maintenance Planning and Integrity in Offshore Facilities Using Machine Learning and Design Science: A Predictive Approach

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Featured Application: A decision support system for optimising anti-corrosive painting maintenance planning in offshore platforms through integrating 3D CAD/CAE models, machine learning for corrosion prediction, and multi-criteria optimisation strategies considering regulatory demands, criticality, and resource constraints.

Abstract: This research presents an innovative solution to optimise maintenance planning and integrity in offshore facilities, specifically regarding corrosion management. The study introduces a prototype for maintenance planning on offshore oil platforms, developed through the Design Science Research (DSR) methodology. Using a 3D CAD/CAE model, the prototype integrates machine learning models to predict corrosion progression, essential for effective maintenance strategies. Key components include damage assessment, regulatory compliance, asset criticality, and resource optimisation, collectively enabling precise and efficient anti-corrosion plans. Case studies on oil and gas platforms validate the practical application of this methodology, demonstrating reduced costs, lower risks associated with corrosion, and enhanced planning efficiency. Additionally, the research opens pathways for future advancements, such as integrating IoT technologies for real-time data collection and applying deep learning models to improve predictive accuracy. These potential extensions aim to evolve the system into a more adaptable and powerful tool for industrial maintenance, with applicability beyond offshore to other environments, including onshore facilities.

Keywords: offshore maintenance; corrosion prediction; maintenance optimisation; machine learning; multi-criteria decision making; reliability centred maintenance



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1. Introduction

Maintenance strategies are crucial in offshore activities, as they involve significant environmental, social, and financial risks. In this sector, it is estimated that maintenance costs alone account for 40% of total costs, with a large portion linked to inadequately planned maintenance activities [1]. Consequently, given these factors and the nature of the asset-intensive sector comprising hundreds of continuously operating equipment, maintenance management is considered highly critical [2]. From the viewpoint of offshore installations, corrosion is the primary factor impacting the longevity and reliability of offshore assets, with 80% of the total maintenance costs in the oil and gas exploration industry related to corrosion. Studies estimate that 20% to 30% of these costs could be saved by adopting good corrosion management practices, including inspection and prevention strategies [3]. Consequently, maintenance planning represents a crucial strategic process within industrial plants, particularly for equipment requiring prolonged and comprehensive inspections [4]. In this context, performing the right task at the right

time with the right equipment is essential to ensure that the facility remains in a reliable operational condition [2].

1.1. Research Gaps and Questions

For complex technical systems like offshore platforms, traditional maintenance management approaches such as Risk-Based Inspection (RBI) and Reliability-Centred Maintenance (RCM) have been fundamental in enhancing the effectiveness of inspection and maintenance planning [5]. These methodologies provide structured frameworks for prioritising maintenance activities based on risk assessments and the equipment's criticality [6]. However, their implementation often relies heavily on expert judgment and historical data, which may not effectively capture the dynamic nature of corrosion progression.

Recent advancements in artificial intelligence (AI) have significantly transformed corrosion prediction and assessment capabilities [7]. AI-based systems can process and analyse vast inspection data [6], enabling more accurate predictions of corrosion progression patterns [8]. These systems overcome traditional limitations by providing data-driven insights for maintenance decision-making, reducing dependency on subjective assessments [9]. Emerging research indicates that combining RBI/RCM methodologies with AI-driven predictive capabilities offers promising results in maintenance optimisation. For instance, computational intelligence has been successfully applied to transformer maintenance [10], and AI-enhanced RCM systems have significantly improved maintenance efficiency [11]. Comprehensive reviews of the evolution of power system maintenance suggest that this integrated approach represents the future of maintenance strategies [12]. However, despite these advances in the power sector, similar integrated approaches have not been adequately explored or implemented in the oil and gas industry, particularly for offshore facilities [13].

Research has highlighted integrating advanced technologies to enhance decision support in infrastructure management. Digital twins, combining monitoring and simulation, are proposed for risk management in underground gas storage [14] and lifecycle optimisation of civil infrastructure [15]. These advancements aim to improve infrastructure management's sustainability, safety, and efficiency [16]. However, research has not adequately addressed the specific application of these advanced technologies in the context of offshore platforms, particularly in corrosion maintenance and planning for anti-corrosive painting [17]. Despite advances in managing onshore infrastructure, a significant gap exists in integrating 3D CAD/CAE models with decision support systems for offshore platforms [18]. This research gap emphasises the need to develop integrated technological solutions that specifically address the challenges of maintenance and integrity management on offshore platforms, combining the power of machine learning models and optimisation algorithms tailored to this unique environment.

The current research presents a notable gap in addressing the specific application of these advanced technologies in offshore platforms, particularly regarding maintenance planning and the optimisation of anti-corrosive painting [19]. The growing demand for more efficient and risk-based maintenance strategies [20], aimed at reducing the high costs associated with corrosion [21] and improving the reliability of assets in this critical sector, remains a pressing need [21]. Given this scenario, innovative solutions that optimise the inspection and maintenance process in offshore installations, considering the particularities and challenges of this sector, are needed. The Design Science Research (DSR) methodology emerges as a promising approach to addressing this problem, focusing on designing and developing artefacts that solve relevant and complex problems [22].

Given this complex scenario, this study aimed to answer the following research question (RQ):

RQ: How can the DSR approach contribute to developing innovative solutions for maintenance challenges in the offshore sector?

1.2. Research Aims and Contributions

Considering this question, this research aimed to develop a technology to test an integrated analysis and decision support environment based on a machine learning model with computational tools to aggregate real and simulation data, aiming at the maintenance and integrity of surface installations. To accomplish this overarching goal, the following specific objectives (SO) were set.

SO1: Propose a decision support system based on 3D CAD/CAE and machine learning models to optimise maintenance and painting planning on offshore platforms.

SO2: Assess the impact of optimisation strategies (person-hour/PH limits, corrosion integrity, regulatory demand, and criticality) on generating painting plans for offshore platforms.

By integrating the 3D CAD/CAE design model with simulation and inspection data, computational mechanisms will be applied to improve maintenance and integrity planning activities, generating a more predictive and less reactive maintenance plan.

This research is innovative in proposing an integrated approach to improving maintenance planning in offshore installations, focusing on integrity management through anti-corrosive maintenance optimisation. Its originality lies in combining design, simulation, instrumentation, and inspection data with computational mechanisms, applying the DSR methodology to develop the prototype. The main contributions include filling gaps in the literature on corrosion assessment models, developing prototypes as practical tools for optimising painting planning, creating a machine learning model for predicting corrosion progression, conducting case studies on real platforms, and generating knowledge about factors influencing the criticality and progression of corrosion. These contributions offer valuable insights for future studies and decision-making in the offshore sector, promoting the development of more effective solutions to maintenance and integrity challenges.

This work is structured into six sections. Section 1 describes the context and the current challenges in maintenance management and corrosion control in offshore installations, establishing the theoretical foundation of the research. Section 2 presents a structured literature review on offshore maintenance and asset management. Section 3 details the DSR methodology adopted for developing the prototype and the specific tools and approaches employed, such as CAD/CAE modelling and machine learning. Section 4 presents the findings from case studies conducted on oil and gas platforms, highlighting the proposed system's benefits and limitations. Section 5 discusses the current literature's findings, exploring the model's practical and scientific implications. Finally, Section 6 concludes the article, summarising the contributions of the research and suggesting directions for future investigations in the field of maintenance optimisation in offshore infrastructure.

2. Literature Review: Offshore Maintenance and Asset Management

A systematic search strategy was employed to structure the literature review, covering relevant studies published in the last five years. The academic databases selected were Web of Science (WoS) and Scopus due to their broad engineering and applied sciences coverage. The keywords used in the search included "offshore maintenance", "corrosion", "resource optimisation", "structural integrity", and "asset management", ensuring an accurate selection of works directly related to the topic of study. The selection process for the studies involved a thorough analysis, including a review of the titles, abstracts, and, where necessary, the full text of each identified article. Only studies addressing relevant aspects of maintenance planning in offshore environments, corrosion management, and resource optimisation methodologies were considered. This strategy allowed for a solid foundation of references supporting this research's arguments and methodological approach, ensuring that the theoretical framework is aligned with the most recent and pertinent developments in the field.

2.1. Design Science Research for Developing Maintenance Solutions

DSR has emerged as a valuable methodology for developing innovative solutions in various fields, including service design [23] and project scheduling [24]. It offers a systematic approach to creating artefacts, methods, and models while bridging the gap between research and practice [25]. DSR has been applied to complex problems such as distribution system reconfiguration [26] and knowledge management systems [27]. These studies demonstrate the potential of DSR and related methodologies in addressing real-world challenges across diverse domains.

In the context of maintenance for offshore facilities, integrating Design Science Research (DSR) with artificial intelligence technologies has enabled the development of more robust planning and optimisation systems [28]. Integrity management in marine environments represents a challenge where DSR has demonstrated its value [29]. Current research focuses on developing predictive models integrating multiple environmental and operational variables [30]. A crucial aspect in the evolution of DSR has been its ability to incorporate site-specific constraints and dynamic resource allocation [31]. The developed models consider factors such as weather conditions, accessibility, and resource availability, which are fundamental elements in the offshore context [32].

Several studies have investigated the factors influencing offshore outsourcing decisions for application maintenance, identifying critical success factors such as cost, communication, and project management [23]. Opportunistic maintenance has been proposed as a cost-effective solution for offshore wind farms, introducing market-based opportunities [33]. Maintenance cost minimisation models for offshore wind farms have been reviewed, with some strategies reducing annual costs by up to 23% [34]. Additionally, distributed agile patterns have been developed to address the challenges in offshore development, offering guidelines for practitioners adopting agile practices in distributed environments [35]. The integration of these variables has allowed for the generation of solutions that are more closely aligned with the actual needs of the industry [36].

Currently, research has expanded the scope of DSR by incorporating criticality analysis and risk assessment [37]. The models consider technical aspects and economic and environmental factors in decision-making [38]. This holistic approach has resulted in more effective and sustainable maintenance strategies. The current trend in developing solutions through DSR points towards creating more integrated and adaptive systems [39]. Recent research emphasises the importance of combining different technologies and methodologies to address the complexity of offshore maintenance [40]. Incorporating multi-criteria optimisation techniques and real-time data analysis redefines traditional maintenance paradigms [41].

This literature review highlights the importance of a holistic and integrated approach to offshore asset management. Combining machine learning techniques, optimisation methods, and digital twin technologies [42] promises to transform maintenance and integrity management in offshore facilities. However, it also underscores the need for continued research to address the specific challenges of these complex and dynamic environments.

2.2. Decision Support Systems for Offshore Maintenance and Asset Management

ML techniques are increasingly applied to asset management and predictive maintenance in various industries, including power distribution networks [43] and railways [44]. These techniques improve reliability, availability, maintainability, and safety [45]. ML models can enhance decision-making processes, predict the remaining useful life, and detect faults in real time [46]. However, challenges remain in data management, the models' interpretability, and performance evaluation [44]. Despite these challenges, machine learning-based predictive maintenance offers substantial potential to boost efficiency, minimise downtime, and promote sustainability in various industries [47].

Recent research on offshore O&M optimisation has focused on various approaches to address challenges in the maritime and renewable energy sectors. Digital twin technology has been investigated as a means to enhance O&M efficiency and reduce costs in offshore

wind farms [48]. Multi-criteria decision-making (MCDM) methods, such as spherical fuzzy AHP and WASPAS, have been applied to optimise the selection of offshore wind power station sites [49]. Researchers have also investigated condition monitoring, fault diagnosis, and prognosis techniques to enhance maintenance strategies [50]. The integration of MCDM methodologies with quality function deployment has been proposed to improve decision-making processes in offshore renewable energies [51]. These advancements aim to minimise maintenance costs, increase reliability [52], and ensure the sustainable development of offshore wind power systems [53].

Research on offshore maintenance and asset management highlights the complexity of planning and optimising maintenance strategies for offshore assets, particularly wind farms. Decision support systems incorporating machine learning, multi-criteria decision-making, and linear programming are being developed to address the challenges in resource allocation, cost minimisation, and condition monitoring [54]. These systems aim to improve fault diagnosis, prognosis, and maintenance efficiency [55]. The literature reveals a clear trend toward more data-driven, intelligent, and holistic approaches to maintenance planning and optimisation [56]. This aligns closely with the objectives of the proposed prototype, which aims to integrate multiple data sources and advanced analytical techniques to support more effective decision-making in offshore painting planning. The proposed study, with its comprehensive approach integrating 3D modelling, machine learning, and multi-criteria optimisation, has the potential to address some of these challenges and contribute significantly to the field.

3. Materials and Methods

The choice of Design Science Research (DSR) as the methodology for this study was based on its unique ability to integrate scientific rigour with practical relevance, which is especially crucial in developing complex socio-technical systems for offshore maintenance [34]. Unlike other iterative methodologies such as Agile [57] or Lean [58], which primarily focus on process efficiency, DSR provides a structured framework that facilitates both the generation of theoretical knowledge and the creation of implementable practical solutions [59]. Other methodologies, such as Waterfall [60] and the V-Model [61], which are common in software development, do not offer adaptability or focus on the creation of specific artefacts that characterise DSR [62]. Waterfall follows a rigid sequence without early iteration, limiting its effectiveness in systems requiring constant adjustments [63]. The V-Model, although incorporating validation at each stage, is insufficient in dynamic environments. DSR, on the other hand, allows for constant feedback among the design, development, and evaluation stages, fostering technical accuracy and generating knowledge relevant to the specific context of use [62].

As illustrated in Figure 1, the research process is structured around the principles of DSR, integrating various techniques and analytical tools to develop and validate the prototype. This framework not only guides the research process but also directly contributes to creating a portfolio that comprehensively meets the objectives of the investigation. The portfolio structure is based on several key elements that form a cohesive and thorough approach. Each of these elements addresses a crucial aspect of offshore maintenance, providing a solid foundation for developing comprehensive solutions. The research philosophy adopted is based on pragmatism [64], which combines qualitative and quantitative techniques to address the complex problem of offshore maintenance planning. Pragmatism allows for methodological flexibility, which is essential for integrating predictive models, resource optimisation, and condition analysis into a practical decision-support tool [65].

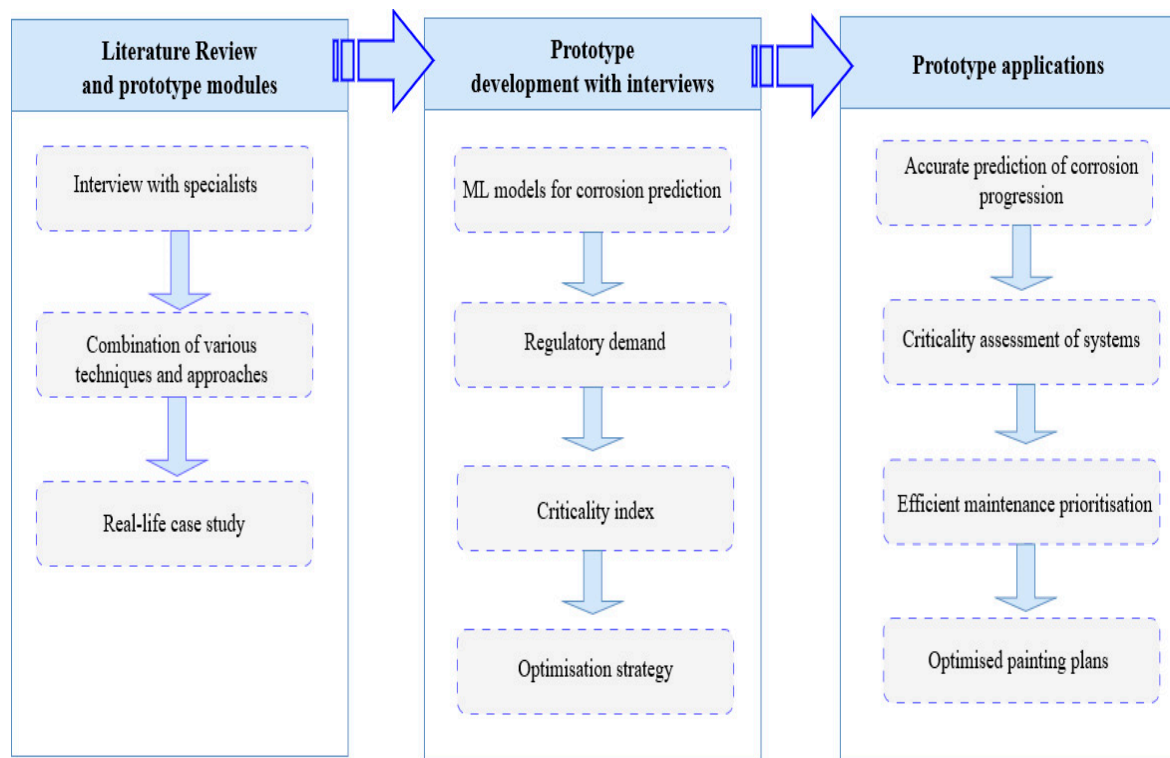


Figure 1. Framework and portfolio aligned with the research objectives for offshore maintenance optimisation.

Firstly, the fundamental components of the framework (predictive models, regulatory demand, and criticality indices) represent specific research projects within the portfolio [66]. A rigorous methodology is a central pillar of the portfolio [67]. The inclusion of problem identification, a literature review, and DSR ensures that each component is grounded in a solid methodological base [68]. This systematic approach guarantees the validity and reliability of the results obtained in each research phase.

The research was applied in its nature [17] and aimed to develop and validate an artefact that addresses specific needs of offshore maintenance management. Additionally, was is a descriptive–explanatory study [69], exploring and describing the characteristics of offshore maintenance while also seeking to explain the relationships among corrosion variables. This combination allowed for a detailed understanding of the problem and facilitated the creation of practical and adaptive solutions.

The integration and synthesis of the individual components are materialised in the development of the prototype [17]. This aspect of the portfolio demonstrates how the individual elements combine to create a holistic solution [70]. The prototype represents the culmination of the research efforts, integrating the various aspects of offshore maintenance into a cohesive and functional tool.

Validation and practical application are crucial aspects of the prototype [71]. The case studies and validation in a real-world context provide empirical evidence of the effectiveness of the proposed solutions [72]. This approach ensures that the solutions developed are theoretically sound and practically applicable in real offshore environments. The contribution to knowledge is reflected in the triangulation of results and the practical and theoretical implications [73]. These elements ensure that the prototype presents results and provides significant insights into offshore maintenance [74]. This approach guarantees that the research has a lasting impact on theory and practice.

The decision to conduct focus groups was based on the need to gather various perspectives and experiences from specialists in offshore maintenance planning and painting [17]. The exploratory and confirmatory focus groups provided detailed feedback at the pro-

prototype's development stages. These were conducted in multiple phases across several meetings and workshops, with a longitudinal approach and continuous improvement through iterations in each phase. This included eight focus groups and workshops for data collection and prototype validation. A convenience sampling method was used, focusing on key specialists in the offshore maintenance area, specifically painting planners and maintenance managers, participating in groups of 2 to 3 people per session, totalling eight work sessions. However, the sample is small, which poses a limitation in generalising the results. The analysis methods included qualitative methods, including focus groups and semi-structured interviews, to gather and confirm the maintenance criteria and prototype decisions. Additionally, quantitative analysis techniques were applied to evaluate and adjust the model using key indicators through dashboards. The main methodological limitation lies in the small sample size and the reliance on insights from a limited number of experts. This could restrict the generalisability of the findings to other platforms or different offshore contexts.

Finally, the prototype's interdisciplinary nature is evidenced in the inclusion of MCDM methods, artificial intelligence applications, and optimisation models [75]. This approach reflects the research's interdisciplinary nature, combining perspectives from multiple fields to address the complex challenges of offshore maintenance [76]. Integrating these diverse perspectives allows for a deeper understanding and more robust solutions to the sector's multifaceted problems. This study employed a DSR approach to develop and evaluate APM, an innovative decision support system prototype for maintenance planning and integrity management in offshore facilities. The DSR process comprises six main stages: problem identification and motivation, definition of the solution's objectives, artefact design and development, demonstration, evaluation, and communication, as shown in Figure 2 [23]. This iterative process allows continuous refinement of the developed artefact based on feedback obtained at each stage [22].

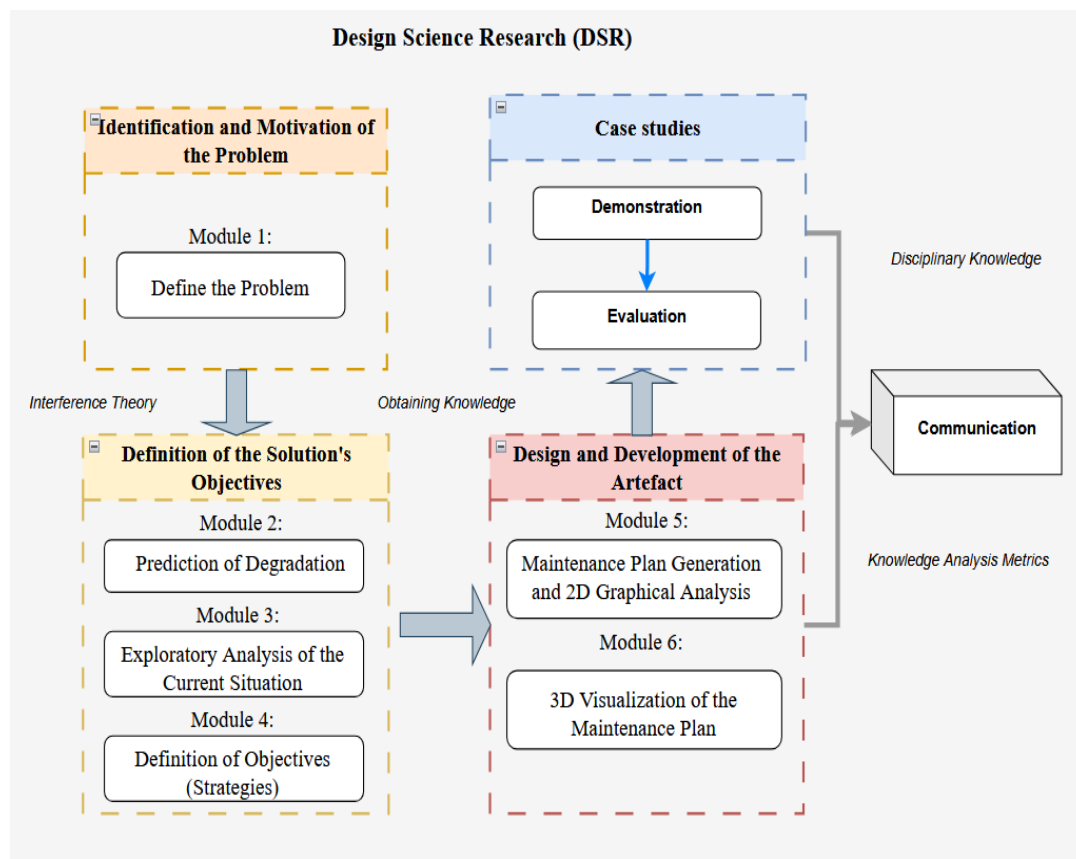


Figure 2. The design science research approach was adapted from Vom Brocke et al. [22].

The problem addressed in this study was the need to improve maintenance and integrity planning activities in offshore installations, focusing on external corrosion. This issue is relevant due to the high costs and risks associated with inadequate maintenance in this context [77]. Recent studies have highlighted the importance of effective maintenance strategies to guarantee the reliability and safety of offshore operations [49]. The APM prototype was developed as an integrated solution composed of six interconnected modules (Table 1).

Table 1. Modules and descriptions of the APM prototype.

#	Module	Description
1	Scope (problem) definition	This module sets the initial parameters of the maintenance project, laying the foundation for effective planning.
2	Degradation progress prediction	This module employs machine learning models, specifically the Random Forest algorithm, to predict corrosion progression based on environmental and operational factors.
3	Exploratory analysis of the current situation	Provides a detailed view of the platform's pre-maintenance condition, using KPIs and graphical visualisations to facilitate understanding of the current situation and the projected scenario if no maintenance actions are taken.
4	Objective definition (strategies)	Allows for the selection of various optimisation strategies, each focused on different critical aspects of maintenance: <ul style="list-style-type: none"> • Maximising the amount of degradation addressed; • Minimising the resources (PH) used to reach a specified degradation target level; • Maximising the criticality of intervened systems; • Maximising compliance with maintenance service requirements (regulatory demand).
5	Maintenance plan generation and 2D graphic analysis	Produces optimised plans and provides visualisations to facilitate understanding and decision-making.
6	3D visualisation of the maintenance plan	Integrates the results with 3D CAD/CAE models for a more comprehensive spatial representation.

The proposed solution combines real and simulated data to generate a more predictive and less reactive maintenance plan. It should also enable the consolidation of the scope of the anti-corrosive painting for use in production plants. Combining data from various sources and utilising advanced analytical methods has shown promise in enhancing maintenance decision-making [78].

At this stage, the artefact (the integrated analysis and decision support environment) was designed and developed according to the defined objectives. Three-dimensional modelling techniques, data integration from multiple sources, and the application of computational mechanisms generated maintenance recommendations [42]. Three-dimensional modelling has been successfully employed to represent and analyse complex systems such as offshore installations [79].

Moreover, integrating data from different sources, such as inspection, condition history, engineering characteristics, and simulations, was essential to gain comprehensive insights into the equipment's conditions [80]. External corrosion data were collected through systematic inspections, and the integrated analysis and decision-support environment was applied to generate optimised maintenance plans based on risk assessment criteria. Demonstration in real offshore contexts validated the artefact's efficacy and applicability in industrial settings [81].

The artefact was evaluated on the basis of the results obtained in the case studies. Performance indicators such as resource allocation efficiency, the effectiveness of damage reduction, improvements in regulatory compliance, and coverage of critical systems were analysed. Feedback from offshore maintenance experts was also collected to refine the

artefact. Rigorous evaluation is crucial to verify whether the artefact met the proposed objectives and generated value for stakeholders [82]. The projects' results are communicated through scientific publications, conference presentations, and offshore industry workshops. This allows for the dissemination of the generated knowledge and the obtaining of additional feedback to improve the developed artefact. Effective communication is essential to promote the adoption and continuous evolution of the artefact [23].

3.1. Integration of Components in the APM Prototype

Integrating modules in the APM prototype represents a complex and multifaceted process involving combining various techniques and approaches to develop an effective decision support tool in painting planning for offshore platforms. This process can be broken down into five primary stages: variable survey, code structuring, definition of the data flow, implementation of optimisation models, and integration of the components in the graphical interface. The implementation leverages several specialised Python libraries: Pandas [83] for data manipulation and analysis of inspection and maintenance records, PuLP [84] for implementing the linear programming optimisation models that drive the different maintenance strategies, sci-kit-learn [85] for advanced analytics and corrosion prediction models, and PySimpleGUI [86] for creating an intuitive user interface. Each strategy is formulated as a linear programming problem with objective functions, the direction of optimisation, decision variables, and appropriate constraints [87]. This integrated approach efficiently handles complex maintenance planning scenarios while providing an accessible interface for maintenance engineers and planners.

The variable survey constitutes a crucial stage for problem modelling, which involves identifying, classifying, and collecting data from competent parties. At this stage, it is fundamental to understand the variables' limits and their relationships and to verify their dependence or independence [88]. Another critical aspect of integration is the definition of the data flow, which involves the import, transformation, and treatment of inspection and regulatory demand data, as well as the calculation of key indicators such as corrosion progress and criticality.

Implementing optimisation models involved developing different strategies (PH limit, corrosion integrity, regulatory demand, and criticality) that met the specific needs of painting planning. Finally, the integration of modules in the graphical interface was carried out by developing an intuitive and easy-to-use interface, which guides the user through the stages of data input, exploratory analysis, simulation configuration, and results evaluation, as shown in Figure 3. The optimisation models and the results in visualisation dashboards are seamlessly integrated into the interface, allowing users to interact with the prototype's functionalities.

The system's structure is designed to capture and process inspection data in various formats, integrating relevant information on corrosion levels, environmental conditions, and regulatory constraints. These data are entered into the system through an interface that allows for the uploading and validating of inspection sheets and specific conditions for each platform, ensuring that the analysis starts from a standardised and consistent basis. Subsequently, the system processes this data using predictive models and multi-criteria analysis techniques, generating visualisations and key metrics, such as the corrosion index and regulatory demands, to facilitate decision-making for maintenance planning. The optimisation model in this study managed each maintenance strategy individually as a single-objective process, allowing each strategy to be executed independently according to the established priority. The system does not automatically perform the selection of the painting planning strategy; rather, it depends on managerial decision-making, where the trade-off among objectives, such as the intervention time and attention to high-criticality areas, is evaluated. In this context, each strategy is executed according to the selected objective function, such as minimising person-hours or prioritising areas requiring more significant corrosion intervention. This approach allows the management to externally decide which strategy best fits each situation's specific objectives and regulatory demands.

Thus, the model optimises resources according to the chosen strategy, providing flexibility and managerial control over resource prioritisation and ensuring an efficient maintenance plan tailored to the operational conditions.

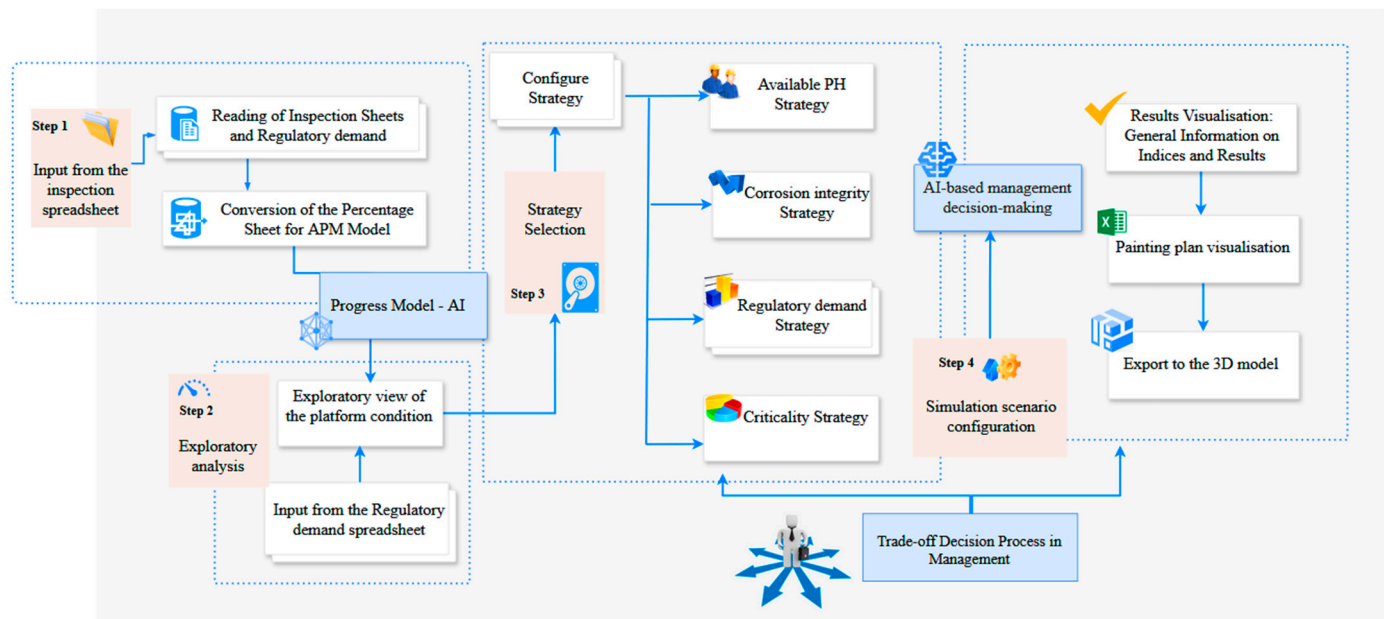


Figure 3. Screen flow and user interactions for the APM tool.

3.2. Case Studies Conducted

Case studies play a fundamental role in validating and demonstrating the applicability of new methodologies and tools developed in scientific research [89]. In this context, case studies were conducted that supported the development of the APM prototype and evaluated the effectiveness of the proposed solutions against the real challenges of maintenance and painting planning on offshore platforms.

The case studies selected for this analysis employed specific selection criteria to ensure the relevance and applicability of the results in offshore contexts. The main parameters taken into account involve corrosion levels, categorised by their severity and specific location within the structure, along with environmental factors like humidity and temperature, which directly impact corrosion progression. These parameters were chosen through a preliminary analysis that identified the variables with the most significant impact on predictive maintenance and the structural integrity of offshore installations. Additionally, consistent parameters were used for each variable in the analysis, such as the number of personnel assigned per team and the duration of person-hours. In this case, each team had a specific number of painters and a set duration, ensuring that the planning criteria remained consistent across all simulations. Some criteria were used for specific advances, while others were applied according to the context of each study, thereby ensuring a robust and coherent application of the results in real conditions.

The case study on the development of APM aimed to validate, test, and demonstrate the applicability of the methodologies and models developed in each research using real-world contexts of offshore oil platforms. A real-world major platform scenario was used to compare the painting plans generated by each strategy (PH limit, corrosion integrity, regulatory demand, and criticality), evaluating the results regarding the remaining corrosion, pending regulatory demand, the criticality of selected systems, and the required resources. Optimising maintenance planning through considering multiple criteria and constraints is a complex problem that demands advanced decision-support tools [90].

Throughout these stages, various data sources were used: semi-structured interviews (with the interview tool updated according to emerging data), observations (e.g., shipments, participation in meetings), and documentary sources (e.g., documents from a large company

in the O&G industry). Several methods were employed to triangulate data from different sources to achieve greater data reliability and a have solid foundation for the constructs and propositions.

A mix of exploratory and confirmatory focus groups was employed to assess the prototype's design. The exploratory focus groups gathered feedback for design changes and the artefact's refinement, serving as a formative evaluation procedure for iterative design improvement. Additionally, a confirmatory focus group was applied to demonstrate the utility of the artefact's design in the application domain. To this end, eight focus group workshops were conducted with painting planning specialists and maintenance managers (two to three participants per workshop, with an average duration of 60 min).

4. Results

The APM prototype represents a significant advancement in integrated maintenance management for offshore platforms, addressing needs comprehensively from conceptual design to operation. This innovative system merges human resource management with technical data, benefiting companies and society. The information regarding the painting area in the system comes from the 3D CAD/CAE tool. This tool uses an identification system that includes the platform, module, sector, and specific system. This detailed categorisation allows for precise planning tailored to the particular needs of each platform component (Figure 4).

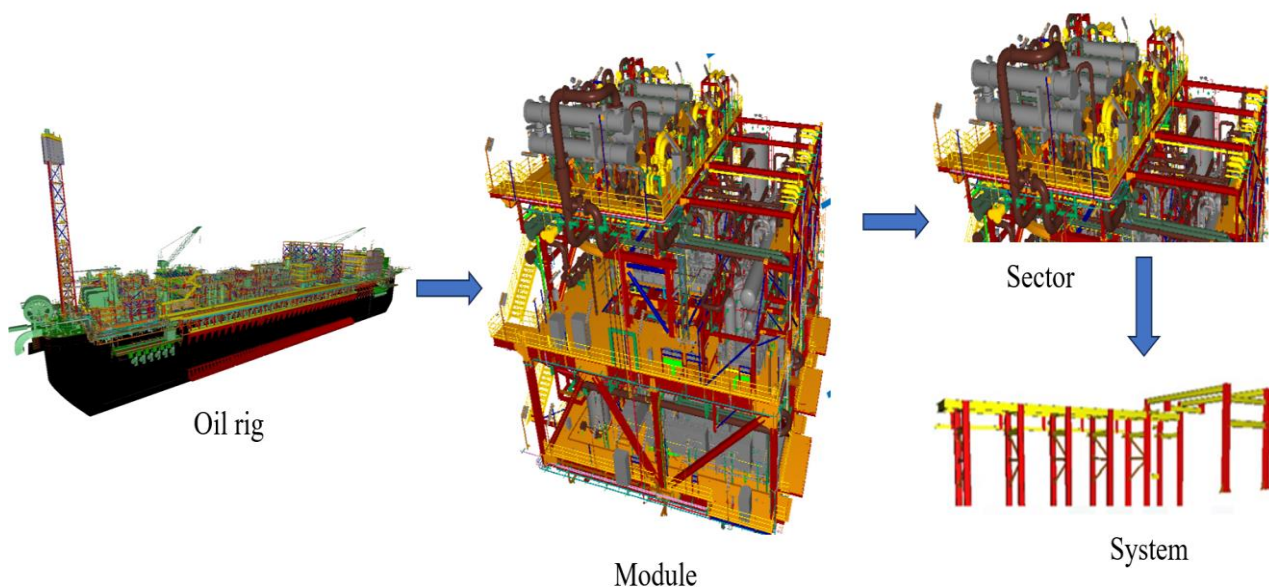
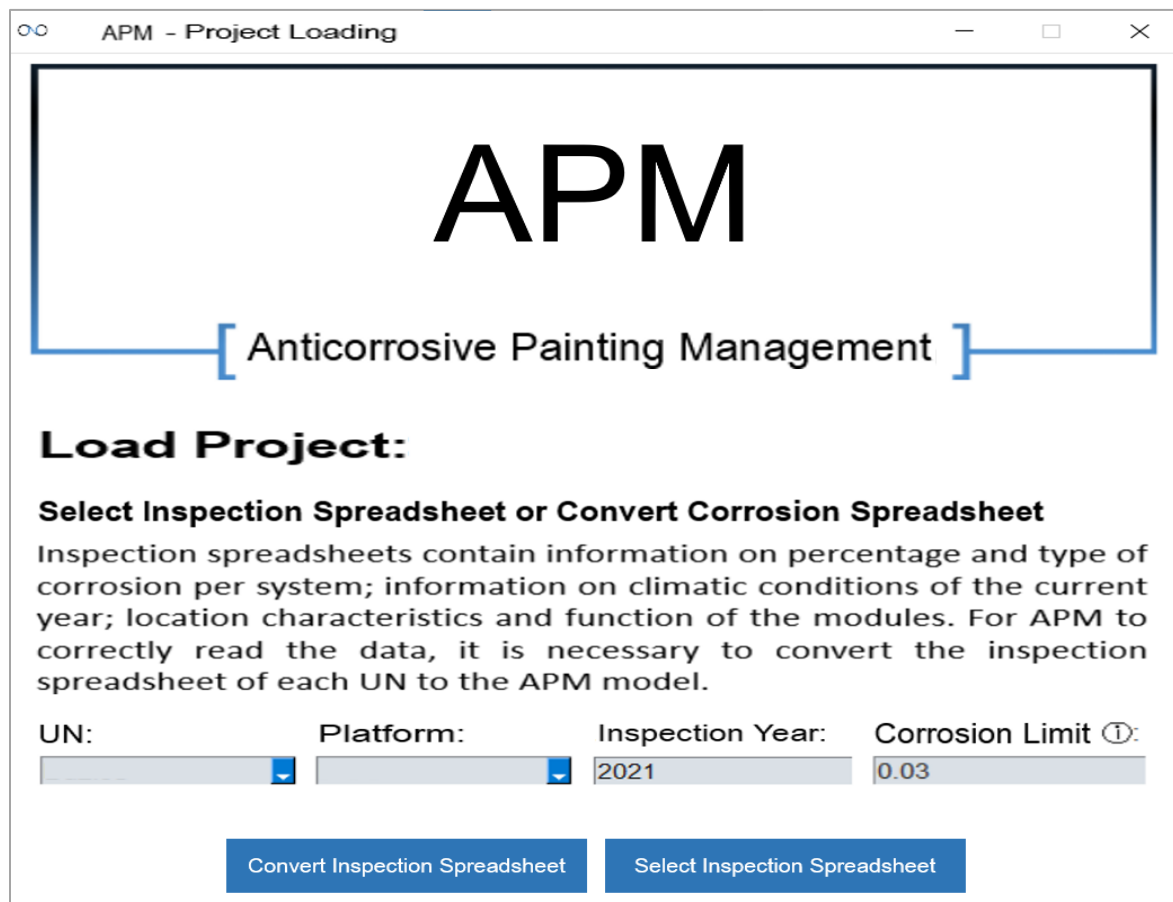


Figure 4. Visualisation of the platform created with the 3D CAD/CAE tool and items.

Figure 4 shows the hierarchical structure of the offshore platform, broken down into modules, sectors, and systems to facilitate the planning process for anti-corrosive maintenance. Each module represents a large section of the platform, the sector is a module subdivision, and the system corresponds to specific components requiring maintenance. The study compared the painting plans generated by each of the four APM strategies for the platform using an inspection spreadsheet containing field-acquired corrosion data from inspectors. The input data for each strategy were identical to maintain comparability. To import the inspection spreadsheets, we selected the “convert inspection spreadsheet” option and inserted the path to the spreadsheet file (Figure 5). Upon selection of the “browse” option, APM validates the input data, and if everything is correct, it automatically infers the corrosion's evolution and proceeds to the next exploratory visualisation screen. This machine learning-based analysis uses historical inspection data to forecast how corrosion will develop over time if no maintenance interventions are performed.



APM - Project Loading

APM

[Anticorrosive Painting Management]

Load Project:

Select Inspection Spreadsheet or Convert Corrosion Spreadsheet

Inspection spreadsheets contain information on percentage and type of corrosion per system; information on climatic conditions of the current year; location characteristics and function of the modules. For APM to correctly read the data, it is necessary to convert the inspection spreadsheet of each UN to the APM model.

UN: Platform: Inspection Year: Corrosion Limit ①:

Figure 5. Home screen of APM: inspection spreadsheet input.

Figure 5 illustrates the data loading interface of the APM system, including a selection field for inspection sheets containing information on corrosion levels and specific climatic conditions for each location. “UN” refers to the specific unit where the study is conducted, “Platform” indicates the platform’s name, “Inspection Year” shows the year of inspection, and “Corrosion Limit” is the corrosion target expected to be achieved during maintenance. Each interface element is clearly labelled to guide the user through uploading and converting the inspection data required for analysis. Before the simulation strategies are configured, the user can view the platform’s condition, based on four indicators: corrosion, painting area integrity, criticality, and regulatory demand (RD). The corrosion indicator presents both the current condition and the AI-predicted future state of the platform, allowing users to visualise how corrosion would progress if no maintenance interventions were implemented. This comparative view helps users understand the potential deterioration trajectory and the urgency of maintenance needs. These indicators provide the user with a general overview (entire platform) and a detailed view (stratification by modules/systems), guiding them in selecting the most appropriate strategy. Additionally, they can clearly understand the scale of resources that need mobilisation to generate an effective painting plan.

Figure 6 provides an exploratory visualisation of the key asset indicators, such as the corrosion index, irreversibility, criticality, and regulatory demands. “Current Average Corrosion” represents the current level of corrosion on the platform, “Irrevest Index” indicates irreversibility, “Criticality Index” shows the criticality of the components, and “RDs Index” reflects the regulatory demands. This information presents the initial condition of the platform before implementing the maintenance and planning. Detailed explanations of each index and its role in the analysis allow the user to interpret the asset’s condition clearly before configuring a maintenance strategy.

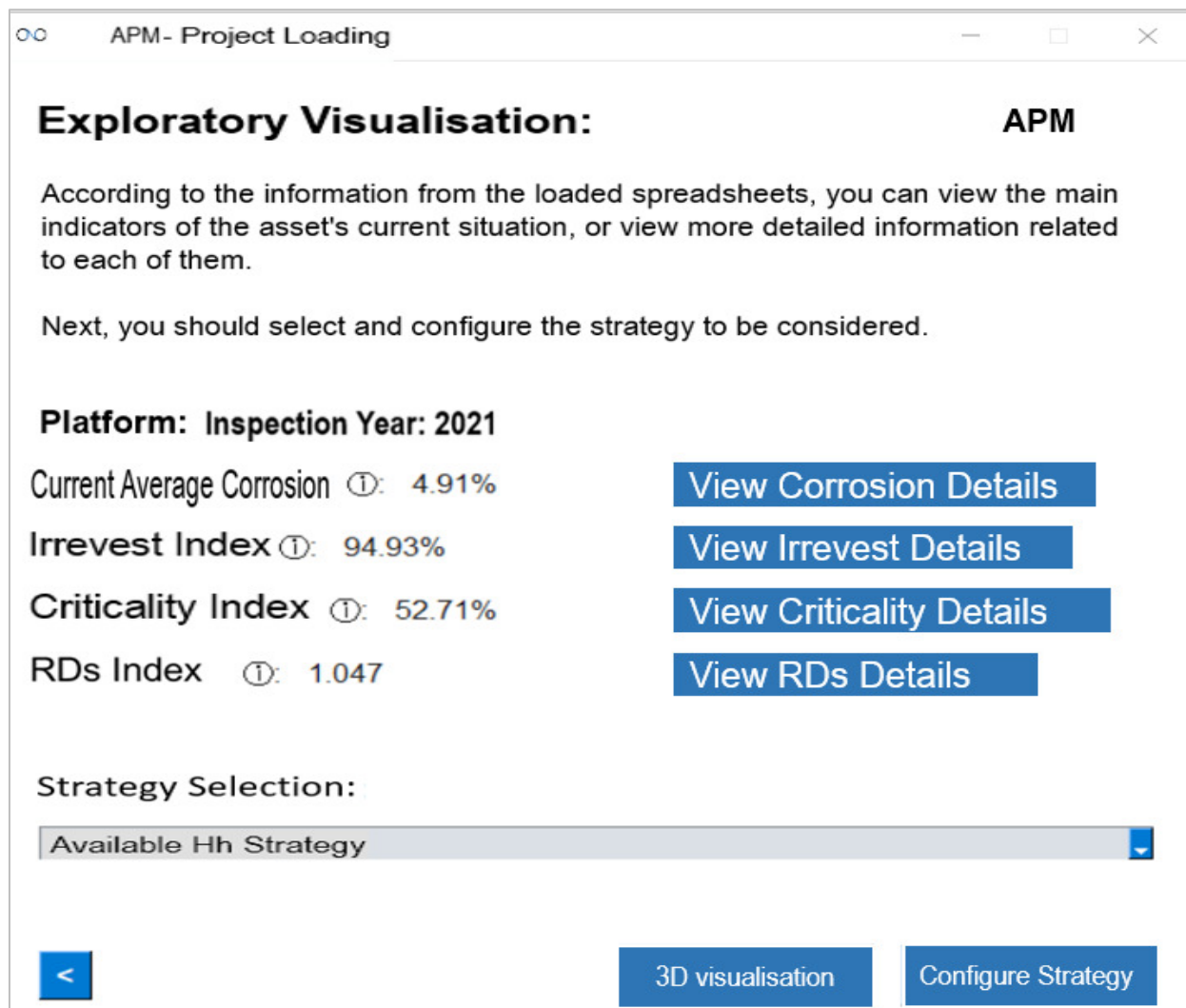


Figure 6. Initial exploratory visualisation screen of the platform's condition.

Two teams were used for the other strategies: Team 1 and Team 2. For Team 1, 84 slots were considered, with a daily availability of 8.5 h for 100 campaign days, totalling 71,400 h. For Team 2, three slots were considered, with a daily availability of 7 h for 365 campaign days, totalling 7665 h. The total PH resulting from the sum of the two teams was 79,065. Additionally, the established target was 3% for the average remaining corrosion of the platform. Proximity consideration is central to all strategies. When this option is selected, APM will calculate the optimal placement of waterjet centres on the platform to generate the most efficient painting plan according to the chosen strategy. For instance, in the corrosion-targeted strategy, the waterjet centres were located near areas with the highest percentage of corrosion. Regarding the regulatory demand strategy (RDS), the waterjet centres were positioned in regions with the highest RD index.

Once the optimal waterjet centres are selected, the program will only consider systems within their operational radius during optimisation, preventing the generation of painting plans that include systems outside the waterjets' operational area. It is important to note that the waterjet centres are assigned to each team, and allocating the services ensures that one team is not selected for tasks within another team's operational area. The user is responsible for defining the number of waterjet centres assigned to each team; that option was not considered in this case (Figure 7).

Scenario simulation **APM**

Simulation Year: 2022

☐ Consider Proximity

Planned Teams

Name	No. of Painters	Duration
Team 1	3.0	365.0
Team 2	84.0	100.0

Figure 7. Simulation configuration screen.

The next stage aims to present the user with a general overview of the painting plan generated in the simulation and compare the platform's condition before and after the execution of the suggested plan. This allows the user to assess whether the painting plan meets their needs and to return to modify the simulation's settings if necessary (Figure 8).

The resources dashboard (Figure 8) presents two visualisations: the distribution of the total painting area by the team about the modules and the total forecasted person-hours (ph) for each team in the respective modules. This visualisation provides an overview of the proposed painting plan, allowing the user to understand where the most significant efforts are concentrated and how the workforce will be distributed across the platform's modules. The "Simulation Indices" table summarises this information, showing each team's total painting area and forecasted person-hours. It also displays the hydro blasting centres selected for each team if the proximity option is selected.

Once the user has generated the simulation, evaluated its main results, and approved it, the tool proceeds to develop the detailed painting plan. The painting plan consists of a table that presents all the calculations performed at the various stages of the tool's simulation. APM allows the painting plan to be saved as an Excel file (.xlsx) to facilitate data manipulation, as highlighted in Figure 9. The various columns that make up the painting plan are detailed below.

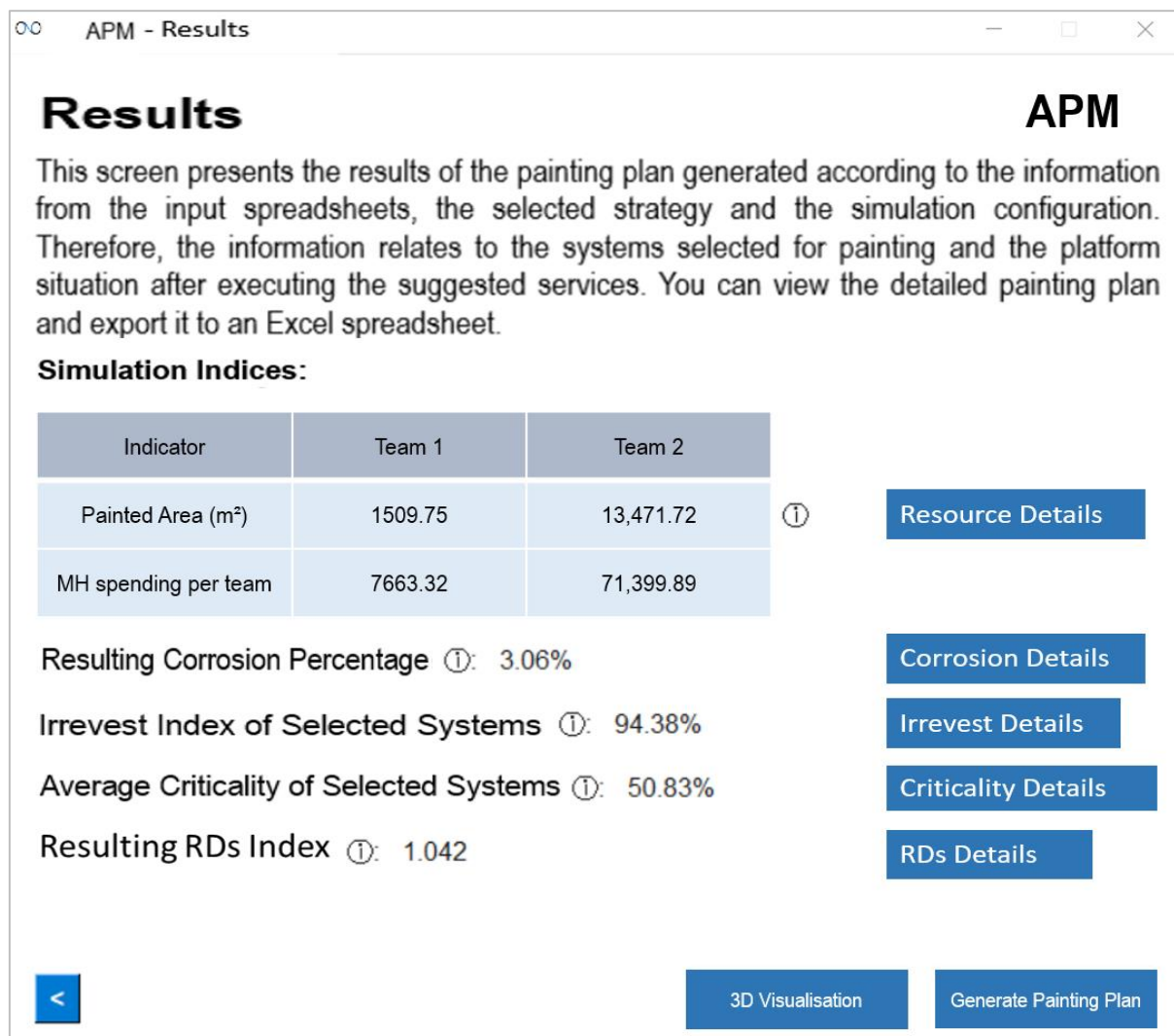


Figure 8. Results visualisation screen.

The painting plan for scheduling maintenance on offshore platforms is divided into three main sections: input data, pre-painting data, and results.

- **Input data:** These include system identifiers (ID, module, sector), painting area, productivity, corrosion levels, environmental conditions (temperature, humidity, wind), and regulatory demands (RDs). It comprehensively overviews the platform's initial condition and maintenance requirements.
- **Pre-painting data:** This section calculates the current and projected corroded areas, estimates corrosion progression using machine learning, determines the required person-hours, assesses the criticality indices, and determines maintenance priorities. It uses the input data to generate projections and prioritise maintenance tasks.
- **Results:** This section details the optimised painting plan, including waterjet centres' locations, assigned teams, areas to be painted, person-hours used, post-maintenance corrosion status, and remaining RDs. It also shows the anticipated impact of the proposed maintenance plan.

APM - Painting Plan

Painting Plan

module	sector	system	area	corrosion	productivity	progress	predicted_base_colour	area_to_paint	necessary_hh
M32	S10	Floor	491.86	0.1	0.3	0.0199	0.1199	491.86	1639.54
M32	S10	Bulkhead	41.49	0.001	0.15	0.0018	0.0028	0.23	1.56
M32	S10	Stairs	16.51	0.0	0.1	0.0014	0.0014	0.05	0.46
M32	S10	Handrails	65.34	0.01	0.1	0.0109	0.0209	13.67	136.68
M32	S10	Equipment	71.7	0.001	0.1	0.0042	0.0052	0.74	7.39
M32	S10	Supports	125.62	0.003	0.1	0.0054	0.0084	2.11	21.06
M32	S10	Structures	62.53	0.003	0.15	0.0114	0.0144	1.8	11.99
M32	S10	Piping, valve and flange	4.31	0.001	0.08	0.0034	0.0044	0.04	0.47
M32	S09	Bulkhead	383.67	0.001	0.15	0.0008	0.0018	1.38	9.23
M32	S09	Stairs	122.82	0.01	0.1	0.0063	0.0163	20.07	200.71
M32	S09	Handrails	36.31	0.003	0.1	0.0059	0.0089	0.65	6.48
M32	S09	Equipment	565.89	0.001	0.1	0.0042	0.0052	5.94	59.38
M32	S09	Supports	17.44	0.01	0.1	0.0071	0.0171	2.97	29.74
M32	S09	Structures	1317.5	0.1	0.15	0.0178	0.1178	1317.5	8783.32
M32	S09	Piping, valve and flange	16.0	0.001	0.08	0.0025	0.0035	0.11	1.42
M32	S08	Bulkhead	313.68	0.001	0.15	0.0006	0.0016	0.98	6.56
M32	S08	Stairs	133.56	0.01	0.1	0.0065	0.0165	22.06	220.56
M32	S08	Handrails	11.38	0.003	0.1	0.0056	0.0086	0.2	1.95
M32	S08	Equipment	248.53	0.001	0.1	0.0041	0.0051	2.56	25.59
M32	S08	Supports	25.94	0.01	0.1	0.0076	0.0176	4.57	45.71
M32	S08	Structures	116.46	0.1	0.15	0.0174	0.1174	116.46	776.38
M32	S08	Piping, valve and flange	23.46	0.001	0.08	0.0024	0.0034	0.16	1.97
M32	S07	Bulkhead	435.73	0.001	0.15	0.0007	0.0017	1.52	10.14
M32	S07	Stairs	122.95	0.01	0.1	0.0055	0.0155	19.01	190.14
M32	S07	Handrails	39.67	0.003	0.1	0.0059	0.0089	0.7	7.04
M32	S07	Equipment	147.72	0.001	0.1	0.0044	0.0054	1.6	16.03
M32	S07	Supports	35.8	0.01	0.1	0.0058	0.0158	5.65	56.51
M32	S07	Structures	27.25	0.1	0.15	0.0156	0.1156	27.25	181.7
M32	S07	Piping, valve and flange	25.96	0.001	0.08	0.0025	0.0035	0.18	2.29
M32	S06	Bulkhead	350.86	0.01	0.15	0.0037	0.0137	48.01	320.08
M32	S06	Stairs	172.29	0.01	0.1	0.0057	0.0157	27.08	270.8
M32	S06	Handrails	0.67	0.01	0.1	0.0074	0.0174	0.12	1.17
M32	S06	Equipment	31.12	0.001	0.1	0.0046	0.0056	0.35	3.5
M32	S06	Supports	25.57	0.01	0.1	0.0068	0.0168	4.29	42.91
M32	S06	Structures	95.81	0.1	0.15	0.0178	0.1178	95.81	638.75
M32	S06	Piping, valve and flange	20.84	0.003	0.08	0.0043	0.0073	0.39	4.88
M32	S05	Bulkhead	305.03	0.01	0.15	0.004	0.014	42.71	284.73
M32	S05	Stairs	115.27	0.01	0.1	0.0064	0.0164	18.93	189.29
M32	S05	Handrails	25.97	0.003	0.1	0.0068	0.0098	0.51	5.09
M32	S05	Equipment	33.74	0.001	0.1	0.0039	0.0049	0.33	3.31

APM

Save.xlsx

Figure 9. Visualisation of the painting plan.

APM integrates these data to generate optimised maintenance plans, enabling efficient resource management and effective prioritisation of maintenance tasks on offshore platforms. After the maintenance plan has been finalised, APM can export the results directly to a 3D CAD/CAE platform model, providing a comprehensive spatial visualisation of the planned maintenance activities (Figure 10). This 3D visualisation capability allows maintenance teams to understand the spatial distribution of the planned interventions better, optimise work sequences based on physical proximity, and identify potential access or logistical challenges. Areas selected for maintenance are highlighted in the 3D model using a color-coded system with two views: a corrosion distribution map (left) and a painting plan (right). In the painting plan view, the blue-coloured areas highlight the specific sections selected for maintenance intervention, allowing for targeted painting work based on the identified corrosion patterns.

Comparison of the Results

APM is a tool that offers the user four distinct strategies for formulating a painting plan tailored to meet business needs according to the assumptions of each strategy. In this context, the painting plans generated by these strategies were compared: the PH limit, corrosion integrity, regulatory demand, and criticality. The aim was to give the user a general overview of each strategy's performance and the platform's final condition across specific metrics. The figures below (Figures 11 and 12) compare the strategies according to the remaining value, i.e., they attest, respectively, to the value of the average corrosion and the regulatory demand index resulting after optimisation, considering each strategy.

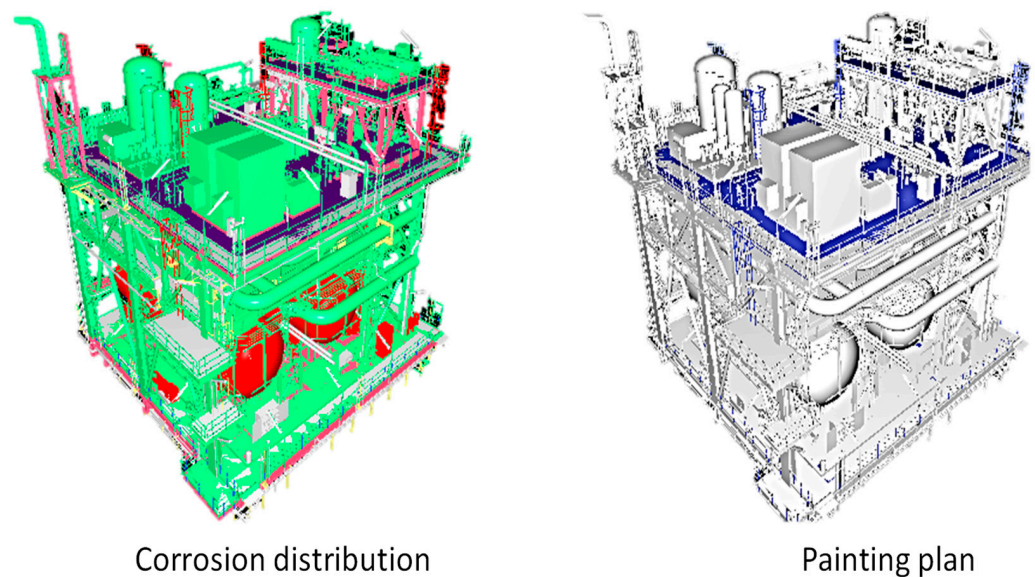


Figure 10. Visualisation of a 3D CAD/CAE model of the platform.

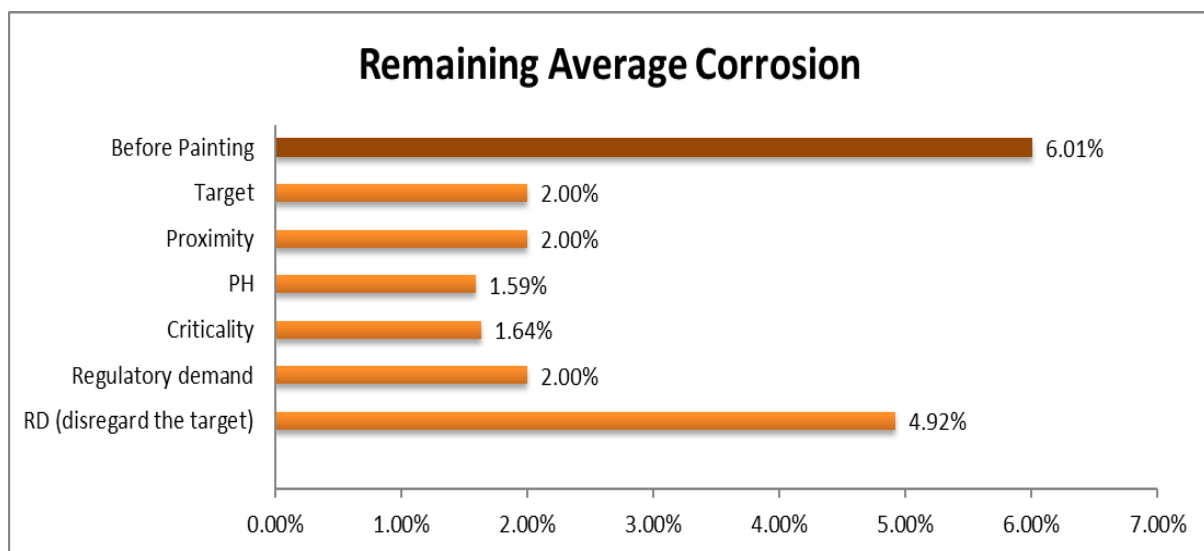


Figure 11. Remaining average corrosion (comparison of strategies).

The performances of the strategies regarding the remaining average corrosion are very similar due to the restricted corrosion integrity assigned to each of them. The PH strategy is the only one that generates a lower remaining percentage, as it is not assigned a corrosion value, since the target to be achieved is the decision variable of this model. Notably, the regulatory demand strategy with the “disregard target” option produces a higher percentage of remaining corrosion because it focuses solely on reducing regulatory demands without considering any corrosion targets. This single-objective focus explains why this strategy, while effective at addressing regulatory requirements, may result in suboptimal corrosion control outcomes compared with other strategies that explicitly consider corrosion targets in their optimisation criteria.

The results showed that most strategies achieve similar remaining average corrosion levels because they are constrained by the same corrosion integrity target, except the PH strategy. When analysing the remaining regulatory demand index, the regulatory demand strategy performs significantly better than other strategies, as it specifically optimises for this objective. The other strategies show limited impact on reducing the regulatory demand index because they do not explicitly consider this factor in their optimisation criteria;

instead, they focus on their respective primary objectives (corrosion control, resource utilisation, or the system’s criticality).

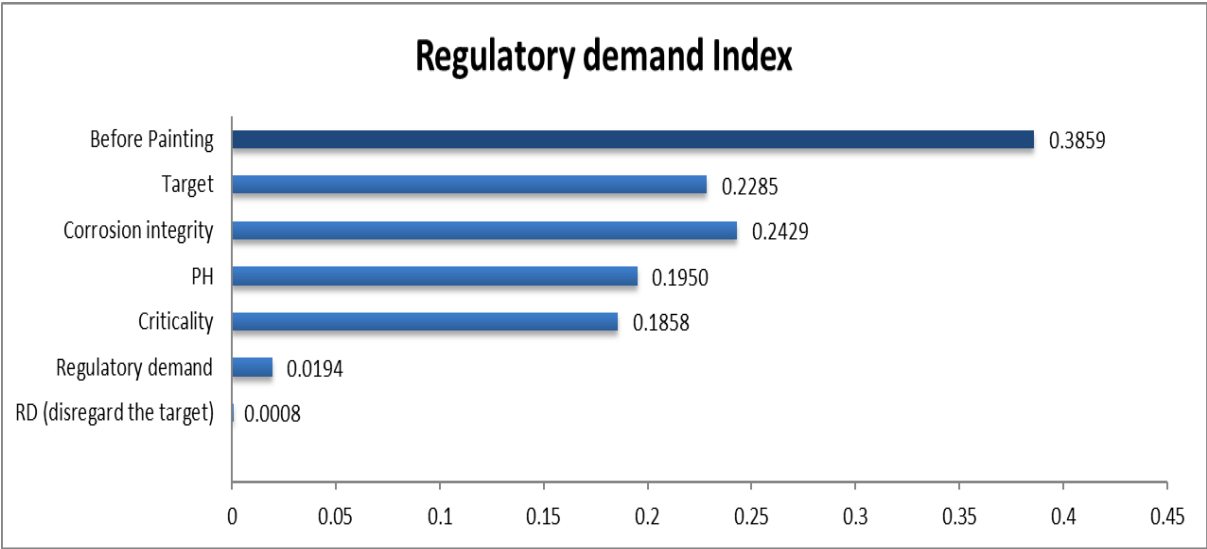


Figure 12. Remaining regulatory demand index (comparison of strategies).

Figure 13 compares how different strategies address high-criticality systems through their maintenance plans. Out of 472 high-criticality systems identified before painting, the criticality strategy selects 308 systems for maintenance, demonstrating the highest coverage of critical systems among all strategies. This superior performance is expected, since it is the only strategy explicitly incorporating criticality information in its optimisation criteria. Notably, the regulatory demand strategy with disregarded targets shows significantly lower coverage, including only 144 high-criticality systems, focusing solely on regulatory compliance without considering the system’s criticality. These results demonstrate the effectiveness of the criticality strategy in prioritising maintenance for systems that are most critical to platform operations.

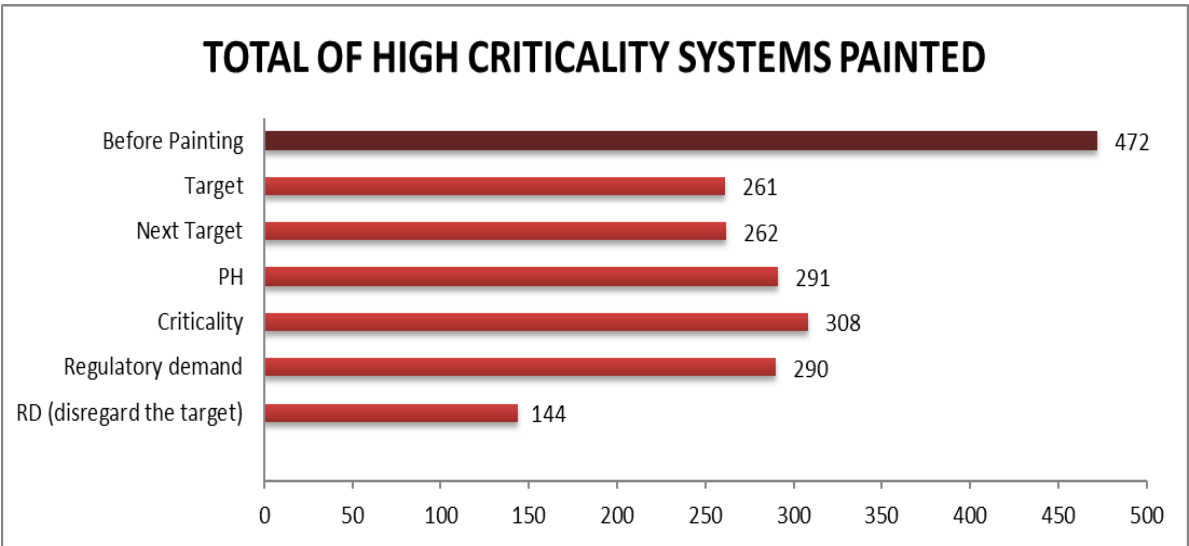


Figure 13. Criticality index of selected items (comparison of strategies).

Therefore, each strategy should be used to achieve specific objectives. While most strategies achieve similar levels of corrosion mitigation, they differ significantly in resource utilisation. Notably, the target strategy is efficient, achieving the desired corrosion con-

trol objectives while consuming considerably fewer person-hours than other approaches. To support this analysis, a detailed comparison of the different maintenance planning strategies implemented in the APM system is presented, focusing specifically on the PH limit (Figure 14). This analysis is crucial for understanding how each approach utilises the available resources and aligns with the maintenance objectives, particularly highlighting the trade-offs between resource consumption and maintenance outcomes across different strategies.

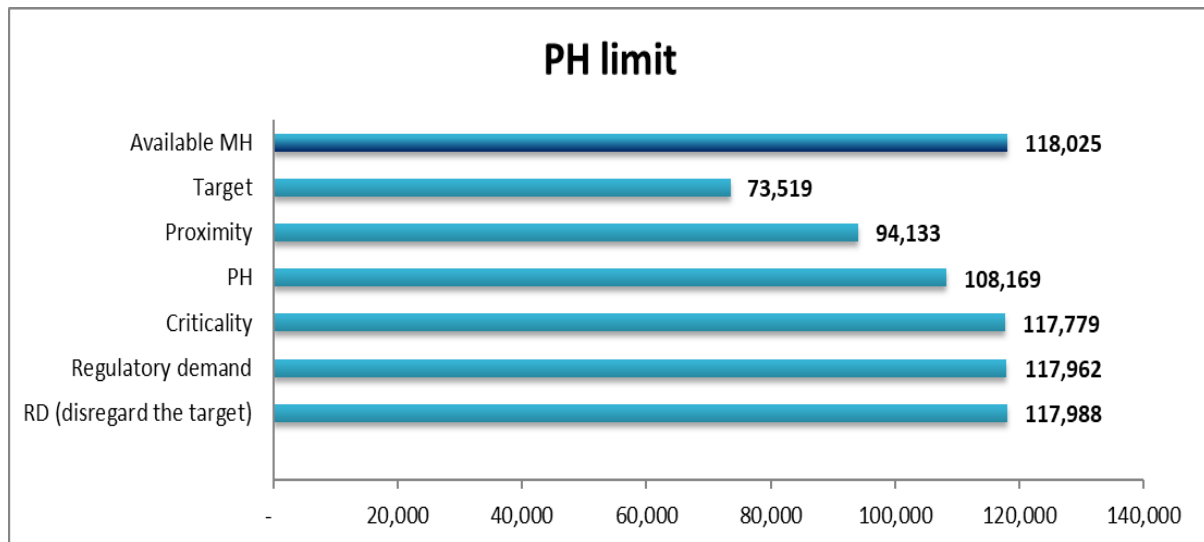


Figure 14. PH limit index (comparison of strategies).

The analysis of resource utilisation reveals significant trade-offs between different maintenance strategies. The PH strategy uses nearly 100% of available person-hours and achieves the highest corrosion reduction, but it does not optimise for regulatory demands or system criticality. In contrast, the target strategy demonstrates high efficiency by achieving the desired corrosion levels while consuming significantly fewer PH, though it also does not account for regulatory demands or criticality factors. The criticality and regulatory demand strategies utilise almost all the available person-hours while meeting the corrosion target. Still, each prioritises different objectives—the former focuses on critical systems while the latter addresses regulatory compliance requirements. These results demonstrate that APM can effectively adjust the resource allocation according to the strategic priorities. This adaptability allows maintenance managers to choose the strategy that best aligns with their particular requirements: whether to prioritise maximum corrosion reduction (the PH strategy), resource efficiency (the target strategy), critical system maintenance (the criticality strategy), or regulatory compliance (the regulatory demand strategy). The choice ultimately depends on the platform’s current priorities and constraints.

5. Discussion

The triangulation of results obtained from the different case studies in this research allows for a more comprehensive and well-grounded view of the APM prototype’s contributions to maintenance and painting planning in offshore platforms. By combining evidence generated through different methods, data sources, and theoretical perspectives, triangulation strengthens the credibility and robustness of the conclusions, increasing confidence in the effectiveness of the developed tool [91]. This approach provides more precise control over critical areas for structural integrity, demonstrating that the model addresses the regulatory compliance needs, optimises resources, and improves strategic planning in high-demand environments.

One of the triangulation strategies applied was methodological triangulation, which compared the results obtained through different approaches, such as evaluating the per-

formance of the machine learning model for predicting corrosion progression, using the regulatory demand index and the criticality index in real-world contexts, and analysing the painting plans generated by APM, considering different optimisation strategies. The convergence of positive results obtained from these different methodologies reinforces the validity and usefulness of APM in supporting maintenance and painting planning for offshore platforms [82].

These findings are consistent with previous studies on predictive maintenance and asset management [92], highlighting the importance of optimised, multifactorial planning for operational sustainability in hostile environments [71]. Incorporating machine learning and multi-criteria optimisation in APM goes beyond traditional approaches, aligning with Reliability-Centred Maintenance (RCM) theories that emphasise the control of critical variables such as corrosion in strategic assets [6].

Another strategy employed was data triangulation, which compared information collected from various sources, such as inspection histories, regulatory demand spreadsheets, criticality assessments of the systems, and feedback from APM users. The consistency of the insights generated from these multiple data sources increases the reliability of the conclusions regarding the prototype's effectiveness [93]. For example, the triangulation of the case study results demonstrates that integrating corrosion progression prediction models, the regulatory demand index, and the criticality index in APM allows for optimised painting plans, considering multiple relevant criteria for offshore assets' integrity management. Figure 15 compares the different maintenance strategies for the painted areas.

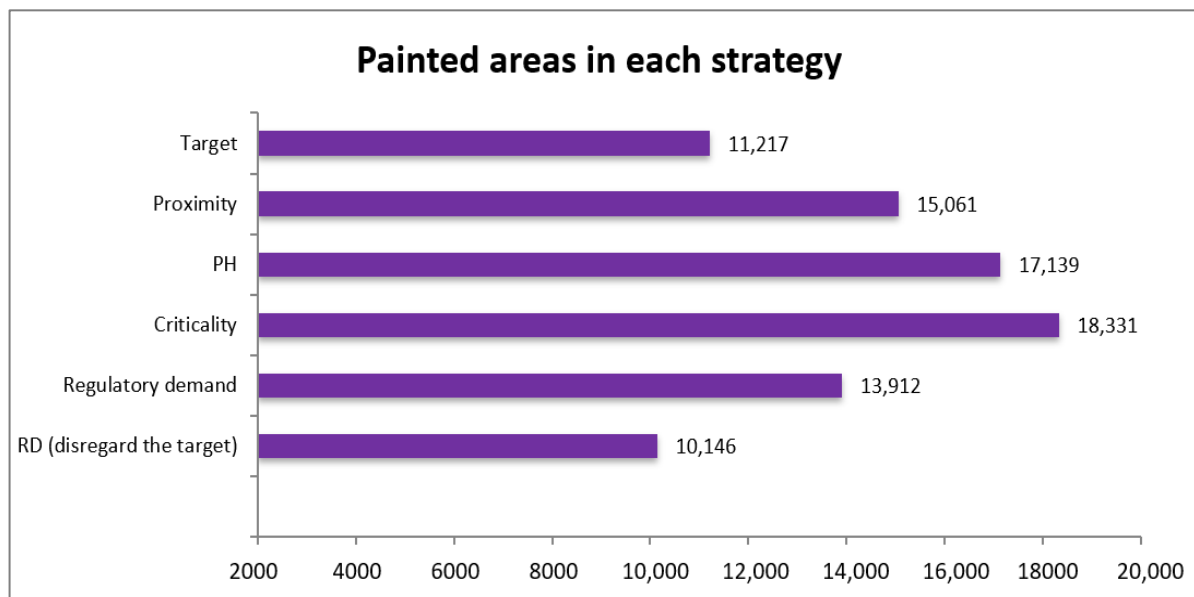


Figure 15. Painted area (comparison of strategies).

The comparison of maintenance strategies reveals compelling patterns in resource allocation and area coverage for offshore installation maintenance. The criticality strategy emerges as the most comprehensive, prioritising the most vulnerable and vital zones for structural integrity, demonstrating its effectiveness in addressing critical systems despite high resource demands. Closely following that is the PH strategy, showing strong optimisation of the available labour resources while achieving significant reductions in corrosion without specifically addressing the regulatory demands or the system's criticality. In contrast, the target strategy presents an intriguing efficiency profile, achieving the necessary maintenance objectives with notably lower resource consumption. This suggests a highly optimised approach that meets the designated corrosion control targets without exhausting the available resources. The regulatory demand strategy reflects a focused approach to the requirements of compliance, though this coverage reduces to 10,146 m² when disregarding

specific targets. These variations in the painted area reflect how different priorities and approaches in maintenance management can lead to diverse resource allocation strategies, each adapted to particular preservation and operational efficiency objectives.

Theoretical triangulation was also applied, interpreting the case study results through different conceptual perspectives, such as RCM, asset management, MCDM, and DSR theories. APM's ability to adhere to the principles and assumptions of these diverse theories, along with its integration of AI models to improve the accuracy and efficiency of corrosion prediction [7], reinforces its conceptual foundation and relevance in the application domain. Furthermore, the triangulation of positive feedback from APM users (collected through interviews, focus groups, and surveys) with the objective results of the case studies strengthens the practical utility and applicability of the prototype, indicating its potential to deliver real value to offshore maintenance and painting teams [94]. This triangulation of subjective perceptions with empirical evidence enhances the external validity and transferability of the research findings, underscoring the contribution of AI to informed and efficient decision-making in offshore maintenance environments.

The choice of the DSR methodology for the creation of APM confirms its relevance in complex and dynamic scenarios such as offshore platforms, where flexibility and adaptability are essential. Studies in DSR [24] highlight that this approach allows continuous iteration and real-time adjustments, reinforcing the value of APM as an adaptive and continuously improving system for maintenance planning. The compatibility of APM with theories such as RCM and MCDM provides a robust, multi-dimensional conceptual framework, emphasising its potential for application in other industrial sectors [51].

Finally, researcher triangulation was also employed, involving different team members in analysing and interpreting the case study results, seeking for a consensus and divergences in their perceptions. The agreement among multiple investigators' assessments of APM's effectiveness increases the objectivity and impartiality of the conclusions. By integrating evidence from different sources, methods, and theoretical perspectives, triangulation strengthens the validity and relevance of the findings, demonstrating that the developed prototype is an effective and innovative tool to support maintenance and painting planning on offshore platforms. It overcomes the limitations of traditional methods and creates tangible value for organisations in the sector.

The applicability of the APM system in various offshore environmental contexts represents a consideration for its global implementation. Although the case studies focus on specific platforms, the system shows potential for adaptation to different marine environmental conditions, ranging from the Arctic to tropical zones, each with its particular maintenance and corrosion challenges. Arctic environments introduce variables such as freeze–thaw cycles and sea ice formation [95], while tropical zones present challenges related to high humidity and intense UV radiation exposure [71]. Temperate environments, in turn, require consideration of significant seasonal variations [96]. The system's adaptability is implemented through environmental adjustment modules, correction factors for the corrosion rates, and modifications of the optimisation algorithm according to each location's specific conditions. Nonetheless, when changing the context, the algorithm must be retrained with new environment-specific data, which does not affect the system's structure but incorporates additional variables to ensure the accuracy of predictions and the effectiveness of the generated maintenance plans. This flexibility enhances the global utility of the system as an offshore maintenance management tool, enabling its effective implementation across diverse marine environmental conditions and improving the accuracy of predictions and the effectiveness of the generated maintenance plans.

6. Conclusions

This study has effectively addressed the main research question through the systematic application of DSR. The iterative DSR process, which ranged from problem identification to evaluation and communication of the artefact, enabled a comprehensive approach to the

specific challenges of offshore maintenance, resulting in a robust system adaptable to the sector's needs.

The research fulfilled SO1 through the development of the APM prototype. This tool integrates 3D models with advanced computational tools and incorporates multiple functional modules that address various aspects of maintenance planning. SO2 was achieved through the triangulation of the case study results, enabling an evaluation of the impact of different optimisation strategies on the generation of painting plans and providing valuable insights into the effectiveness of each approach.

Integrating artificial intelligence techniques, specifically machine learning models for corrosion progression prediction, has proven crucial in enhancing the accuracy and efficiency of maintenance planning. This data-driven approach optimises resources and contributes significantly to environmental sustainability by minimising waste and extending the lifespan of offshore structures. APM's ability to process and analyse large volumes of historical data enables more informed and proactive decision-making, fundamentally transforming maintenance management in offshore environments.

The APM prototype represents a significant advancement in the digitalisation of maintenance project management, offering a human-centred approach that balances technical, regulatory, and environmental demands. Integrating AI in the decision-making process allows for more accurate predictions of asset degradation, facilitating timely preventive interventions; dynamic optimisation of maintenance plans in response to changing conditions; the analysis of complex scenarios by considering multiple variables simultaneously; and continuous improvements in maintenance strategies through machine learning.

The methodology and framework developed in this study offer significant contributions that can be generalised and replicated in developing other integrity management systems. In particular, integrating 3D models for visualisation and planning presents an innovative paradigm that could be extended to various types of critical infrastructure. The modular structure of APM provides an adaptable framework for other asset management contexts, demonstrating how AI can customise solutions for different industrial sectors.

The validation process through case studies and focus groups, as well as visualisation of the results and strategy comparison techniques, offer robust methodologies that can be replicated in developing and evaluating other decision-support systems in maintenance.

However, this study presents some limitations. The system's applicability has primarily been tested in the context of offshore platforms, and its effectiveness in other industrial settings has yet to be evaluated. Furthermore, reliance on high-quality historical data for training machine learning models may limit its implementation in scenarios with insufficient or unreliable data.

For future work, exploring several areas that would expand the proposed system's functionality and applicability is recommended. One key improvement would be the integration of Internet of Things (IoT) technologies to enable continuous real-time data collection, which would enhance the predictive capabilities and allow for a more immediate response upon detecting anomalies. Incorporating IoT sensors at critical points of the infrastructure would allow constant monitoring of the environmental and structural factors, optimising the precision of the maintenance models.

Another relevant direction for future research is adapting the system to onshore installations, where the operational requirements and environmental conditions differ significantly from those of offshore platforms. This would require adjustments in the optimisation algorithms and prioritisation criteria, tailoring them to the specificities of onshore environments. Additionally, implementing specific simulations for different types of onshore installations would help validate and adjust the model in these contexts.

Finally, integrating advanced machine learning techniques would enable the system to continuously adapt and improve using collected data, optimising maintenance schedules more precisely and efficiently. These enhancements would extend the system's applicability and increase its effectiveness and robustness across various industrial environments.

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