Multi-objective decision making for maintenance planning of deteriorating offshore floating systems

Multi-objective decision making for Maintenance Planning of deteriorating Offshore Floating Systems

by

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Glory to God in the highest

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Abstract

Maintenance planning program of offshore assets is a complex activity due to its impact on the operational and safety risks and consequences, dependence on personnel resource availabilities, site constraints due to operational requirements and environmental factors, and uncertainties related to various vulnerabilities on asset. This thesis elaborates the challenges on offshore maintenance frameworks and have carried out a review of recent state-of-the-art literature from which have observed that the current state-of-the-art does not incorporate site constraints of the asset related to offshore personnel resource availability and impact of time required to carry out activities, into the maintenance plan and its impact on other activities due to the maintenance. Also, it has been identified that dynamic and autonomous resource allocations for maintenance activities are not employed in the offshore maintenance planning program that allows each maintenance item to independently adjust its resource allocation based on the time required to complete the activity, to improve the resource utilisation.

In this work, a novel approach has been utilised to formulate a maintenance plan optimisation problem for a Floating Production Storage and Offloading Facility (FPSO) that maximises the maintenance personnel resource utilisation and enable FPSO condition enhancement, considering the priorities with respect to design features, operating conditions, deteriorations, and the consequences of not doing the maintenance, taking into consideration the personnel resource time required for activity completion. To find the Pareto-optimal solution, an overall objective function has been developed corresponding to maintenance priorities with respect to Stress Unity Check, Fatigue Damage Ratio, Bending Moment Ratio, Shear Force Ratio, Degree of Corrosion Scale, Degree of Metal Loss, Safety Risks in the event of not doing maintenance and Financial Risks in the event of not doing maintenance, taking into consideration the personnel resource time required for activity completion using the weighted sum approach. This formulation provides flexibility to direct the focus of the overall objective function towards any one or more of the objective functions by adjusting their respective weight according to the maintenance strategy followed, which would supplement the Regulatory oversight requirements of the FPSO.

Also, in this work, a novel work management framework has been proposed that comprises of Deep Q-Reinforcement Learning (DQN) problem formulation as a solution to multi-objective optimisation problem for maintenance activities of FPSOs. The framework enables carrying out activities that have minimal site constraints, considering the design features, operating conditions, deteriorations, consequences of not doing the activities and time required to complete the activities, to get higher weighted sum of the completion times at short time as possible, whereby achieving higher resource utilisations. A greedy algorithm benchmarks the performances of DQN model and a hybrid model comprising of greedy and DQN parameters. This formulation enables achieving the optimal path for carrying out activities that liquidates the risks to the asset's performance, which would in turn supplement the Regulatory oversight requirements of the FPSO.

Chapter1

Introduction

1.1 Background and Motivation

With the emergence of nuclear industry in the 1900s, the risks associated with any accidents in that industry became a main concern, due to the very high consequences involved. With that, there was a wide emphasis on the predictive methodologies with the aim to lower any potential risks. This approach was subsequently passed on to other industries including, petrochemical, offshore and marine sectors. The offshore asset is an integration of various floating systems, having individual needs on maintenance, governed by their design features, operating conditions, deterioration mechanisms and risks involved in not doing the maintenance activity. The practical site constraints encountered have an impact on the maintenance execution and the utilisation of resources, which generally not get accounted for in the maintenance strategies. This in turn reduce the effectiveness and confidence of the maintenance framework. The research work detailed in the subsequent pages have been based on this philosophy and investigate the merits and weaknesses on the current practises in maintenance frameworks with the aim to develop an effective maintenance management approach for offshore floating systems addressing the site constraints of personnel availability and impact of time required to carry out activities, governed by overall risks and site constraints, whereby enhancing the effectiveness and confidence of the framework.

1.2 Research Gaps

Through an extensive and comprehensive literature survey, the following gaps were found:

• It has been identified that the current state-of-the-art literature does not incorporate specific site operational constraints of the asset related to predicted offshore personnel resource availability for the maintenance activity, due to maximum allowable bed space, impact of time required to carry out activities and its impact on other activities due to this maintenance.

• Also, it has been identified that there is no evidence to support that adaptive timetabling happens such that dynamic and autonomous resource allocations for maintenance activities take place in the offshore maintenance planning systems that allows each maintenance item to independently adjust its resource allocation based on the time required to complete the activity, to improve the resource utilisation.

• It has also been noted that the expectation is that maintenance planning enables personnel resource allocations, such that the resources are accessible on demand, confirm quality service on demand, provide maintenance activities on demand and provide maintenance with lower costs; however, it would be challenging to have different systems served independently with a proper resource allocation made according to their own requirements.

• It has been concluded that there exists scope for further research works that addresses the site constraints of personnel resource availability, impact of time required to carry out activities and its impact on asset condition due to the maintenance execution, by examining machine learning and deep reinforcement learning network based artificial intelligence approach that would reduce the human intervention and bring consistency, considering the design features, actual condition of the component, site constraints, deterioration factors, consequences of not doing the activities, time required to complete the activities and investigating the impact on key maintenance performance indicators regarding resource allocations and resource utilisations. This would in turn optimise resources without compromising safety and efficiency while maintaining or lowering the risk levels in the life cycle.

1.3 Research Problems and Challenges

An optimised strategic planning of maintenance activities would be required satisfying Regulatory and Owners' requirements, without compromising safety and reliability of the asset, within the constraints of maintenance duration, activity completion, resource availability due to offshore bed space restrictions. It has been noted that the maintenance performance indicators widely considered relates to the asset availability, reliability, and safety compliance, whereas the site constraints and impact of time required to carry out activities are not regarded as a performance indicator in any of the literature, which is a major limitation of the existing frameworks, as the availability of bed space offshore for any activity is the prime performance indicator for any maintenance execution.

It has been noted that probabilistic assessment models, Bayesian Networks and Multi-objective optimisation techniques have been widely used in the literature for optimisation of maintenance activities. Most of these methods generate a set of pareto optimal solutions and use some additional criterion or rule to select one particular pareto optimal solution as the solution of the multi-objective problem. There exists scope for further research work that would incorporate site constraints and impact of time required to carry out activities including the Offshore resource availability into the maintenance plan and its impact on asset condition due to the maintenance execution.

Even though many good maintenance models and frameworks are available in the literature, there still remains a significant gap in incorporating the overall risks and site constraints into the maintenance program. Most of the methodologies take into account the failure events of only few selected critical components and criteria, without integrating with the complete system and associated overall risks. In order to achieve the optimum maintenance plan, the operational and environmental uncertainties, maintenance uncertainties, unpredictive resource availability for maintenance execution, uncertainties related to damage and degradation mechanisms, uncertainty of failure occurrence and the deviations from design assumptions needs to be assessed and considered.

The maintenance planning also needs to be integrated with the inspection plans and offshore resource availability to achieve a credible implementation plan incorporating the overall risks. The constraints of Offshore personnel availability for the maintenance activity due to maximum allowable bed space is a factor not considered in any of the frameworks identified in the literature review. This is a major limitation of the existing state-of-the art maintenance frameworks. There are still research gaps in frameworks, towards incorporating the overall risks, practical site constraints encountered mainly with regards to the availability of bed space onboard for the personnel and impact of time required to carry out activities.

1.4 Research Aims and Objectives

The aim of this research work was to develop an effective maintenance management approach for offshore floating systems, governed by overall risks and site constraints and thereby enhancing the effectiveness and confidence of the framework.

This research is organised in the following 3 main objectives:

Research Objective 1: Investigate the maintenance frameworks and offshore operational conditions, addressing the significance of overall risks and site constraints in better decision making for maintenance planning, so as to develop an algorithm for multi-objective decision making for maintenance planning.

Research Objective 2: Investigate how the logic behind qualitative risk assessment on prioritisation of activities on the asset and managing the risks could be incorporated into multi-objective decision making for maintenance planning.

Research Objective 3: Investigate how to employ artificial intelligence to enhance the effectiveness of maintenance frameworks for offshore floating systems, by incorporating overall risks, operational priorities, and site constraints.

1.5 Research Questions

The main research questions that were addressed in this work were as follows:

• Investigate how the site constraints, overall risks associated to an offshore asset and their consequences could be incorporated into the maintenance and repair planning of the offshore floating systems.

• Investigate how to describe the condition of offshore floating systems and evaluate their repair and maintenance requirements and how to estimate and optimise the repair and maintenance costs, using engineering techniques.

• Investigate how to predict the condition of offshore floating systems and estimate repair and maintenance costs at a future point of time and how to evaluate the optimum repair and maintenance strategy, using artificial intelligence techniques.

The above-mentioned questions were addressed by way of the research methodology detailed in the following section.

1.6 Research Objective and Methodology

1.6.1 Research Objective 1

The relation between maintenance frameworks, offshore operational conditions, overall risks and operational constraints were addressed, employing information from other published literature of corrosion rates of ships. Also, simulation of scenarios were made based on published data and real life experience. The commercially available loading calculator has been employed to parametrically define the geometric model. The results were studied in depth in order to develop the algorithm for multi-objective optimisation of maintenance planning. In this part of the research a novel feature-engineering algorithm has been designed that incorporate the impact of time required to complete the activities on the optimisation objectives of Floating Production Storage and Offloading Facility (FPSO) design features, operating conditions, deteriorations, consequences of not doing the maintenance and the personnel resource availability for activity completion. Also, the benchmarking of the algorithm has been carried out by comparing the parameters, with and without considering the time required to complete the task, which reflects influence of the time required to carry out the activity, on the prioritisation of activities.

The evaluation of the model has been carried out by comparing the priorities for each scenario based on 3 different loading conditions of the FPSO – light load condition, medium load condition and full load condition. The performance of the greedy algorithm has been evaluated in terms of the personnel resource allocation and resource utilisation. To evaluate the satisfaction of resource allocation, the weighted sum of the task completion times based on the priorities have been considered. To evaluate the satisfaction of resource utilisation, it has been considered that the higher weighted sum of the completion times at as short time as possible, leads to higher resource utilisations. This algorithm will leverage behaviours from operating scenarios, which later has been used as an input to artificial intelligence algorithm.

1.6.1.1 Research Contribution

The deliverables of this objective were:

Through an extensive and comprehensive literature survey it has been identified that the current state-of-the-art literature does not incorporate site operational constraints of the asset related to offshore personnel resource availability for the maintenance activity, due to maximum allowable bed space, impact of time required to carry out activities and its impact on other activities due to this maintenance.

Also, it has been identified that there is no evidence to support that dynamic and autonomous resource allocations for maintenance activities take place in the offshore maintenance planning systems that allows each maintenance item to independently adjust its resource allocation based on the time required to complete the activity, to improve the resource utilisation. It has also been noted that the expectation is that maintenance planning enables resource allocations, such that the resources are accessible on demand, confirm quality service on demand, provide maintenance activities on demand and provide maintenance with lower costs; however, it would be challenging to have different systems served independently with a proper resource allocation made according to their own requirements.

This review work leads to the journal manuscript titled 'Recent Advances and Future Trends on Maintenance Strategies and Optimisation Solution techniques for Offshore sector', which has been published in Elsevier Journal - Ocean Engineering 250, 110986 (2022) [see the list of publications -1].

A maintenance plan optimisation problem was formulated that maximise the maintenance personnel resource utilisation and enable FPSO condition enhancement, considering the priorities with respect to design features, operating conditions, deteriorations, and the consequences of not doing the maintenance, taking into consideration the personnel resource time required for activity completion.

This has been achieved by developing a FPSO main deck maintenance system model incorporating design features, operating conditions, deteriorations, consequences of not doing the maintenance and the personnel resource estimated to complete the activity. To enable the problem formulation, a novel approach has been utilised such that the decision variables for each location on the FPSO have been normalised between the maximum and minimum values along the length of FPSO in order to bring the variables related to the functionality in proportion with that at other locations along the FPSO, and also to enable scaling all of the decision variables and whereby their respective objective functions to the same magnitude. Also, a novel approach has been employed for the multi-objective optimisation of FPSO main deck maintenance activities, such that to find the Pareto-optimal solution, an overall objective function has been developed as a linear combination of the multiple objective functions corresponding to maintenance priorities with respect to normalised Stress Unity Check, Fatigue Damage Ratio, Bending Moment Ratio, Shear Force Ratio, Degree of Corrosion Scale, Degree of Metal Loss, Safety Risks in the event of not doing maintenance and Financial Risks in the event of not doing maintenance respectively, taking into consideration the personnel resource time required for activity completion. Depending on the priority of the objective function when compared to other objective functions, a relative weight has been associated to the prioritised objective function, using the weighted sum approach. Also, the formulation enables maximisation and minimisation of the objective functions and provides flexibility to direct the focus of the overall objective function towards any one or more of the objective functions by adjusting their respective weight according to the maintenance strategy followed.

1.6.2 Research Objective 2

The benchmarking and analysis of the algorithm from Objective 1 for problem formulation of FPSO main deck maintenance, was carried out, by comparing the parameters, with and without considering the time required to complete the task, which reflects influence of the time required to carry out the activity, on the prioritisation of activities.

1.6.2.1 Research Contribution

The deliverables of this objective were:

A novel multi-objective optimisation of maintenance activities has been formulated whereby a greedy algorithm has been proposed, which incorporates the impact of time required to complete the activities on the optimisation objectives of design features, operating conditions, deteriorations, consequences of not doing the maintenance and the personnel resource availability for activity completion. The greedy algorithm follows the problem-solving pattern of making the locally optimal choice at each step with the hope of finding the globally optimal solution. It works step by step looking at the immediate situation and chooses the steps that provide immediate benefits. This in turn enables achieving the most feasible solution immediately. Also, greedy algorithm is computationally cheaper, easier to implement and good approximations are obtained, and hence chosen for this work.

The benchmarking of the algorithm has been carried out by comparing the parameters, with and without considering the time required to complete the task, which reflects influence of the time required to carry out the activity, on the prioritisation of activities.

The performance of the greedy algorithm has been evaluated in terms of the personnel resource allocation and resource utilisation. To evaluate the satisfaction of resource allocation, the weighted sum of the task completion times based on the priorities have been considered. To evaluate the satisfaction of resource utilisation, it has been considered that the higher weighted sum of the completion times at as short time as possible, leads to higher resource utilisations.

Also, for multi-objective optimisation, an overall objective optimisation problem has been proposed by linear combinations of the multiple objective functions and depending on the priority of an objective function when compared to other objective functions, a weighting factor could be associated to the prioritised objective function, using the weighted sum approach.

The novel approaches employed in this work for multi-objective optimisation of FPSO maintenance activities, leads to the journal manuscript titled ‘Novel Multi-objective Optimisation for Maintenance Activities of Floating Production Storage and Offloading Facilities’, of which submitted to Elsevier Journal - Applied Ocean Research, in October 2021- Manuscript no. APOR-D-21-00884 [see the list of publications -2].

1.6.3 Research Objective 3

In order to bypass the challenges identified in Objective 2, an artificial intelligence algorithm has been developed that comprises of Deep Q-Reinforcement Learning (DQN) problem formulation as a solution to multi-objective optimisation problem. The goal was to achieve the best trade-off between the turnaround time for the activities and liquidating the risks to the asset’s performance, based on completion of activities in the work management system.

1.6.3.1 Research Contribution

The deliverables of this objective were:

A sophisticated artificial intelligent tool able to bypass the challenges and limitations identified in sections 2 and 3, has been developed such that a novel work management framework has been proposed that enables carrying out activities that have minimal site constraints, considering the design features, operating conditions, deteriorations, consequences of not doing the activities and time required to complete the activities, to get higher weighted sum of the completion times at short time as possible, whereby achieving higher resource utilisations.

A greedy algorithm benchmarks the performances of DQN model and a hybrid model comprising of greedy and DQN parameters, with respect to average number of timesteps per episode – the smaller number of timesteps per episode means agent take minimum steps/shortest path to reach the target; average rewards per timestep – the larger the reward means the agent is doing the right thing; the solution provides execution of maintenance activities having minimal site constraints leading to better resource utilisation and completion of activities; average number of penalties per episode – the smaller the number, the better performance of agent. It has been noted that overall, the hybrid and the DQN models achieve better results when compared with the Greedy model, towards task completion time and liquidating the risks to the asset's performance.
The novel approach employed in this work for multi-objective optimisation with Deep Q-Reinforcement Learning for FPSO maintenance activities, leads to the journal manuscript titled 'Novel Multi-objective Optimisation with Deep Q-Reinforcement Learning (DQN) for Maintenance Activities of Floating Production Storage and Offloading Facilities', of which submitted to Taylor & Francis Journal – Ships and Offshore Structures, in February 2022 – Manuscript no. 220812080 [see the list of publications -3].

A future research direction has been proposed incorporating DQN algorithm and have positioned the succeeding research that could in turn lead to the development of a comprehensive maintenance management tool that would be consistent, unaffected by human factors and incorporates the integration of the risks and site constraints on the overall Offshore operations. Also, the tool could be adapted to predict the asset condition in future and could be used to estimate repair costs, schedule repairs, evaluate consequences of repair strategy.

1.7 Structure of the Thesis

The thesis is divided into six main chapters, which includes this chapter as introduction, and states the background and motivation behind this research work. The remainder of the chapters are organised as follows.

An investigation of the current state of the art literature on maintenance strategies, and optimisation solution techniques for offshore sector have been carried out in Chapter 2, to identify scope for further research work to enhance the effectiveness and confidence of the maintenance frameworks.

In Chapter 3, a novel multi-objective optimisation problem for maintenance activities has been formulated, that maximise the maintenance personnel resource utilisation and enable FPSO condition enhancement, considering the priorities with respect to design features, operating conditions, deteriorations, and the consequences of not doing the maintenance, taking into consideration the personnel resource time required for activity completion.

In Chapter 4, benchmarking and evaluation of the machine learning algorithm has been carried out, in terms of the personnel resource allocation and resource utilisation by comparing parameters, with and without considering the time required to complete the task. Also, for multi-objective optimisation, the overall objective optimisation problem has been proposed by linear combinations of the multiple objective functions, using the weighted sum approach.

Chapter 5 proposes a novel work management framework that comprises of DQN problem formulation as a solution to multi-objective optimisation problem, to enable carrying out activities that have minimal site constraints, considering the design features, operating conditions, deteriorations, consequences of not doing the activities and time required to complete the activities, to get higher weighted sum of the completion times at short time as possible, whereby achieving higher resource utilisations. A greedy algorithm benchmarks the performances of DQN model and a hybrid model comprising of greedy and DQN parameters.

Chapter 6 proposes a future research direction incorporating DQN algorithm and have positioned the succeeding research that could in turn lead to the development of a comprehensive maintenance management tool, which would be consistent, unaffected by human factors and incorporates the integration of the risks and site constraints on the overall offshore operations.

Chapter2

Literature Review

2.1 Introduction

This Chapter reviews existing literature on maintenance strategies, and optimisation solution techniques for offshore sector. Maintenance strategies are a prominent factor in offshore maintenance management due to the high resource costs involved and due to the fact that they are a mitigation against the rate of deteriorations through age. The maintenance strategies of offshore systems are governed by the operational requirements and regulatory compliance in terms of seaworthiness and safety of the asset. The key maintenance performance indicators include maximising the asset availability and reliability, maintaining safety and regulatory compliance, and minimising the costs. The maintenance activities are planned and prioritised based on the associated consequences, within the constraints of manpower and material availability. The prioritisation of offshore maintenance activities is based on the activity's impact on the control measures that liquidate the risks to the asset's performance. On one hand, offshore maintenance planning is facing expectations to optimise the maintenance regimes to minimise the costs related to resources and labour, and to improve the asset availability and reliability, while maintaining safety compliance. It is expected that the offshore maintenance planning system enables carry out activities that have minimal site constraints, to get higher resource utilisation and reduce operating costs.

It would be challenging to have different offshore systems served independently with a proper resource allocation and resource utilisation, taking into consideration the site constraints, while maintaining interference between production critical and safety critical activities.

Major contribution made by this Chapter is that, by carrying out an extensive and comprehensive literature survey, the following gaps were found:

• The current state-of-the-art literature does not incorporate site constraints of the asset related to offshore personnel resource availability for the maintenance activity, due to maximum allowable bed space, impact of time required to carry out activities and its impact on other activities due to this maintenance. There exists scope for further research work that would incorporate these site constraints, the completion time of activities and its overall impact into the maintenance plan. The criticality of other systems in the Offshore asset would also need to be incorporated employing the current condition data, to enhance the confidence of the strategy.

• There is no evidence to support that dynamic and autonomous resource allocations for maintenance activities take place in the offshore maintenance planning systems that allows each maintenance item to independently adjust its resource allocation based on the time required to complete the activity, to improve the resource utilisation. It would be expected that maintenance planning enables resource allocations, such that the resources are accessible on demand, confirm quality service on demand, provide maintenance activities on demand and provide maintenance with lower costs. However, it would be challenging to have different systems served independently with a proper resource allocation made according to their own requirements. In that respect, the maintenance models have to incorporate the site operational constraints related to personnel resources, impact of time required to carry out activities and its impact on the overall activities in the maintenance planning system.

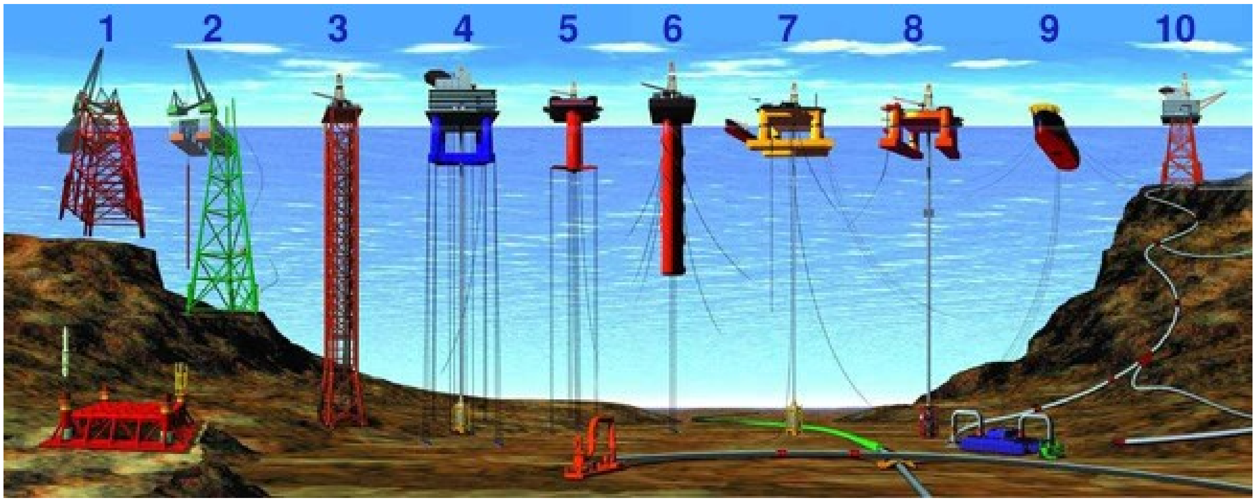

Figure 2.1: Offshore Oil and Gas Systems [1]

2.2 Offshore sector and maintenance requirements

The offshore structures installed in the ocean for oil and gas exploration and extraction, and for power generation from wind are the main assets that categorise as offshore sector.

The various offshore oil and gas systems indicated in Figure 2.1 could be categorised as Fixed Platforms (1, 2), Tower Platforms (3), Tension Leg and Mini-tension leg platforms (4, 5), Spars (6), Semi-submersibles (7, 8), Floating Production, Storage and Offloading Facilities (9), Sub-Sea tie-back to Platforms (10).

The various offshore wind floating structures indicated in Figure 2.2 could be categorised as Spars (a), Semi-submersibles (b), Mooring stabilised Tension Leg Platforms (c).
The maintenance would be required on an offshore equipment or component when its properties deteriorate by age and reach the point of affecting the performance and safety. Maintenance would control or slow down the rate of deterioration and an optimum maintenance plan would fulfil the requirements and repair strategy. The maintenance frequency would be based on the age, the maintenance history, findings from inspections and the rate of

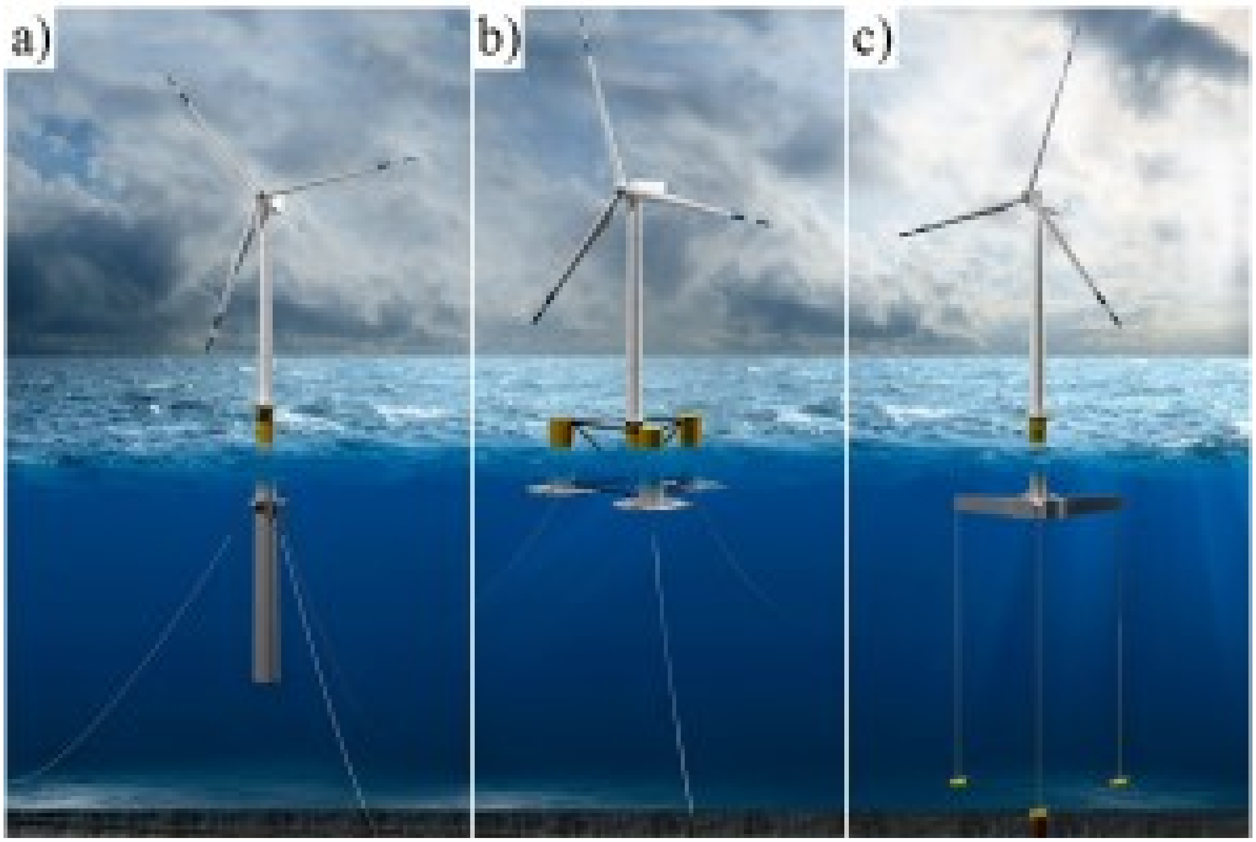

Figure 2.2: Offshore Wind floating structures [2]

deteriorations. The various considerations include operational priorities and critical service vulnerabilities, safety compliance and production performance, prioritisation of activities and overall risks, uncertainties on damage and deterioration mechanisms and deviations from design assumptions and conditions, criticality of maintenance and impact assessment of consequences in the absence of maintenance and condition for maintenance, controls, and mitigations.

The typical damage and deterioration mechanisms on offshore assets includes corrosion, cracks, and deformations/imperfections, which forms the basis for what normally goes wrong in an asset's life. An evaluation of the deterioration mechanisms, deterioration rates, the associated uncertainties and their acceptance criteria would be required to accurately quantify the risk and failure events. The assumptions made during the component design and risk evaluations could become invalid due to various operational and environmental factors such as unexpected scenarios due to extreme weather conditions, loading/offloading patterns, functionality of critical equipment, faults/errors in gauging and monitoring devices. Also, the deviations during the fabrication and manufacturing phases such as geometric and material imperfections, workmanship depending on quality control, regulatory and shipyard practices, plays a vital role on the state of degradations. The skills of the maintenance personnel and performance of maintenance tools, which varies on individual cases would play a critical role in the effectiveness of the maintenance program. A review of causes behind incidents in offshore oil and gas facilities has found that >50% of the fire incidents analysed were related to piping system and machinery equipment failure, as per S Z. Halim et al. 2018 [3].

The Figure 2.3 above shows the corrosion and cracks found on offshore platform structures.

The Figure 2.4 shows the corrosion rate for the inner bottom plates, based on statistics

Figure 2.3: Corrosion on gratings and Cracks on plates of Offshore structures [4]

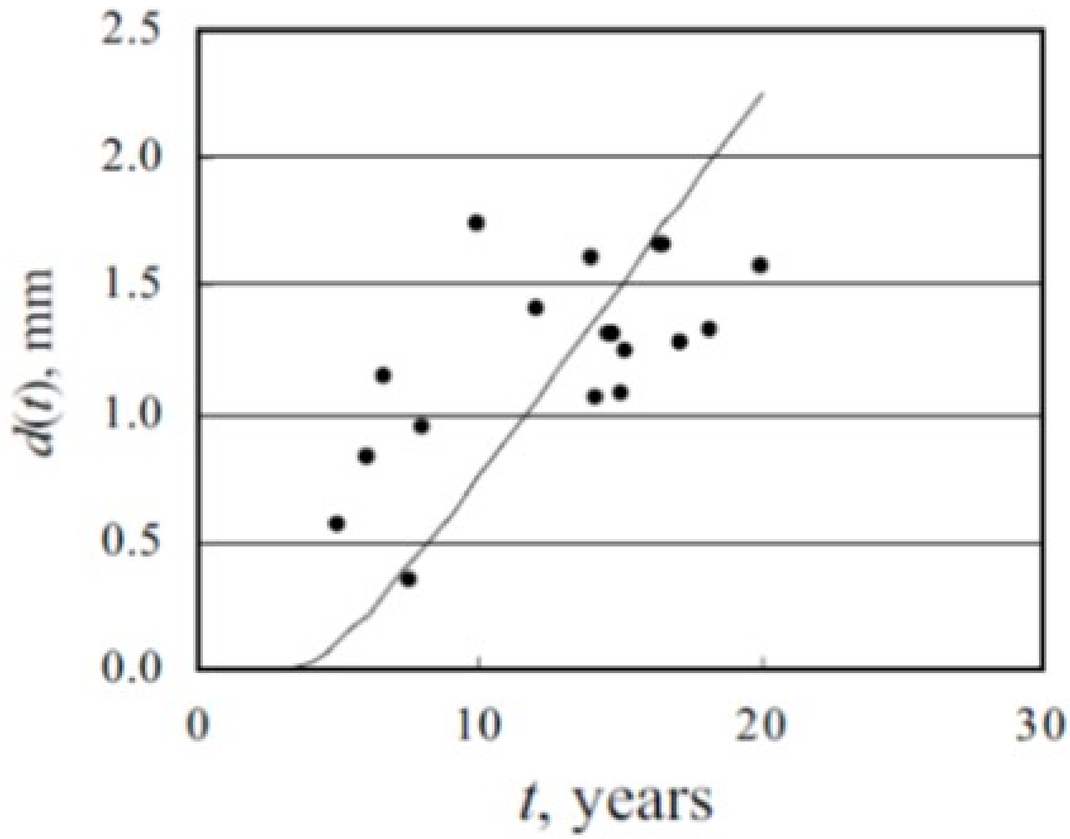

Figure 2.4: Loss of plating thickness from corrosion, for inner bottom plates [5]

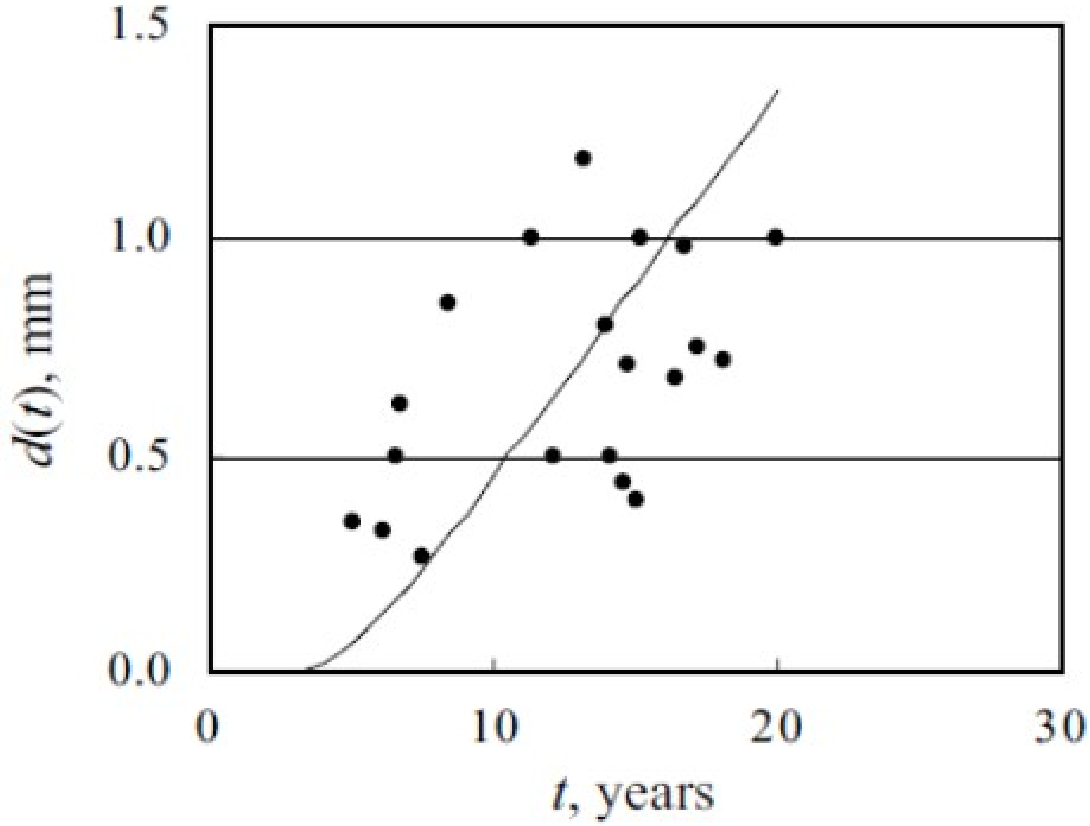

Figure 2.5: Loss of plating thickness from corrosion, for side shell plates [5]

of measurement data.

The Figure 2.5 shows the corrosion rate for the side shell plates of bulk carriers, based on statistics of measurement data.

Corrosion rates of offshore structures depends on the effectiveness of cathodic protections, cargo composition, inert gas properties, temperature of cargo and maintenance activities on the structures. The corrosion rate varies depending on the function and location of the structural component, as indicated in Figures 4 and 5.
Coatings and cathodic protection systems forms the major controls and mitigations in offshore environment against corrosion, whereas the safety factors and allowances incorporated

in the design forms the controls against fatigue cracks and deformations, as detailed by J K. Paik et. al. 2004, 2003 [6, 7]. The condition of coating systems determines the level of fabric maintenance to be carried out on the structural and piping system component, whereas the consequent metal loss determines the amount of metal repair work to be executed. In the case of machinery equipment, the running hours and the equipment performance results determine the level of maintenance to be carried out.

2.3 Maintenance resources and site constraints

The maintenance resources referred in this paper are the technicians available to perform the tasks. The maintenance activities have resource requirement in terms of time to complete the task, and the maximum and minimum allowable resources for the activity. The performance of resource allocation could be checked by resource utilisation and the quality-of-service satisfaction of the maintenance activity with a time varying number of maintenance activities. The allocated resource of a maintenance activity on the work management system would be the fraction of the work management system resource that is currently allocated and being used by the maintenance activity. When a maintenance activity is planned, an initial amount of resource would be reserved to it among all the available offshore resources, based on the minimum resource requirement of the maintenance activity that is known to the work management system initially.

The resource utilisation and quality of service utility models could be used to check the utility checks of maintenance items and maintenance activities. In this paper, the resource utilisation has been used to check if the allocated maintenance window for the maintenance activity is utilised. Also, resource utilisation would indicate the usage of the available maintenance window effectively for the maintenance activity, such that higher weighted sum of the task completion times at as short time as possible, would lead to higher resource utilisations.

The site constraints that are encountered for maintenance activities include access restrictions, conditions of work, personnel and equipment availability, weather conditions, technician capabilities and impact on other activities. Shadow areas and locations with accessibility issue, restricted access spaces that require additional risk assessment prior accessing, overside sections that need boat cover and additional risk assessment prior accessing, locations having presence of continuous water and need special equipment for carrying out maintenance, locations with accessibility issues during normal operations and need to be dealt during a pre-specified period such as plant shut down as an opportunistic work, are typical site constraints on an offshore asset.

2.4 Maintenance planning program

The Figure 2.6 indicates an overview of maintenance planning program. The maintenance strategies are tasks that could be considered to restore the desired functionality. The maintenance processes and the analyses techniques develop a series of maintenance strategies to achieve the desired goals, with a feedback loop to maintenance strategies for continuous improvement of the maintenance program.

2.4.1 Analyses – Modelling techniques

This section investigates the recent developments in modelling/ optimisation techniques for maintenance planning that could be employed at operational stages. The rationalisation of the offshore maintenance planning could be assisted by numerous procedures applied in a wide variety of areas. However, a rational or optimum maintenance planning could not be carried out by introducing only one procedure; to achieve the object, every important aspect

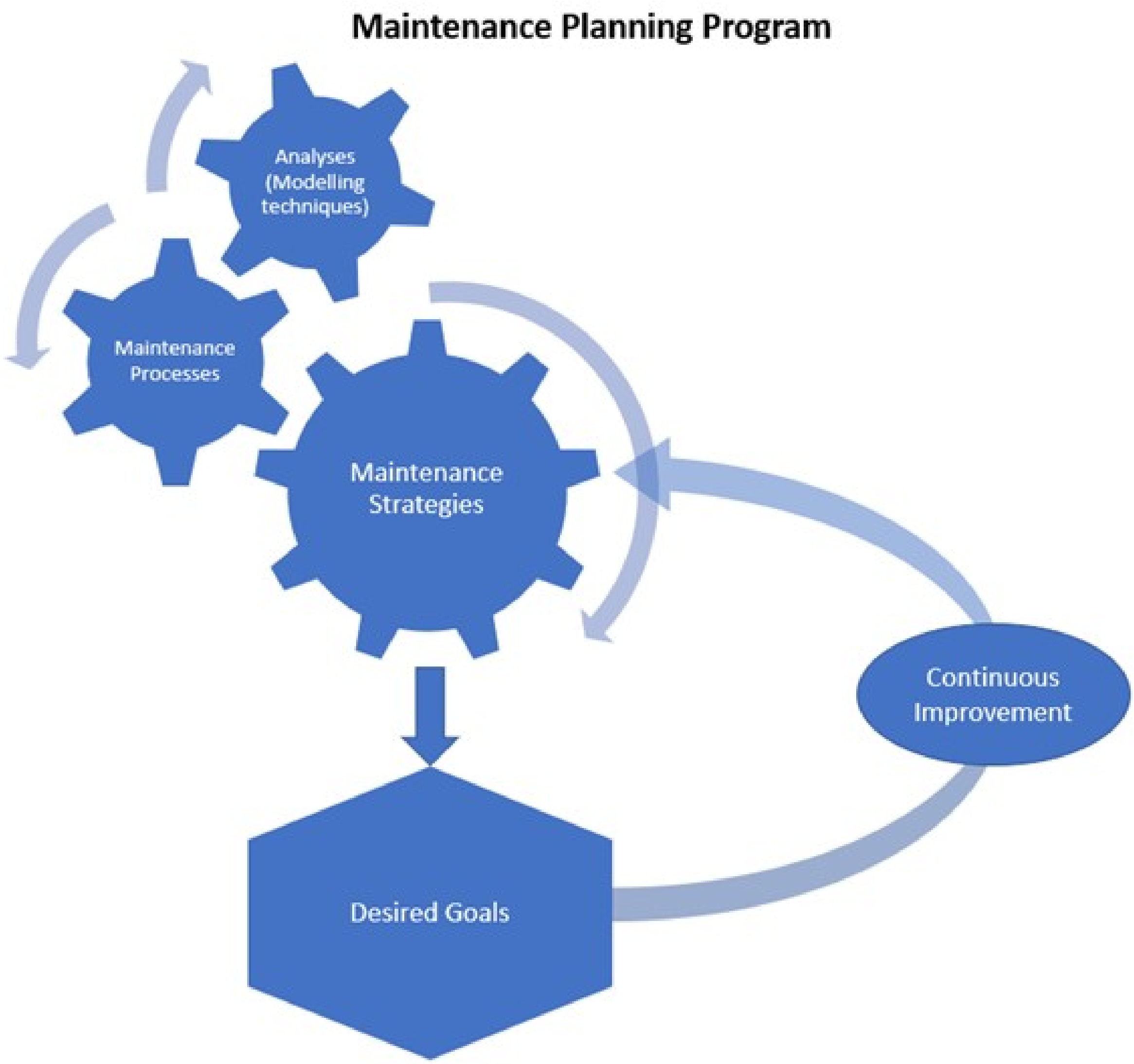

Figure 2.6: Maintenance planning program overview

must be taken into consideration. In an offshore maintenance planning optimisation problem, the decision variables cannot be chosen arbitrarily; rather, they must satisfy certain specified functional and other requirements. The offshore maintenance plan development is a typical optimisation problem involving multiple and frequently contradictory objective functions and constraints.

As the objective functions and constraints in the offshore maintenance plan optimisation problem would be considered as linear functions of the design variables, the problem could be classified as a linear programming problem, which could be stated in the following form, as stated by S I. Gass. 1984 [8].

$$Find\ X = x_1, x_2, x_3, ...x_n,\ which\ minimises\ f(X) = \sum_{i=1}^{n} c_i x_i \tag{2.1}$$

subject to the constraints

$\sum_{i=1}^{n} a_{ij}x_i\ =\ b_j,\ j\ =\ 1,\ 2,\ ....,m$

$x_i\ >= 0,\ i\ =\ 1,\ 2,\ ....n$

where $c_i,\ a_{ij},\ b_j$ are constants

The existing literature related to analyses techniques to develop the maintenance strategies to achieve the maintenance goals have been reviewed and an insight to the modelling and optimisation techniques, objective functions, decision variables and constraints considered in the current research have been summarised in Table 2.1.

Table 2.1: Analyses techniques for maintenance planning

Ref. / Year	Equipment	Analyses			
		Modelling/ Optimisation technique	Objective functions	Decision variables	Constraints
H. Hesabi et al. 2022	Modular Aero-Propulsion System Simulation of a Commercial Turbofan Engine	Deep Learning / Mathematical Programming	Minimise the total cost under intermission break time limitation	Maintenance cost	Limited time available to perform maintenance
W. Zhu et al. 2019	Offshore wind turbine	Bayesian Network/ Monte-Carlo simulations	Ensure performance of the wind turbine, maximise short- and long-term profits, and optimise maintenance grouping, minimise logistic cost and downtime loss.	Failure modes, Logistic delays, Weather conditions	Uncertainties related to logistic delays and weather conditions

D. Fan et al. 2019	Offshore wind farms	Mixed particle swarm optimization (MPSO) / Discrete Wolf pack search (DWPS)	Minimise maintenance cost	Travel cost of vessel, technician cost, loss of profit without accomplishing the maintenance in the defined period and weather windows	Discrete weather windows, maintenance technicians and vessels availability
Z. Lin et al. 2020	Offshore wind turbine	Linear and Non-linear models			
A. Mentes and O. Turan. 2019	Offshore wind turbine	Resilience Engineering	Ability to learn, anticipate, monitor and respond to emergency	Human and organizational factors	Maintenance failures
M. Yazdi et al. 2020	Offshore facility platform	Pythagorean fuzzy DEMATEL / Mathematical Programming	Reduction of the critical root events and subsequently the system's failure	Reliable expert elicitation procedure	Risk reduction worth (RRW) and Birnbaum importance measures (BIM) employed to identify and rank in order the basic events leading

					to the Top Event (TE).
S. Zhong et al. 2019	Offshore wind farms	Fuzzy multi-objective nonlinear chance-constrained programming model / 2-phase solution framework integrating the operational law for fuzzy arithmetic and the non-dominated sorting genetic algorithm II for multi-objective programming	Reliability maximisation and cost minimisation	Wind speed, power demand and generation, and the maintenance cost	Maintain sufficient net power reserves

Y. Li and Z. Hu. 2021	Offshore oil and gas facilities	Regression and Multi-criteria Decision Analysis	Asset retirement obligations of liabilities and expenses to be settled	Features of Environmental , Health and Safety, Technic/ Feasibility, Socio-economic and Financial	Potential ecosystem impacts, and gain or damage to hydrodynamic state
H J. Hwang et al. 2018	LNG FPSO	Markov model & Bayesian network-based approaches	Remaining useful life, Maintenance cost	State of the equipment, Types of failures that could occur	Economic benefits, Degree of severity in case of failure
M N. Scheu et al. 2019	Offshore wind turbine	Risk-based model	Minimise operational expenditure, Downtime reduction	Failure modes of the components	System criticality
B. Zhang and Z. Zhang. 2021	Offshore wind farm	Non-linear programming / Deterministic optimisation problem	Maximize the total wind farm power production	Starting and conducting status of maintenance tasks as well as the on/off status of wind turbine operations. Levels of power productions and the	Relationship constraints between maintenance status and turbine operating on/off status, Environmental constraints of tidal conditions, wind

				spinning reserve.	conditions, Wind Farm Operational constraints of power balance constraints, spinning reserve limitations.
M. Zagorowska et al. 2020	Offshore turbomachine	Linear and exponential non-linear regression in an expanding moving window framework	Additional operational profits and reduced energy consumption	Degradation indicator	Detection window
P. Zhou and P T. Yin. 2019	Offshore wind farm	Artificial Neural Network model / Opportunistic condition-based maintenance optimisation	Effective maintenance cost	Maintenance lead time	Failure conditions
J. Kang and C G. Soares. 2020	Offshore wind farm	Dynamic reliability threshold model incorporating Monte-Carlo simulation to	Achieve more extended use of a maintenance opportunity	Maintenance costs, Maintenance times	Maintenance schedules

		conduct random sampling			
M. Li et al. 2020	Offshore wind turbine	Non-homogeneous Continuous-Time Markov Process	Minimise the total maintenance cost	Maintenance cost per unit of time, Degradations	Maintenance schedule
I. Lazakis and S. Khan. 2021	Offshore wind farms	Mathematical models for daily route planning and Failure models / OptiRoute	Fuel Consumption , Vessels Routing, Maintenance Scheduling	Climate, Vessel Specifications & Fleet Configuration, Wind Farm Attributes, Turbines Failure Attributes, Cost	Operational constraints of technician and equipment carrying capacity of Crew Transfer Vessel
M. Abbas and M. Shafiee. 2020	Marine Structures	Fault tree analysis, Bayesian Network, Statistical and Stochastic models, multi-criteria decision analysis, Artificial Intelligence			

		and Machine Learning			
M P. Asuquo et al. 2019	Marine and offshore machinery	Fuzzy-TOPSIS	Identify the best, most appropriate, and acceptable maintenance strategy to be adopted	Reliability, Equipment and Labour Cost Effectiveness, Safety, Availability and Downtime	Costs and benefits for their subsequent implementatio n
A. Jamshidi et al. 2019	Offshore wind turbine	FMEA, FMECA, RBI, FCM (Fuzzy Cognitive Maps), Bayesian Network			
C. Stock-Williams and S K. Swamy. 2019	Offshore wind farm	Meta-heuristic model / Genetic Algorithm-Travelling Merchant Problem	Best possible Transfer Plan	Each possible solution or individual is encoded into a decision vector, Cost to Completion, Total energy output of the wind farm over the day	Weather accessibility, Technician availability, Technician shift times, number of technicians allowed simultaneously onto a turbine

Y. Lu et al. 2018	Offshore wind turbine	Artificial Neural Network life percentage prediction model	Determining optimal maintenance interval value to minimise the total maintenance cost	Conditional failure probabilities	Defined inspection intervals
A H. Schrotenboer et al. 2018	Offshore wind farms	Adaptive Large Neighbourhood Search heuristic model embedded in a Monte-Carlo Simulation	Minimise the costs of the chosen routes	Number of technicians of a particular type at the depot in a period, Selected route.	Each vessel could only perform a single trip per period. All nodes are visited exactly once throughout the time horizon. Limit the use of technicians of the selected vessel routes to the number of technicians being allocated. Technician allocation obeys the availability of technicians.

R d O. Werneck et al. 2021	Well production	Recurrent Neural Networks	Well production and pressure forecasting	Production data, Injection data, Well's pressure	Production impacts
C. Diallo et al. 2019	Multicomponent systems	Selective Maintenance Problem	Maximise reliability of the system. Minimise maintenance cost	Total duration of maintenance activities. Length of Intermission breaks. Maintenance performed by repairperson. Repairperson is hired/ utilised.	Within total budget available. One and only maintenance pattern is selected per subsystem. Achieved reliability is equal or greater than the required minimum reliability. When a repairperson is hired, their total maintenance work time does not exceed the break duration.
H. Seiti et al. 2019	Process Units	D-Fuzzy Axiomatic Design (D-FAD) method, is a	Evaluate the alternatives for replacement intervals with	Best Replacement Time	Expected cost function, Availability, Safety

		combination of fuzzy axiomatic design and D numbers	respect to criteria with the associated risks. Cost function		
O. Ahmadi et al. 2020	Atmospheric storage tanks	Fuzzy Decision-making trial and evaluation laboratory (DEMATEL) outputs in Bayesian network	Determination of leading indicators validity, importance, and practicability	Failures, Hot work	Risk influence factors
Y. Liu et al. 2020	Coal Transportation	Kijima type II model and discrete time finite horizon Markov decision process Deep Reinforcement Learning Algorithm	Minimise the total maintenance cost and time	Maintenance cost per unit of time. Maintenance Actions	Maintenance resources
M A J u h. Broek et al. 2019	Offshore wind farm	Simulation model	Minimise total maintenance cost	Maintenance cost per unit of time. Delay between offshore activities. Operational	Weather restrictions due to wave height and wind speed. Component failure rates

				costs. Production rate.	
O. Ozguc. 2020	FPSO	Global and local finite element models & Hydrodynamic 3-D panel model	Minimise cumulative fatigue damage	Fatigue parameters of stress range and number of cycles	Hot spot stresses and notch stresses per load component
G. Zou et al. 2021	Marine Structures	Probabilistic crack growth model	Minimise maintenance cost	Life cycle costs, Fatigue parameters, Inspection findings	Uncertainties
D. Yang et al. 2018	Aircrafts	Heuristic sequential game algorithm	Reducing the repair frequency and cost	Remaining useful lifetimes (RUL) of all the key subsystems	Reliability of the phased mission
M. Yazdi et al. 2019	Process facilities	Non-linear model / Bi-objective fuzzy structure optimization model	Minimise the safety investment and accident probability	Health & Safety importance, Time allocation, Cost, Environmental enhancement,	Budget limitation, Safety factors

				Reputation importance	
D. Fan et al. 2021	Subsea Equipment	Reliability model with stochastic dependency / Collaborative particle swarm optimization algorithm	Optimal group maintenance plan	Maintenance Cost, PM duration, PM interval, Corrective maintenance duration	System availability, Failure rate
G M. Galante et al. 2020	Continuous and discontinuous operating systems	Mathematical programming	Maximise the system's reliability		Uncertain environment
J. Matias et al. 2020	Gas lift oil well	Remaining Useful Life (RUL) estimation model	Maximise production and economic objectives	Equipment health indicators, Plant data	System dynamics, Safety constraints, Operational constraints
Y. Han et al. 2021	Safety Critical Equipment on Offshore Installations	Hybrid dynamic risk modelling methodology that combines dynamic Bayesian	Provide dynamic real time risk profile predictions	Dynamic variables	Human errors, Functional failures

		network (DBN) technique and support vector regression (SVR) algorithm			
M. Yazdi et al. 2020	Chemical Plant	Integrated model of DEMATEL (decision-making trial and evaluation laboratory) methodology with Best-Worst method (BWM) and Bayesian network (BN)	Risk factors	Number of accidents, Cost, Training, Flexibility, Reputation.	Uncertainties, Inconsistencies in human judgements
G. Rinaldi et al. 2021	Offshore wind farms	Probabilistic model - Monte Carlo Simulations	Maximise Production, minimise revenue losses, Minimise Operations & Maintenance costs	Metocean data, Planned Maintenance data, Vessel Characteristics , Reliability data, Procurement and repair time	Reliability, Availability, Maintainability

M. Viera et al. 2022	Offshore wind support structures	Stochastic model based on Monte Carlo method	Provide insights on the impact of structural health monitoring systems and other farm parameters on the total energy output of a certain farm	Turbine capacity, Number of Farm Turbines, Expected Operational Life, Expected Farm Capacity Factor, Interval between Inspections, Structural Health Monitoring Detection rate, Farm Monitoring Rate	Economic constraints
K. Chaabane et al. 2020	Manufacturing systems	Integrated non-linear programming formulation with a solution method based on genetic algorithm	To find the optimal decisions minimising the total maintenance and labour costs while ensuring a minimum reliability level during missions	Number of missions, System Parameters, Repairpersons	Minimum reliability during mission, break duration, Effective age of the components at the end of the break

Y. Han et al. 2019	Offshore installations	Dynamic data model, Classification model, Maintenance decision model	Minimise the total risk level while reducing the maintenance cost	Observed Samples, Observed failures, Maintenance time intervals	Degradation rate, Parameter uncertainty
E U. Olugu et al. 2021	Offshore Oil and Gas industry	Spherical fuzzy sets modified-Delphi Model	Technical performance, environmental performance, economic performance and social performance	Maintenance improvement, maintenance efficiency, management of resources, waste management, responsibility & Regulations, cost-effectiveness, investments, indirect economic impacts, skill improvement, occupational health & safety, maintenance employee, and social responsibility & Regulations	

A. Khatab et al. 2019	Manufacturing systems	Non-linear and integer mathematical model / Selective Maintenance and Repairpersons assignment optimisation model (SMRAOM)	Reliability, Maintenance cost and duration	Number of missions, System Parameters, Cost of new component, Cost of reconditioned component, Replacement and hiring costs of repairpersons	Maintenance budget, Time constraints, Total repair times is no more than the break duration
T J. Ikonen et al. 2020	Engineering Systems	Mixed integer non-linear programming (MINLP) / Mixed integer non-linear programming (MINLP) based selective maintenance optimisation	Reliability, Maintenance cost and duration	Number of components, System Parameters, Reliability parameters	Maintenance cost budget, Time constraints

A. Garcia-Teruel et al. 2022	Offshore floating wind farms	Time-domain stochastic model, based on the Markov Chain Monte Carlo technique	Production, availability, maintainability, and economic performance	Environmental resource, reliability and power performance of the devices, maintenance vessels and related accessibility due to weather, corrective and preventive maintenance regimes	Capacity factors on O&M Towing strategy and O&M Offshore strategy
B. Yeter et al. 2022	Offshore wind turbines	Structural integrity analysis employing Gaussian kernel for denoising, followed by a time-domain crack growth analysis / Unsupervised machine learning	Techno-economic feasibility of life extension	Environmental and operational parameters, operational expenditures, Structural design data, Wind load data, Material properties	Life extension duration and appropriate discount rate
T N. Schouten et al. 2021	Offshore wind turbine	Mixed integer linear programming model	Maintenance optimisation	Time- varying costs, Power outputs	Cost fluctuations

A H. Schrotenboer et al. 2020	Offshore wind farms	Two-stage stochastic mixed integer programming model	Maintenance optimisation	Time- varying costs, Technician costs	Uncertainty in the maintenance tasks and weather conditions
A L. Ramirez-Ledesma and J A. Juarez-Islas. 2022	Offshore oil platforms	Statistical predictive model	Remaining useful life	Mechanical properties, Chemical composition, hardness and tensile test properties	Component's interaction with atmospheric gases, Non-metallic inclusions associated with localised corrosion by pitting corrosion mechanism
W. Ni et al. 2021	Offloading mooring system of FPSO	High-dimensional Conditional Probability (HCP) method based on First Order Reliability Method	Reduce error divergence	System dimension, number of components, correlation between components, component reliability index (failure probability), load, strength variables,	Relative error

				environmental conditions	
A. Allal et al. 2021	Offshore wind farms	Multi-agent-based modelling and simulation / Ant Colony System (ACS) algorithm	Optimise maintenance tasks routing using boats, minimise cost while keeping high availability of wind turbines	Number of turbines, Maintenance team size, Maintenance types, Choice of maintenance strategies, ACS algorithm parameters	Weather conditions, resources cost, maintenance duration
L. Liu et al. 2022	Transportation system	Multidimensional integration and Monte Carlo simulation approach / Tailored genetic algorithm (GA-UD)	Minimise expected grand total cost with a given reliability threshold	Associated maintenance costs, average durations of different maintenance levels, maintenance times	Limited maintenance resources

S. Adumene et al. 2021	Marine pipelines	Copula-based Monte Carlo (CMC) simulation / Bayesian Network with Copula-based Monte Carlo (BN-CMC) simulation	Microbial corrosion rate prediction, considering the interrelationships between physio-chemical parameters	Geometry of Corrosion parameters, physio-chemical parameters, pipe variables and mechanical properties	Failure mode probabilities
Y. Liu et al. 2018	Coal Transportation	Saddle point approximation / Tailored ant colony optimisation algorithm	Maximize the probability of a system successfully completing the next mission, Optimal maintenance actions	Maintenance budget, Duration of break, Durations of maintenance actions	Duration Uncertainties of the maintenance actions and breaks
M. Li et al. 2021	Offshore wind farms	Mathematical models for opportunistic maintenance model. Degradation failure times of components are modelled as a two parameter Weibull	Reduce the total maintenance costs of offshore wind farm. Determine the optimal combination of variables which would minimise the	Maintenance costs, Number of maintenance levels, Number of maintenance cycles, Age of component, Number of aged components	Maintenance budget, Occurrence probabilities of any impacts

		distribution with scale parameter and shape parameter. The arrival times of the environmental impact are modelled as a non-homogeneous Poisson process.	annual maintenance cost during the whole lifetime.		
C. Zhang et al. 2019	Wind turbines	Markov chain model, Weibull distribution & mathematical models	Minimise the total maintenance and inventory cost over the life cycle horizon, optimal opportunistic maintenance reliability threshold, reorder stock level	Life cycle Maintenance costs, Inventory costs	Maintenance budget, wait time owing to weather restrictions

C. Zhang and T. Yang. 2021	Wind turbines	Mathematical models / Nondominated sorting genetic algorithm (NSGA)	Efficient maintenance planning and resource allocation, prevent unnecessary downtime and reduce operational costs	Maintenance costs	Maintenance budget, weather restrictions
R B. Hageman et al. 2022	FPSO hull	Analytical load distribution model, Simple reliability model, Multiple stochastic models, Weibull and Pareto models, Lognormal and Gumbel model	Maintain target structural reliability	Environmental and Operational parameters	Uncertainty related to the future extrapolation of loads, statistical uncertainty of the long-term sea states, uncertainty introduced through the use of analytical load distribution models, uncertainty in the calculation method

Table 2.1 references:

[9], [10], [11], [12], [13], [14], [15], [16], [17], [18], [19], [20], [21], [22], [23], [24], [25], [26], [27], [28], [29], [30], [31], [32], [33], [34], [35], [36], [37], [38], [39], [40], [41], [42], [43], [44], [45], [46], [47], [48], [49], [50], [51], [52], [53], [54], [55], [56], [57], [58], [59], [60], [61], [62], [63], [64], [65], [66].

It could be noted from the Table 2.1 that probabilistic assessment models, Bayesian Networks and multi-objective optimisation techniques have been widely used in the literature for optimisation of maintenance activities.

2.4.2 Maintenance processes

The maintenance processes develop a series of maintenance strategies to restore the desired functionalities and goals. There are various ways to classify the current maintenance processes. In this paper, maintenance processes have been classified as reliability-centred maintenance, reliability-based maintenance, and performance-based maintenance. A brief discussion of these processes has been provided below.

The reliability-centred maintenance is the process that ensures the systems continue to do as required, in their present operating context. It could be noted that a systematic analysis of the system would be carried out to understand its functions, failure modes of its equipment and to choose an appropriate maintenance to prevent the failure mode from occurring or to detect the failure mode before failure occurs. This involves identifying actions that when implemented would reduce the probability of failure and those actions that would be most cost effective. The reliability of the examined system defines the maintenance plan and does not consider the impact of site constraints, deviations on operating conditions, resource availabilities.

In the reliability-based maintenance, a system would be selected for evaluation and the criticality of the equipment and components in the system would be determined. The developed maintenance model would act as the foundation for applying selective reliability techniques to create an effective reliability strategy. It could be noted that the maintenance prioritisation would be carried out based on this design features, deteriorations, criticality of the equipment and the consequences of not doing the maintenance, however, does not consider the deviations in operating conditions, site constraints and the resources.

The performance-based maintenance involves specifying the performance standards for equipment, instead of the maintenance techniques. It could be noted that this involves defining equipment requirements such as minimum and maximum ranges of operating conditions, availability, and reliability requirements. If there are any changes to the conditions, that would lead to an operational risk assessment and mitigations, however, this approach does not consider the impact of site constraints and resource availabilities.

The existing literature related to maintenance processes for developing the strategies to achieve the desired goals have been reviewed and an insight to the current research have been summarised in Table 2.2.

Table 2.2: Maintenance processes for developing strategies

Ref. / Year	Equipment	Maintenance Processes		
		Reliability-centred maintenance	Reliability-based maintenance	Performance-based maintenance
H. Hesabi et al. 2022	Modular Aero-Propulsion System Simulation of a Commercial Turbofan Engine			✓
W. Zhu and B. Casta. 2019	Offshore wind turbine			✓
D. Fan et al. 2019	Offshore wind farms			✓
Z. Lin et al. 2020	Offshore wind turbine		✓	
S. Zhong et al. 2019	Offshore wind farms		✓	
A. Dehghani and F. Aslani. 2019	Offshore structures			✓
H J. Hwang et al. 2018	LNG FPSO		✓	

B. Zhang and Z. Zhang. 2021	Offshore wind farm		✓	
M. Zagorowska et al. 2020	Offshore turbomachinery			✓
P. Zhou and P T. Yin. 2019	Offshore wind farm			✓
J. Kang and C G. Soares. 2020	Offshore wind farm		✓	
M. Li et al. 2020	Offshore wind turbine			✓
I. Lazakis and S. Khan. 2021	Offshore wind farms			✓
M. Abbas and M. Shafiee. 2020	Marine Structures	✓		
M P. Asuquo et al. 2019	Marine and offshore machinery	✓		
A. Jamshidi et al. 2019	Offshore wind turbine		✓	

C. Stock-Williams and S K. Swamy. 2019	Offshore wind farm		✓	
Y. Lu et al. 2018	Offshore wind turbine			✓
A H. Schrotenboer et al. 2018	Offshore wind farms		✓	
R d O. Werneck et al. 2021	Well production			✓
C. Diallo et al. 2019	Multicomponent systems		✓	
H. Seiti et al. 2019	Process Units		✓	
O. Ahmadi et al. 2020	Atmospheric storage tanks			✓
Y. Liu et al. 2020	Coal Transportation			✓

M A J u h. Broek et al. 2019	Offshore wind farm		✓	✓
O. Ozguc. 2020	FPSO			✓
G. Zou et al. 2021	Marine Structures		✓	
D. Yang et al. 2018	Aircrafts		✓	
M. Yazdi et al. 2019	Process facilities		✓	
D. Fan et al. 2021	Subsea Equipment			✓
N N. Ferreira et al. 2020	Exploration & Production (E&P) platforms in oil and gas industry		✓	
G M. Galante et al. 2020	Continuous and discontinuous operating systems		✓	

J. Matias et al. 2020	Gas lift oil well			✓
Y. Han et al. 2021	Safety Critical Equipment on Offshore Installations			✓
M. Yazdi et al. 2020	Chemical Plant		✓	
G. Rinaldi et al. 2021	Offshore wind farms		✓	
M. Viera et al. 2022	Offshore wind support structures		✓	
K. Chaabane et al. 2020	Manufacturing systems		✓	
Y. Han et al. 2019	Offshore installations			✓
E U. Olugu et al. 2021	Offshore Oil and Gas industry			✓

A. Khatab et al. 2019	Manufacturing systems		✓	
T J. Ikonen et al. 2020	Engineering Systems		✓	
M. Ibrion et al. 2020	Offshore installations	✓	✓	
A. Garcia-Teruel et al. 2022	Offshore floating wind farms	✓		
B. Yeter et al. 2022	Offshore wind turbines		✓	
T N. Schouten et al. 2021	Offshore wind turbine		✓	
A H. Schrotenboer et al. 2020	Offshore wind farms			✓
A L. Ramirez-Ledesma and J A. Juarez-Islas. 2022	Offshore oil platforms			✓

W. Ni, X. Zhang, and W. Zhang. 2021	Offloading mooring system of FPSO		✓	
A. Allal et al. 2021	Offshore wind farms			✓
L. Liu et al. 2022	Transportation system	✓		
S. Adumene et al. 2021	Marine pipelines		✓	
Z. Ren et al. 2021	Offshore wind turbine		✓	
Y. Liu et al. 2018	Coal Transportation		✓	
M. Li et al. 2021	Offshore wind farms	✓		
C. Zhang et al. 2019	Wind turbines	✓		
C. Zhang and T. Yang. 2021	Wind turbines		✓	

R B. Hageman et al. 2022	FPSO hull		✓	

Table 2.2 references:

[9], [10], [11], [12], [15], [67], [17], [19], [20], [21], [22], [23], [24], [25], [26], [27], [28], [29], [30], [31], [32], [33], [34], [35], [36], [37], [38], [39], [40], [41], [68], [42], [43], [44], [45], [46], [47], [48], [49], [50], [51], [52], [69], [53], [54], [55], [56], [57], [58], [59], [60], [61], [70], [62], [63], [64], [65], [66].

It could be noted from the Table 2.2 that reliability-based maintenance and performance-based maintenance processes have been widely used in the literature for developing the maintenance strategies to restore the desired functionality.

2.4.3 Maintenance strategies

The maintenance strategy contains guidelines, activities and decision support systems that would be employed to maintain an equipment and prevent occurrence of a failure event. There are various possible ways to classify the current practices in maintenance activities. In this work, the maintenance strategies have been classified as corrective maintenance, preventive maintenance, condition-based maintenance, run to failure maintenance, opportunistic maintenance, planned maintenance, predictive maintenance, selective maintenance, and risk-based maintenance. A brief discussion of these strategies has been provided below.

The corrective maintenance is a remedial work carried out to identify and rectify a failure event so that the failed system could be restored to an operational condition within the allowable tolerances, as indicated in the work of M. Scheu et. al. 2012 [71]. This involves all engineered or administrative procedures implemented to reduce the likelihood of a failure event. This kind of maintenance would be a reactive activity and not a proactive method of maintenance. This approach would be appropriate for less critical systems and increases the uncertainty of the asset availability and reliability with additional cost involved.

The preventive maintenance is a task carried out regularly on an equipment to minimise the likelihood of failure event and restores the inherent reliability or performance of the equipment, as indicated in the works of R. Martin et. al. 2016 [72]. It could be noted that this activity would be performed at set intervals regardless of whether a failure is about to happen and involves all maintenance activities that would be identified as necessary to provide an acceptable probability of survival to the end of a specified interval for the system. This approach considers the design features, operating conditions, deterioration rates and the consequences of not doing the maintenance, however, does not consider the impact of site constraints and resource availabilities.

The condition-based maintenance is a maintenance plan carried out on a regular or real time basis that is based on the use of Condition Monitoring to determine when a remedial action is required, as indicated in the works of J. Shin and H. Jun 2015 [73], M. Lewandowski and S. Oelker 2014 [74], and J I. Alizpurua et. al. 2017 [75]. This involves carrying out maintenance action before the failure event occurs, by assessing the equipment condition including operating environments and predicting the risks of failure in a real time, based on data collected. A major limitation of the approach is in the accuracy of diagnostics and prognostics that plays a crucial part in the effectiveness of condition-based maintenance optimisations. Also, the reliability of the condition sensors has a great impact on the effectiveness of this approach.

The run-to failure maintenance involves allowing an equipment to run until failure and thereafter a remedial activity is carried out, as indicated in the work of M S. Kan et. al. 2015 [76]. However, it could be noted that this approach would be acceptable only if the risk of failure is acceptable and would be applied mainly for low priority equipment and could lead to increased downtime if not implemented appropriately.

The opportunistic maintenance is a type of preventive maintenance that employ convenient replacement of equipment or components by taking advantage of an unplanned or planned shutdown of the system, with maintenance resources available on location, as indicated in the work of A. Martinetti et. al. 2017 [77]. This approach could be employed for activities that cannot be carried out during normal operations due to redundancy issues, and the equipment for which there is no imminent integrity, safety or production risks identified, however, this approach impacts the preventive replacement cost on economic benefit.

The planned maintenance is a scheduled maintenance activity that involves getting rid of a component at or before a specified age limit regardless of its condition at the time, as indicated in the works of K. Tracht et. al. 2013 [78]. It could be noted that this activity would restore the capability of the equipment at or before a specified age limit and regardless of its condition at the time, to an acceptable probability of survival to the end of another specified interval. This approach considers the design features, assumptions on operating conditions, deterioration rates and the consequences of not doing the maintenance, however, does not consider the impact of site constraints, deviations on operating conditions and resource availabilities.

The predictive maintenance involves condition monitoring using measurement and signal processing methods, that enables diagnose and predict system condition during operation. A mathematical model for predictive offshore maintenance based on prognosis and health management, has been developed by A. Raza and V. Ulansky 2017 [79] for a periodically inspected system. A major limitation of this strategy is that it is dependent on the reliability of the smart technologies and sensors.

The selective maintenance involves finding the subset of components and the level of maintenance activities needed on components to enhance the probability of successfully carrying out the next mission after a finite break between two successive maintenance missions, as performing all required maintenance activities could not be possible due to limitation on maintenance resources during the breaks, as indicated in the works of H. Hesabi, et. al. 2022 [9].

The risk-based maintenance focuses on optimising the maintenance programs recognising that the main goal of maintenance is to prevent failures that affect the safety and reliability of the operating assets. This would be achieved by developing the program that focuses the maintenance resources at areas and components of greater concern and providing a methodology that determines the optimum combination of maintenance frequency and methods, as indicated in the works of G. Ford et. al. 2015 [80]. Hence, there is a continuous improvement aspect to the risk-based maintenance process that allows re-evaluation of risk and maintenance activities. The development of offshore risk-based maintenance involves identifying the potential failure events of each component or area; identify the initiating events that lead to those failures; determining the progression of failure sequences and the consequences of the failure events; prioritise and rank the risk associated with that event; selecting an appropriate maintenance program that could mitigate the failure events and the events that lead to those failures. Provided, the design features, operating conditions, deteriorations, and site constraints are incorporated in the risk-based approach, that would lead to a comprehensive maintenance strategy for the asset.

The existing literature related to maintenance strategies to achieve the desired goals in a maintenance program have been reviewed and an insight to the current research have been summarised in Table 2.3.

Table 2.3: Maintenance strategies to achieve the desired goals in a maintenance program

Year / Ref	Maintenance Strategies								
	Corrective Maintenance	Preventive Maintenance	Condition based Maintenance	Run to failure maintenance	Opportunistic maintenance	Planned maintenance	Predictive maintenance	Selective maintenance	Risk based maintenance
2022 [8]							✓	✓	
2019 [9]					✓	✓			
2019 [10]						✓			
2020 [11]		✓							
2019 [12]		✓							✓
2020 [13]	✓								✓

A. Dehghani and F. Aslani. 2019		✓							
Y. Li and Z. Hu. 2021						✓			
H J. Hwang et al. 2018			✓						
M N. Scheu et al. 2019			✓						✓
B. Zhang and Z. Zhang. 2021						✓			
M. Zagorowska et al. 2020							✓		
P. Zhou and P T. Yin. 2019			✓		✓		✓		
J. Kang and C G. Soares. 2020		✓			✓				

M. Li et al. 2020		✓			✓				
I. Lazakis and S. Khan. 2021						✓			
M. Abbas and M. Shafiee. 2020]	✓	✓	✓						✓
M P. Asuquo et al. 2019		✓	✓	✓					
A. Jamshidi et al. 2019									✓
C. Stock-Williams and S K. Swamy. 2019	✓	✓			✓	✓			
H N. Teixeira et al. 2020			✓						
Y. Lu et al. 2018			✓						

A H. Schrotenboer et al. 2018	✓	✓			✓	✓			
R d O. Werneck et al. 2021							✓		
C. Diallo et al. 2019								✓	
H. Seiti et al. 2019		✓							✓
O. Ahmadi et al. 2020									✓
Y. Liu et al. 2020								✓	
M A J u h. Broek et al. 2019	✓	✓	✓		✓	✓			
O. Ozguc. 2020							✓		
G. Zou et al. 2021			✓						

D. Yang et al. 2018			✓					✓	
M. Yazdi et al. 2019									✓
D. Fan et al. 2021	✓	✓	✓						
N N. Ferreira et al. 2020	✓	✓							
G M. Galante et al. 2020								✓	
J. Matias et al. 2020							✓		
Y. Han et al. 2021		✓							✓
M. Yazdi et al. 2020									✓

G. Rinaldi et al. 2021						✓			
M. Viera et al. 2022			✓						
K. Chaabane et al. 2020								✓	
Y. Han et al. 2019		✓							
E U. Olugu et al. 2021	✓	✓				✓			
A. Khatab et al. 2019								✓	
T J. Ikonen et al. 2020								✓	
M. Ibrion et al. 2020	✓	✓					✓		✓

A. Garcia-Teruel et al. 2022	✓	✓							
B. Yeter et al. 2022									✓
T N. Schouten et al. 2021		✓	✓						
A H. Schrotenboer et al. 2020		✓				✓			
A L. Ramirez-Ledesma and J A. Juarez-Islas. 2022									✓
W. Ni et al. 2021									✓
A. Allal et al. 2021	✓	✓	✓						
L. Liu et al. 2022								✓	

S. Adumene et al. 2021									✓
Z. Ren et al. 2021	✓	✓	✓		✓	✓	✓		✓
Y. Liu et al. 2018			✓					✓	
M. Li et al. 2021		✓			✓				
C. Zhang et al. 2019		✓			✓				
C. Zhang and T. Yang. 2021		✓							
R B. Hageman et al. 2022									✓

Table 2.3 references:

[9], [10], [11], [12], [13], [14], [15], [67], [16], [17], [18], [19], [20], [21], [22], [23], [24], [25], [26], [27], [28], [81], [29], [30], [31], [32], [33], [34], [35], [36], [37], [38], [39], [40], [41], [68], [42], [43], [44], [45], [46], [47], [48], [49], [50], [51], [52], [69], [53], [54], [55], [56], [57], [58], [59], [60], [61], [70], [62], [63], [64], [65], [66].

It could be noted from the Table 2.3 that preventive maintenance, risk-based maintenance and condition-based maintenance strategies have been widely used in the literature to restore the desired functionalities and goals.

2.4.4 Desired goals of maintenance program

This section categorises the desired goals of maintenance program into key influencing factors, key considerations and key performance indicators, so as to evaluate the effectiveness of the program.

The Figure 2.7 indicates an overview of desired goals of maintenance program categorised into key influencing factors, key considerations and key performance indicators.

The major offshore maintenance performance indicators include asset availability, reliability, safety compliance, regulatory compliance, manpower costs, activity completion, cost related to activity duration, increase in efficiency, consistency, offshore practices, onshore practices, and site constraints related to environmental factors. The main factors that influence offshore maintenance performance are rate of deterioration mechanisms, measures to mitigate deteriorations, rectification of anomalies and the failure consequences. The typical damage and deterioration mechanisms on offshore assets includes corrosion, cracks and deformations, imperfections that forms the basis for what normally goes wrong in an asset's life. An evaluation of the deterioration mechanisms, deterioration rates, the associated uncertainties and their acceptance criteria would be required to accurately quantify the risk and failure

Key Influencing Factors

- Owner's strategy
- Regulatory requirements
- Design conditions
- Design assumptions
- Operational conditions
- Operational requirements
- Environmental conditions
- Safety considerations
- Maintenance duration
- Maintenance frequency
- Personnel resource availability
- Material resource availability
- Failure probability

Key Considerations

- Operational priorities
- Rate of deterioration mechanisms
- Measures to mitigate deteriorations
- Rectification of anomalies
- Failure consequences
- Uncertainties
- Acceptance criteria
- Design deviations
- Fabrication and manufacturing deviations
- Operational deviations
- Skills of personnel
- Performance of maintenance tools
- Planned unit downtime

Key Performance Indicators

- Availability
- Reliability
- Safety compliance
- Regulatory compliance
- Manpower costs
- Activity completion
- Cost related to activity duration
- Increase in efficiency
- Consistency
- Offshore & onshore practices
- Site constraints related to environmental factors
- Site constraints of available beds offshore
- Impact of time required to carry out activities

Figure 2.7: Categorisation of desired goals of maintenance program

events. The assumptions made during the component design and risk evaluations could become invalid due to various operational and environmental factors such as unexpected scenarios due to extreme weather conditions, loading-offloading patterns, functionality of critical equipment, faults-errors in gauging and monitoring devices. Also, the deviations during the fabrication and manufacturing phases such as geometric and material imperfections, workmanship depending on quality control, regulatory and shipyard practices, plays a vital role on the state of degradations. The skills of the offshore maintenance personnel and performance of maintenance tools, which varies on individual cases would play a critical role in the effectiveness of the maintenance program. Also, the planned unit downtime is another major consideration to be made towards planning the maintenance program.

The key factors that influence the offshore maintenance planning involves maintenance duration, maintenance frequency, regulatory compliance, owners strategy, design conditions, design assumptions, environment conditions, operational conditions, operational requirements, safety compliance, resource availability with respect to man power and materials, costs, failure probability, risks of not carrying out the maintenance, risks with doing the maintenance, business risks, safety risks and environment risks.

The offshore maintenance activities would be prioritised to address top vulnerabilities that impact safety and reliability of the asset and based on the activity's impact on barriers that will liquidate the risks to the asset's performance. The critical component prioritisation would be done by a risk assessment that needs to be carried out based on the probability of occurrences of the failure events, the consequences of failure events and those events that lead to those failures, anomalies, repairs, and planned maintenance activities. The probability of failure would be determined by the relative frequency of failure; influence of degradation mechanisms on the relative frequency; analysis of data and detailed analysis. The various allowances and safety factors for various components determine the probability of the failure mode occurrence.

The corrective activities would reduce the likelihood of the safety event occurrence, by addressing the failure modes related to that event. The maintenance activities on production impacting equipment would liquidate the risks to the asset's production performance and hence would be prioritised accordingly. The corrective repair and preventive maintenance activities on safety critical and production impacting equipment would take priority over other general service activities while planning the maintenance activities in each schedule window. The plan would be primarily constrained by the available bed space on board that limits the number of activities executed in a scheduled period. The offshore operational constraints related to material availability, execution readiness on support activities, isolations, risk assessments and permit requirements would determine the readiness of the activity at a schedule window. Also, environmental constraints related to weather, wind and sea state conditions that impacts execution of activities would define the execution priority.

The risk models categorise the offshore activities to - high, medium, low - based upon the probability of failure event occurrence and the consequence on safety, economics, and the environment. The activity with the highest consequence and probability rating would be used to determine the overall risk. The risk would be dependent on the business plans and procedures of the asset's operating companies. The risk evaluations would identify potential events, their mitigated and unmitigated consequences with respect to safety and economic inputs, their likelihood of occurrence and the associate risk with respect to safety, environment and economic impacts, barriers that are in place, their effectiveness and any other factors that could change the magnitude of the risk.

The safety consequence assessment of not doing the activity employs the acceptance criteria for relevant component, whereas the environmental consequence would be estimated using the data on material volume and the environmental sensitivity of the area affected. The economic consequence assessment relies on the remedial cost and financial impact of the failure event on the business. This involves estimating the time required to design and implement a repair, estimating the business impact during the outage period and defining the lost or deferred revenue.

The economic consequence assessment relies on the remedial cost and financial impact of the failure event on the business. This involves estimating the time required to design and implement a repair, estimating the business impact during the outage period and defining the lost or deferred revenue. The machinery and structural failure consequences could generally be managed in a more controlled manner when compared with that of the pressure system failures. Some maintenance activities could be carried out while the equipment is online, whereas others require equipment or system shut down. This defines the window when the maintenance could be scheduled in and nested with.

In the case of FPSO's, the asset availability and reliability form the basis for production performance and relates to the actual quantity of oil and gas produced, water and gas injected, and gas flared, with respect to the respective target values. Any deviations from the target values would impact the production performance and business objectives. The maintenance activities on production impacting equipment would liquidate the risks to the asset's production performance and hence would be prioritised accordingly.

The existing literature related to desired goals of maintenance programs have been reviewed and an insight to the current research have been summarised in Table 2.4.

Table 2.4: Desired goals of maintenance program

Ref. / Year	Desired Goals of Maintenance Program												
	Availability	Reliability	Safety Compliance	Regulatory Compliance	Manpower Costs	Activity Completion	Cost related to Activity Duration	Increase in efficiency	Consistency	Offshore & Onshore practices	Site constraints related to environmental factors	Site constraints of available beds Offshore	Impact of time required to carry out activities
H. Hesabi et al. 2022					✓	✓	✓						
W. Zhu et al. 2019						✓	✓				✓		
D. Fan et al. 2019					✓	✓					✓		
Z. Lin et al. 2020		✓											
A. Mentes and O. Turan. 2019	✓	✓											

M. Yazdi et al. 2020	✓	✓											
S. Zhong et al. 2019							✓				✓		
A. Dehghani and F. Aslani. 2019			✓										
Y. Li and Z. Hu. 2021			✓	✓						✓	✓		
H J. Hwang et al. 2018	✓	✓	✓	✓				✓					
M N. Scheu et al. 2019							✓						
B. Zhang and Z. Zhang. 2021								✓			✓		
M. Zagorowska et al. 2020								✓					
P. Zhou and P T. Yin. 2019						✓							

J. Kang and C G. Soares. 2020		✓				✓	✓				✓		
M. Li et al. 2020						✓	✓						
I. Lazakis and S. Khan. 2021											✓		
M. Abbas and M. Shafiee. 2020	✓	✓											
M P. Asuquo et al. 2019	✓	✓	✓			✓	✓						
A. Jamshidi et al. 2019		✓											
C. Stock-Williams and S K. Swamy. 2019	✓	✓			✓	✓	✓				✓		
H N. Teixeira et al. 2020						✓	✓						
Y. Lu et al. 2018						✓	✓						

A H. Schrotenboer et al. 2018	✓	✓			✓	✓	✓				✓		
R d O. Werneck et al. 2021	✓							✓					
C. Diallo et al. 2019		✓			✓	✓	✓						
H. Seiti et al. 2019	✓	✓	✓										
O. Ahmadi et al. 2020			✓							✓			
Y. Liu et al. 2020						✓	✓						
O C M. Hernandez et al. 2021				✓									
M A J u h. Broek et al. 2019	✓	✓				✓					✓		
O. Ozguc. 2020	✓		✓	✓									

G. Zou et al. 2021	✓	✓					✓						
D. Yang et al. 2018		✓				✓							
M. Yazdi et al. 2019		✓	✓			✓	✓						
D. Fan et al. 2021	✓					✓	✓						
N N. Ferreira et al. 2020	✓	✓	✓	✓									
G M. Galante et al. 2020		✓				✓							
J. Matias et al. 2020	✓		✓								✓		
Y. Han et al. 2021			✓		✓								
M. Yazdi et al. 2020			✓			✓							

G. Rinaldi et al. 2021	✓	✓				✓	✓				✓		
M. Viera et al. 2022		✓				✓	✓						
K. Chaabane et al. 2020		✓			✓	✓	✓						
Y. Han et al. 2019			✓			✓	✓						
E U. Olugu et al. 2021			✓	✓	✓	✓	✓	✓					
A. Khatab et al. 2019	✓	✓			✓	✓	✓						
T J. Ikonen et al. 2020	✓	✓			✓	✓	✓						
M. Ibrion et al. 2020		✓	✓	✓							✓		

A. Garcia-Teruel et al. 2022	✓	✓				✓	✓				✓		
B. Yeter et al. 2022		✓	✓			✓					✓		
T N. Schouten et al. 2021	✓	✓				✓	✓						
A H. Schrotenboer et al. 2020	✓				✓	✓	✓				✓		
A L. Ramirez-Ledesma and J A. Juarez-Islas. 2022	✓								✓		✓		
W. Ni et al. 2021		✓	✓								✓		
A. Allal et al. 2021	✓				✓	✓	✓	✓			✓		
L. Liu et al. 2022	✓	✓			✓	✓	✓						

S. Adumene et al. 2021	✓	✓						✓					
Z. Ren et al. 2021	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		
Y. Liu et al. 2018	✓	✓			✓	✓	✓						
M. Li et al. 2021	✓	✓			✓	✓	✓	✓			✓		
C. Zhang et al. 2019	✓	✓			✓	✓	✓	✓			✓		
C. Zhang and T. Yang. 2021	✓	✓			✓	✓	✓				✓		
R.B. Hageman et al. 2022	✓	✓	✓	✓							✓		

Table 2.4 references:

[9], [10], [11], [12], [13], [14], [15], [67], [16], [17], [18], [19], [20], [21], [22], [23], [24], [25], [26], [27], [28], [81], [29], [30], [31], [32], [33], [34], [35], [82], [36], [37], [38], [39], [40], [41], [68], [42], [43], [44], [45], [46], [47], [48], [49], [50], [51], [52], [69], [53], [54], [55], [56], [57], [58], [59], [60], [61], [70], [62], [63], [64], [65], [66].

It could be noted from the Table 2.4 that site constraints of available beds offshore and the impact of time required to carry out activities have not been considered as a key performance indicator/ desired goal in any of the literature reviewed in this work, which is a major limitation of the existing frameworks, as the availability of bed space offshore for any activity is the prime performance indicator for any maintenance execution. Towards this, there exists scope for further research work that would incorporate site constraints of available beds offshore and impact of time required to carry out activities including the Offshore resource availability into the maintenance plan and its impact on asset condition due to the maintenance execution, to achieve the optimal maintenance strategy.

2.5 Discussion

It has been noted that the maintenance performance indicators widely considered relates to the asset availability, reliability, and safety compliance, whereas the site constraints of personnel resource availability and impact of time required to carry out activities are not regarded as a performance indicator in the existing literature, which is a major limitation of the existing frameworks, as the availability of bed space offshore for any activity is the prime performance indicator for any maintenance execution. It has been noted that probabilistic assessment models, Bayesian Networks and Multi-objective optimisation techniques have been widely used in the literature for optimisation of maintenance activities. There exists scope for further research works that would incorporate practical site constraints on personnel resource availability and impact of time required to carry out activities into the maintenance plan and its impact on asset condition due to the maintenance execution, in order to achieve the optimal maintenance strategy.

Also, no dynamic and autonomous resource allocations for maintenance activities take place in the offshore maintenance planning systems that allows each maintenance item to independently adjust its resource allocation based on the time required to complete the activity, to improve the resource utilisation. In that respect, the maintenance models have to incorporate the site operational constraints related to personnel resources, environmental factors, and its impact on the overall activities in the maintenance planning system.

2.6 Conclusion

It could be concluded that there exists scope for further research works that addresses the site constraints of personnel resource availability, impact of time required to carry out activities and its impact on asset condition due to the maintenance execution, by examining machine learning and deep reinforcement learning network based artificial intelligence approach, considering the design features, actual condition of the component, site constraints, deterioration factors, consequences of not doing the activities, time required to complete the activities and investigating the impact on key maintenance performance indicators regarding resource allocations and resource utilisations.

Chapter3

Novel Multi-objective Optimisation for Maintenance Activities of Floating Production Storage and Offloading Facilities

3.1 Introduction

Through an extensive literature survey carried out, it has been identified that the current state-of-the-art literature does not incorporate site constraints of the asset related to offshore resource availability for the maintenance activity, due to maximum allowable bed space, impact of time required to carry out activities and its impact on other activities due to this maintenance. This is a major limitation of the existing state-of-the art maintenance frameworks. There exists scope for further research works that would incorporate site constraints related to availability of personnel resources for the maintenance activity into the maintenance plan, its impact on other activities due to the maintenance execution, and impact of time required to carry out activities.

In this Chapter, it is proposed that the above-mentioned gaps could be addressed by examining machine learning, considering the design features, actual condition of the component, site constraints, deterioration factors, consequences of not doing the activities, time required to complete the activities and investigating the impact on key maintenance performance indicators regarding resource allocations and resource utilisations.

In summary, the following contributions are made in this Chapter:

- A novel approach has been utilised to formulate a maintenance plan optimisation problem that maximise the maintenance personnel resource utilisation and enable Floating Production Storage and Offloading Facility (FPSO) condition enhancement, considering the priorities with respect to design features, operating conditions, deteriorations, and the consequences of not doing the maintenance, taking into consideration the personnel resource time required for activity completion. The decision variables for each location on the FPSO have been normalised between the maximum and minimum values along the length of FPSO in order to bring the variables related to the functionality in proportion with that at other locations along the FPSO, and also to enable scaling all of the decision variables and whereby their respective objective functions to the same magnitude.
- A novel approach has been employed for the multi-objective optimisation of FPSO main deck maintenance activities, such that to find the Pareto-optimal solution, an overall objective function has been developed as a linear combination of the multiple objective functions corresponding to maintenance priorities with respect to normalised Stress Unity Check, Fatigue Damage Ratio, Bending Moment Ratio, Shear Force Ratio, Degree of Corrosion Scale, Degree of Metal Loss, Safety Risks in the event of not doing maintenance and Financial Risks in the event of not doing maintenance respectively, taking into consideration the personnel resource time required for activity completion. Depending on the priority of the objective function when compared to other objective functions, a relative weight has been associated to the prioritised objective function, using the weighted sum approach. Also, the formulation enables maximisation and minimisation of the objective functions and provides flexibility to direct the focus of the overall objective function towards any one or more of the objective functions by adjusting their respective weight according to the maintenance strategy followed.

3.2 Related work

The existing literature related to analyses techniques to develop the maintenance strategies for offshore floating systems have been reviewed and the highlights in current literature have been summarised in Table 3.1.

Table 3.1: Analyses techniques to develop maintenance strategies for offshore floating systems

Ref. / Year	Equipment	Paper highlights
D. Fan et al. 2019	Offshore wind farms	This work proposes a hybrid heuristic optimization of maintenance routing and scheduling for offshore wind farms, with the following highlights: - Indicates that routing, and scheduling of maintenance are very important for operation and maintenance cost reduction. - Mixed particle swarm optimization (MPSO) has been applied to seek a desired mapping relation between vessels and wind farms. - A discrete Wolf pack search (DWPS) has been introduced to optimise the maintenance route under all constraints. - Objective is to minimise maintenance cost, considering the parameters of travel cost of vessel, technician cost, loss of profit without accomplishing the maintenance in the defined period and weather windows. The constraints being discrete weather windows, maintenance technicians and vessels availability. - This work demonstrates a new hybrid heuristic optimization technique integrated with MPSO and DWPS to support the multiple round trips to the bases during maintenance.

S. Zhong et al. 2019	Offshore wind farms	This work proposes a preventive maintenance scheduling problem of wind farms in the offshore wind energy sector which operates under uncertainty due to the state of the ocean and market demand, with the following highlights: - A fuzzy multi-objective nonlinear chance-constrained programming model has been developed with reliability and cost criteria and constraints to obtain satisfying schedules for wind turbine maintenance. - To solve the optimisation model, a 2-phase solution framework integrating the operational law for fuzzy arithmetic and the non-dominated sorting genetic algorithm II for multi-objective programming has been developed. Pareto-optimal solutions of the schedules were presented to form the trade-offs between the reliability maximization and cost minimization objectives.
A. Dehghani and F. Aslani. 2019	Offshore structures	This work provides a comprehensive review on common damages or deterioration of fixed steel jackets used as substructures in offshore petroleum and wind industry as well as strengthening, modification and repair (SMR) techniques developed for these platforms, which is an integral part of life extension programme, after assessing fitness for purpose (FFP) of the structure. It has been demonstrated that the fatigue loading exerted by wave and wind actions is one of the main loading type experienced by these platforms. Also, fatigue failure would be one of the major concerns for offshore platforms due to the fact that they are extensively subjected to repeated forces form waves and wind during their service life. High

		corrosion rate in splash zone accelerates the initiation and growth of fatigue cracks that usually occur at the weld toes due to the presence of weld toe undercuts and other defects caused by welding processes.
Y. Li and Z. Hu. 2021	Offshore oil and gas facilities	This work carries out a review of the tool models in the pre-decommissioning stages of offshore oil and gas facilities, with the following highlights: - It has been found that regression analysis and Multi-criteria Decision Analysis (MCDA) method are the efficient algorithms and methodology. MCDA could get rid of the support for data to some extent by using experts' opinions, however, the use of too many qualitative methods and expert-defined criteria makes this method not objective enough and inefficient in actual use. For regression analysis, the abundance and detail of the data significantly affects the performance of regression equation. The insufficient historical data could lead to overfitting of the regression equation. - It has been identified that the core problems of the current decision-making model is the lack of basic data and the incomplete Multi-criteria Decision Analysis method. The formulation of criteria and the sub-criteria requires incorporating uncertainty and randomness into qualitative and quantitative evaluations, to enhance its ability to adapt to random problems.

H J. Hwang et al. 2018	LNG FPSO	This work proposes a condition-based maintenance (CBM) system for LNG FPSO, with the following highlights: - Data driven approaches have been employed for CBM implementation in this work. - The proposed system analyse the data obtained from various sensors in order to identify abnormalities of equipment, to diagnose fault conditions, to predict the deteriorated states of equipment, and to provide timely maintenance support. - The configuration management and CBM platform that acts as a traffic signal between CBM functions have been proposed in this work.
B. Zhang and Z. Zhang. 2021	Offshore wind farm	This work proposes a methodology that integrates the maintenance scheduling and the power production planning in an offshore wind farm into an asynchronous scheduling framework, with the following highlights: - The methodology addresses the differences of maintenance scheduling and the power production planning in terms of decision timescales and response speeds. - This work demonstrates the formulation of the two optimisation problems into a two-stage adaptive optimisation model considering interactions between maintenance activities and power productions. - The accessibility to offshore wind turbines influenced by vessel availability and metocean conditions were incorporated into the model formulation so that maintenance constraints of

		offshore wind farms were more comprehensively addressed.
P. Zhou and P T. Yin. 2019	Offshore wind farm	This work proposes an opportunistic condition-based maintenance (OCBM) strategy for offshore wind farm in terms of predictive analytics, with the following highlights: - This work considers the effect of changeable maintenance lead time on the implementation of a planned maintenance decision, by carrying out a comprehensive analysis of the maintenance actions, economics and the remaining useful life reliability. - Also, this work demonstrates an opportunistic condition-based maintenance optimisation model defined by the condition maintenance threshold and opportunistic maintenance threshold.
J. Kang and C G. Soares. 2020	Offshore wind farm	This work proposes an opportunistic strategy that minimise the maintenance cost for offshore wind farms, considering degradation process, the maintenance effectiveness uncertainty and the waiting time caused by the changeable marine environment, with the following highlights: - The rolling horizon approach has been employed to renew the maintenance schedule based on the operating data. - The uncertainty of maintenance effectiveness has

		been addressed by introducing two-parameter age reduction factors and the extra downtime results from changeable marine weather.
I. Lazakis and S. Khan. 2021	Offshore wind farms	This work proposes a computationally effective heuristic optimisation and cluster strategy for optimal daily or short-term route planning and scheduling under the presence of operational constraints, with the following highlights: - An optimal operational planning methodology based on two types of vessels - Service Operation Vessel and Crew Transfer Vessel, used separately and combined. - Verification of the proposed framework carried out under different operational scenarios. - The optimisation framework considers climate data, vessels specifications, failure information, wind farm attributes and cost-related specifics. The series of overall operational tasks were divided into sequential sessions, including maintenance crew pick-up and drop-off tasks while the vessel routing optimisation performed for all sessions separately.

M. Abbas and M. Shafiee. 2020	Marine Structures	This work provides an overview of the state-of-the-art and future trends in asset maintenance management strategies applied to corroded steel structures in extreme marine environments, with the following highlights: - The corrosion prediction models as well as industry best practices on maintenance of marine steel structures have been detailed. In this regard, several deterministic and probabilistic models have been detailed that predict the corrosion rate of marine steel structures as a function of the exposure period, environmental conditions and material properties. - It has been demonstrated that the existing models involve considerable uncertainties in data collection and analysis for accurate modelling of the combined effects of environmental factors on overall corrosion loss in marine structures. To overcome this, some applications of advanced technologies such as computerized maintenance management system (CMMS), Bayesian network (BN), artificial intelligence (AI), and multi-criteria decision analysis (MCDA) to maintenance optimisation of corroded steel marine structures have been detailed.

C. Stock-Williams and S K. Swamy. 2019	Offshore wind farm	This work identifies that there is potential to automate the daily maintenance planning of offshore wind farms as the managers and schedulers need to manage large numbers of wind turbine visits every day, in order to carry out repair of faults, inspections and to conduct scheduled service operations. Daily schedules become a choice of which all maintenance activities are to be conducted, taking account of the constraints on weather conditions, shifts, vessel and technician capabilities and availability, and the impact of activities on wind farm profitability. - The objective was to achieve the best possible Transfer Plan, within the constraints of weather accessibility, technician availability, technician shift times, number of technicians allowed simultaneously onto a turbine. - This work demonstrates that insufficient attention has been paid to the use of metaheuristics coupled to sophisticated offshore wind farm simulations that allow much simpler incorporation of realistic constraints and evaluation of outcomes. There is potential to use Artificial Intelligence to support this process for developing Plans that account automatically for the many interacting variables and uncertainties.

A H. Schrotenboer et al. 2018	Offshore wind farms	This work proposes a Technician Allocation and Routing Problem for offshore wind farms (TARP) to jointly optimise the daily allocation of technicians to Operations and Maintenance (O&M) bases, and the daily vessel routes transporting those technicians to offshore wind farms, in order to perform maintenance activities in a given time horizon, with the following highlights: - A Two-Stage Adaptive Large Neighbourhood Search heuristic has been demonstrated to solve the TARP and two variants. The first variant restricts the allocation of technicians to O&M bases to be constant throughout time, whereas the second variant takes an allocation as given. - The Two-Stage Adaptive Large Neighbourhood Search has been embedded in a Monte–Carlo simulation to study the impact of the technician sharing in different practical scenarios of offshore wind maintenance service logistics. - This work demonstrates that the Two-Stage Adaptive Large Neighbourhood Search provides high quality and often optimal solutions.
O C M. Hernandez et al. 2021	Offshore wind installations	This work presents a review of the environmental impacts of the installation, operation and maintenance (O&M), and decommissioning of offshore wind technologies, with the following highlights: - An activity–stressor–receptor–impact framework has been employed by which the possible impacts of an environmental stressor on a specific receptor could be identified for each activity, including pile driving, cabling and blade rotation. - Also, the case study addresses impact on

		biological resources, protected areas and offshore wind spots considering atmospheric analysis along the coastline.
M A J u h. Broek et al. 2019	Offshore wind farm	This work proposes a simulation model of a wind farm maintenance system to assess the effectiveness of jack-up sharing policies compared to leasing, with the following highlights: - The work demonstrates that by sharing the cost of employing a jack-up vessel, it could be possible for service providers to lower cost compared to the vessel leasing (VL) policy. - With VL policy, the cost of maintenance would be considered a variable cost that depends on the chartering and lease time. - With the resource sharing policies - vessel sharing (VS) and vessel & harbour sharing (VHS) -, a part of the costs of maintenance becomes a fixed cost, whereby purchasing a jack-up vessel provides economic benefits than vessel leasing. The larger the collaboration, the lower the individual share of the fixed capital.
O. Ozguc. 2020	FPSO	In this work, the fatigue analyses have been performed on the FPSO side shell longitudinal structural elements attached to the typical transverse bulkhead and web frame at mid ship area, using component stochastic and full spectral procedure. - Also, the comparison of fatigue damage estimates using these two methods under the effect of vertical and horizontal bending in combination have been demonstrated. - The analyses have been performed in accordance with three loading conditions such as fully loaded, intermediate and ballast conditions.

		- The spectral fatigue analysis approach produces a stress transfer function, which in turn contributes to the generation of the power spectral density function. - The work demonstrates that combining the spectral moments with Palmgren-Miner law provides the cumulative fatigue damage of the FPSO.
G. Zou et al. 2021	Marine Structures	This work proposes a probabilistic maintenance optimisation approach exploiting value of information (VoI) computation and Bayesian decision optimisation. Also, the work presents a detailed comparative study on Value of Information (VoI), Life Cycle Cost (LCC) and reliability based fatigue inspection and maintenance optimisation approaches in structural engineering, with the following highlights: - The work demonstrates that the VoI based approach takes all available maintenance strategies into account (both with and without involving inspections) and could reliably yield optimal maintenance strategies, whether the VoI is larger than or equal to zero. When the VoI is equal to zero, LCC and reliability-based Condition Based Maintenance (CBM) optimisation could lead to suboptimal maintenance strategies.

G. Rinaldi et al. 2021	Offshore wind farms	This work proposes a methodology to calculate the capital and operational indicators of a floating wind farm over its project lifetime, with the following highlights: - A set of computational models have been used to reduce the uncertainties in the estimation of the technical and economical parameters, whereby introduces stochastic operation and maintenance modelling for uncertainty reduction. - The effect of using detailed operation and maintenance models and strategies allow a better estimation of operational cost. - The work demonstrates sizeable contribution of operational expenses towards the cost of energy.
M. Viera et al. 2022	Offshore wind support structures	This work proposes a stochastic approach to evaluate the benefits in operation and maintenance costs that could arise from the use of structural health monitoring systems on the support structures of offshore wind, with the following highlights: - The stochastic model was developed based on a Monte Carlo simulation, providing both a tool to produce a sensitivity analysis on the system performance, as well as insights on the impact of structural health monitoring systems on the total energy output of a certain farm. - The work demonstrates that structural health monitoring systems could indeed be an asset for offshore wind operation, however other parameters influence their potential and attractiveness to farm owners. - It is the relation between the interval between inspections, the monitoring ratio or the rate of

		monitored turbines, and the detection rate of the monitoring systems that matters to farm owners. - The stochastic model was developed in such a way that it is flexible enough to incorporate industrial data, such as real Mean Time Between Failures. Also, the model was developed with the goal of not benefiting the implementation of structural health monitoring systems over on-site inspections.
A. Garcia-Teruel et al. 2022	Offshore floating wind farms	This work performs a Life Cycle Assessment (LCA) of floating offshore wind farms using an Operations & Maintenance (O&M) model to evaluate the environment impact, with the following highlights: - A detailed O&M model has been employed in this work representing unplanned maintenance events based on failure rates, using site specific metocean conditions to calculate weather windows and considering vessel characteristics to calculate fuel consumption. - The O&M model employs a time-domain stochastic approach, based on the Markov Chain Monte Carlo technique, to model all the relevant aspects of an offshore wind farm operation, including environmental resource, reliability and power performance of the devices, maintenance vessels and related accessibility due to weather, and both corrective and preventive maintenance regimes. - From the simulations, a series of results describing the farm energy production, availability, maintainability and economic performance were

		obtained. This O&M model was used to estimate the contributions of the O&M activities to the LCA assessment. These were considered through the fuel consumption during offshore operations and transits, as well as the number of spare parts used for replacements of failed components. - The work demonstrates that O&M activities have a significant environmental impact in floating offshore wind farms and need to be considered in detail. It has been found that the operational phase was often not well considered or represented in previous LCA studies.
A H. Schrotenboer et al. 2020	Offshore wind farms	This work presents the Stochastic Maintenance Fleet Transportation Problem for Offshore wind farms (SMFTPO), in which a maintenance provider determines an optimal, medium-term planning for maintaining multiple wind farms while controlling for uncertainty in the maintenance tasks and weather conditions, with the following highlights: - A two-stage stochastic mixed integer programming model has been provided or the SMFTPO settings, and solved using Sample Average Approximation. - The work demonstrates that the method of bundling maintenance tasks results in overestimating medium term maintenance costs. Also, it was shown that incorporating additional constraints to incentivise quickly scheduling maintenance tasks is costly in a multiple wind farm setting. As the value of the stochastic solution is large, considering the uncertainty is a requirement,

		while on the other hand the expected value of perfect information is relatively small.
W. Ni et al. 2021	Offloading mooring system of FPSO	This work proposes a modified approximation method for failure probability estimation of high-dimension structural systems with numerous correlated failure modes, with the following highlights: - The method considers component correlation, reliability index, reliability index ratio and the correlation between the current and weakest failure modes that improves the accuracy and applicability of the method to different-configuration systems. - The work demonstrates that the proposed method could restrain error divergence more effectively than the existing approximation methods especially when the number of failure modes and the correlation between them increase. - The proposed method has also been proved to be applicable to fast reliability calculation of practical offshore engineering systems, such as side by side offloading mooring system of Floating Production Storage and Offloading facility (FPSO).
A. Allal et al. 2021	Offshore wind farms	This work proposes a simulation optimisation approach for the routing and the scheduling of maintenance for offshore wind farms in order to minimise cost while keeping a high availability of wind turbines, with the following highlights: - An Ant Colony System (ACS) algorithm has been used to optimise maintenance tasks routing using boats. - A multi-agent-based modelling and simulation has been introduced to deal with the complexity of the

		system. In order to make the proposed approach more realistic, several parameters and constraints have been considered such as weather conditions, resources cost, maintenance duration. - The efficiency of the proposed maintenance policy (with routing) has been demonstrated by adopting an approach based on a simulation optimisation of Operation & Maintenance tasks for Offshore Wind Farm using ACS algorithm running under NetLogo program. - The strategy involves making a tour when an event starts a maintenance. The ACS algorithm explores all combinations of turbines and returns the optimal tour for the maintenance teams. - The tour policy allows to increase the use of resources, reduce overall maintenance cost and increase Equipment Health Factor (EHF) of each turbine. Despite the increase in the number of preventive maintenances, the number of costly corrective maintenance was reduced that would explain the reduction of the overall costs. In turn, the quantity of produced energy was increased also due to the improvement of availability rate of wind turbines. - Also this work demonstrates the efficiency of the simulation optimisation approach to resolve dynamic, stochastic and complex problems, where several optimisation processes were executed in different moments during the simulation.

M. Li et al. 2021	Offshore wind farms	This work proposes a maintenance strategy for offshore wind farms integrating three types of maintenance opportunities, with the following highlights: - In addition to the maintenance opportunities created by degradation failures and incidents, an age-based opportunistic maintenance strategy has been introduced to improve the trigger of preventive dispatch. - The simulation method has been used to represent the maintenance scenarios and to evaluate the average annual maintenance costs. - The proposed strategy considers the number of aged components and is termed multiple age-based opportunity (MABO) strategy. The age-based opportunity will be created when the number of aged components reaches a predetermined value. - The comparative analysis under the based scenario for a 10-turbine farm demonstrates that the MABO and single age-based opportunity (SABO) strategies could both reduce about 11.9% cost than non-age-based opportunity (NABO) strategy.
R B. Hageman et al. 2022	FPSO hull	In this work, several sources of uncertainty of the hull structure of an FPSO have been quantified, with the following highlights: - Two years of continuous monitoring data have been used to quantify several sources of uncertainties. These sources include uncertainty related to the future extrapolation of loads and statistical uncertainty of the long-term sea states which would be quantified using a Bayesian resampling scheme. Also, the uncertainty introduced through the use of analytical load

		distribution models have been addressed. Finally, the uncertainty in the calculation method has been quantified. - These data were used in a case study for the particular FPSO which has been monitored to demonstrate their practical application employing a reliability model. - Multiple stochastic models for the long-term description of loads were examined. Besides the traditional Weibull model, the less frequently used Pareto, Lognormal and Gumbel model were tested and compared against an uncertainty model based on a spectral fatigue assessment. - The work demonstrates that the Pareto and Weibull models were considered appropriate models and were found to be comparable against design stage analyses, whereby the inclusion of measurement data in Risk Based Inspection analysis for the presented FPSO case results in prolongation of the inspection intervals from initially planned 3 years to new interval of 7 to 11 years, depending on the load model, with recommendation for repetition of the analysis at regular intervals to further improve the inspection scheduling and to maintain the target structural reliability.
M. Yazdi et al. 2020	Chemical Plant	This work proposes a decision-making framework that captures dependency of the risk factors and the source of information. This was achieved by integrating DEMATEL (decision making trial and evaluation laboratory) methodology with Best-Worst method (BWM) and Bayesian network (BN).

		The work demonstrates that the proposed methodology adequately deals with some shortages of typical decision-making methods that includes: - satisfy all the decision makers opinions to accept the final results as much as possible. - compute the optimum relative weight of decision-makers in a group decision making problem. - provide a systematic way that Bayesian structural network is constructed based on multiple decision-makers opinions. - provide probabilistic inference and decision-makers support in the uncertain environment according to the DEMATEL technique. - compromises a systematic approach to update the result in a dynamic environment. - modify and develop the decision-making model with supplementary information and data.
M. Yazdi et al. 2019	Offshore facility platform	This work proposes an extension to DEMATEL (decision making trial and evaluation laboratory) named Pythagorean fuzzy DEMATEL on a common probabilistic safety analysis for Quantitative risk assessment, with the following highlights: - Objective was to tackle existing shortages in prioritising Corrective Actions with consideration of causal influence of criteria of cost, benefit, efficiency or effectiveness in decision making process. - This work indicates that there would be difficulty in dealing with dynamic interrelations between factors such as considering the sequence of a group of Corrective Actions on an identified critical basic event. However, a multivariate analysis covering

		all sequences would have enough capability to cope with this situation.
H. Hesabi et al. 2022	Modular Aero-Propulsion System Simulation of a Commercial Turbofan Engine	This work proposes a predictive selective maintenance framework using deep learning and mathematical programming, with the following highlights: - Objective is to minimise total cost under intermission break time limitation. - Total cost is composed of maintenance and failure costs, which depends on success probabilities of the subsequent missions. - To estimate the success probabilities, the optimization model interacts with a long short-term memory model, which is based on a data driven approach that takes into account the real work condition implemented in various systems. - This work demonstrates the ability of predictive selective maintenance framework to predict the health condition of various components with accuracy and deals with the selective maintenance of series systems.
C. Diallo et al. 2019	Multicomponent systems	This work proposes a bi-objective imperfect selective maintenance optimisation model for a series-parallel multicomponent system, with the following highlights: - A mathematical model has been developed to optimise the trade-offs between the total maintenance cost and the system reliability based on the decision maker's preferences.

		- The weighted sums approaches are used to obtain the set of Pareto optimal solutions showing trade-off between reliability and total maintenance cost. - Numerical experiments indicate that the proposed model reaches valid maintenance decisions. Also, it was shown that when high system reliability is required, the optimal decision is not significantly affected by the decisionmaker's preference for one objective or the other.
Y. Liu et al. 2020	Coal Transportation	This work proposes a selective maintenance optimisation for multi-state systems that could execute multiple consecutive missions over a finite horizon, with the following highlights: - The work demonstrates that selective maintenance strategy could be dynamically optimised to maximise the expected number of future mission successes whenever the states and effective ages of the components become known at the end of the last mission. - The dynamic optimisation problem that accounts for imperfect maintenance has been formulated as a discrete time finite horizon Markov decision process with a mixed integer discrete continuous state space. Based on the framework of actor critic algorithms, a customised deep reinforcement learning method has been put forth. - Also, a postprocess has been developed for the actor to search the optimal maintenance actions in a large-scale discrete action space, whereas the techniques of the experience replay, and the target network has been utilised to facilitate the agent training.

D. Yang et al. 2018	Aircrafts	This work proposes a sequential game algorithm with state backtracking for a fleet of aircrafts to reduce the maintenance frequency and costs under the constraint of reliability, with the following highlights: - A heuristic sequential game approach for Fleet-level Selective Maintenance (FSM) under a phased mission scheme with short breaks has been demonstrated in this work. - The problem has been formulated with the objective of reducing the repair frequency and cost, within the constraints of the reliability of the phased mission. The variables being the remaining useful lifetimes (RUL) of all the key subsystems.
G M. Galante et al. 2020	Continuous and discontinuous operating systems	The work demonstrates mathematical programming formulation of the selective maintenance problem with the aim to maximise the system's reliability under an uncertain environment. - This work proposes a Dempster-Shafer theory (DST) based approach to deal with uncertainty of components' reliability data in the selective maintenance problem, with the following highlights: - A constrained optimisation model has been developed for the system's reliability maximisation, by referring to a system that has to function for a certain timeframe such as mission time or time between turnarounds, ensuring a high reliability level at the same time. - Under the DST framework, experts' opinions were converted into belief masses and opportunely aggregated by means of the Yager combination rule.

K. Chaabane et al. 2020	Manufacturing systems	This work proposes a selective maintenance problem (SMP) model for jointly optimising maintenance and assignment decisions in a system running multiple missions, with the following highlights: - An integrated non-linear programming formulation has been developed, and a solution technique proposed based on the genetic algorithm. - The SMP addresses five joint decisions: selection of components to maintain, selection of maintenance levels performed on the selected components, identification of breaks where maintenance tasks are performed, repairpersons selection, and maintenance tasks assignment to selected repairpersons. - The objective was to minimise the total maintenance and labour costs for a maintenance plan that guarantees a given reliability threshold. - The work demonstrates that the mixed cohort composition of the repair crews performed equally or better than the uniform cohorts, especially when differences, in terms of costs and required maintenance times are sufficiently large between maintenance workers.
A. Khatab et al. 2019	Manufacturing systems	This work proposes a variant of the selective maintenance problem (SMP) where a mixture of new and reconditioned/remanufactured parts were used to carry out replacements, with the following highlights: - The concept of a statistical mixture was employed to calculate the reliability function of components

		selected from a mixed population of new and reconditioned spare parts. - A mixed integer nonlinear programming model of the SMP was developed and optimally solved. - Numerical experiments indicate how reconditioned spare parts impacts the SM decisions.
T J. Ikonen et al. 2020	Engineering Systems	This work proposes a selective maintenance problem (SMP) model to improve the efficiency of selective maintenance optimisation for industrial scale problems, while still guaranteeing the optimality of the solution, with the following highlights: - A statistical analysis of lifetime data has been incorporated into selective maintenance optimization, focusing on datasets with bathtub-shaped failure rates. - Also, two improvements were proposed to the efficiency of mixed integer non-linear programming (MINLP) based selective maintenance optimisation. The first is the avoidance of component replacements due to the infant mortality period of the component, which reduces the reliability. The second is the convexification of two MINLP models, involving only replacement, or replacement and repair, actions. - The work demonstrates that the improvements enable MINLP based methods to tackle large scale selective maintenance optimisation problems with up to 1000 system components.

L. Liu et al. 2022	Transportation system	This work proposes a multi-mission selective maintenance and repairpersons assignment model where the durations of missions, maintenance actions, and breaks are stochastic, with the following highlights: - The proposed selective maintenance program (SMP) could assist maintenance decision-makers to make four decisions - determining maintenance levels of components, determining number of hired repairpersons, assigning maintenance actions, and determining sequence of maintenance actions for each repairperson. - Due to the stochasticity of durations, the completion probability of the selected maintenance action was obtained by computing a multidimensional integration, and the Monte Carlo simulation approach has been employed to evaluate the completion probability of the selected maintenance actions. - The proposed model has been transformed into an optimisation problem constrained by the limited maintenance resources and the objective to minimise the expected grand total cost with a given reliability threshold. - A tailored genetic algorithm (GA-UD) has been developed to solve the resulting optimisation problem, and the standard deviation of the grand total cost of the best maintenance strategy in each scenario was evaluated by the Monte Carlo simulation approach. - The work demonstrates that considering the stochasticity of the durations could not only ensure that the system meets the mission reliability

		requirement, but also reduce the grand total cost by making some reasonable maintenance strategies.

Table 3.2: Principal Dimensions of modelled FPSO

Length between perpendiculars	300m
Moulded Breadth	50m
Moulded Depth	30m

Table 3.1 references:

[11], [15], [67], [16], [17], [19], [21], [22], [24], [25], [28], [30], [82], [36], [37], [38], [46], [47], [53], [56], [58], [59], [63], [66], [45], [40], [9], [32], [35], [39], [42], [48], [51], [52], [60].

3.3 System formulated multi-objective problem formulation for FPSO Main Deck maintenance

A FPSO main deck modelled in this work is estimated to be of a 10-year-old hull with the principal dimensions as indicated in Table 3.2.

The commercially available loading calculator has been employed to parametrically define the geometric model.
The Profile view of the modelled FPSO has been shown in Figure 3.1, and the Elevation and Plan views shown in Figure 3.2.

3.3.1 Maintenance window model

Let n denotes the maintenance plan, k_m a single maintenance activity, in the maintenance window denoted by $C_{k_m,n}$. Let B be the resource availability in the window,$h_{k_m,n}$ and $h_{k_m,l}$ the quality of services, $sigma^2$ the extent of activity completion, then the minimum

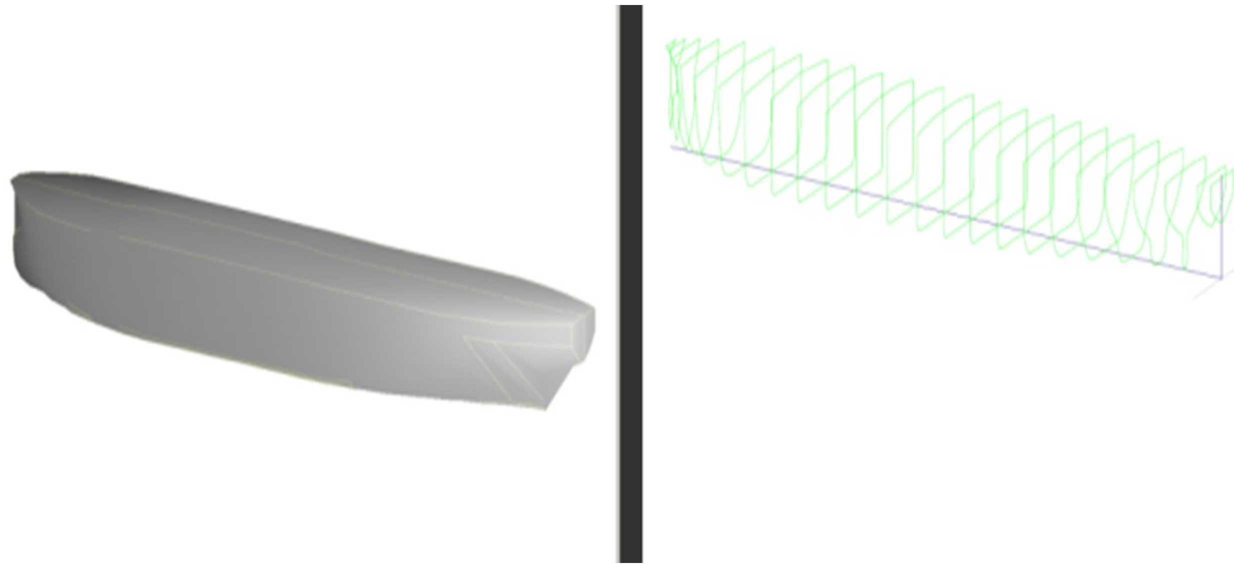

Figure 3.1: Profile of the modelled FPSO

maintenance window required for a maintenance activity could be expressed as follows, as in the works of G. Sun, et. al. 2019 [83].

$$C_{k_m,n} \;=\; B\ log_2(1 \;+\; \frac{P_n \mid h_{k_m,n} \mid^2}{\sum_{l\,\in\,N,\,l\neq\,n} P_l \mid h_{k_m,l} \mid^2 \;+\; \sigma^2}) \tag{3.1}$$

Where P_n and P_l denotes the space of all polynomials of degrees less than or equal to n and l respectively, and the log_2 transformation normalises the expression and enables proportional changes rather than additive changes.

3.3.2 Offshore resource model

Offshore resources considered in this work are the professional technicians available to perform the tasks, which include personnel already doing the work, or could do the work that needs to be done on the various systems, which require a portion of the resource allocations. The maintenance activities have resource requirement in terms of time to complete the task,

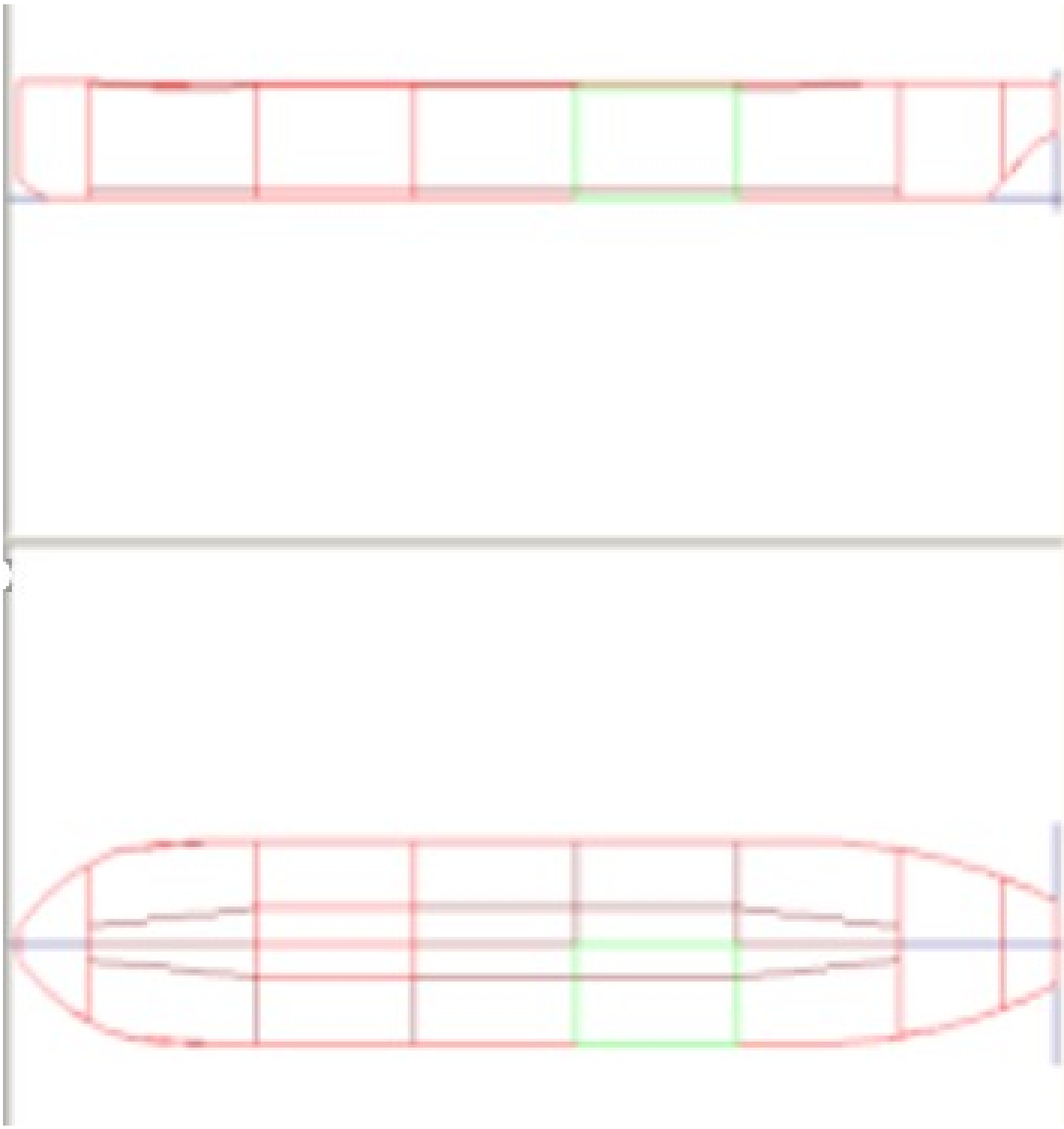

Figure 3.2: Elevation and Plan views of modelled FPSO

and the maximum and minimum allowable resources for the activity. The minimum resource requirement for the activity would be the initial resource allocation for the activity. Further allocation of resources would be carried out by monitoring the status of the activity based on the predicted progress as per pre-defined results. The resource estimations take place by adapting the quality-of-service requirements of individual systems.

The performance of resource allocation could be checked by resource utilisation and the quality-of-service satisfaction of the maintenance activity with a time varying number of maintenance activities. The expectation would be that the performance of one maintenance system does not affect the other, and thus the performance isolation for quality of service would be important. The overall resource availability in the work management system of the offshore asset would be split up for the individual maintenance activities, and there would be a need to map and schedule the resources efficiently. The unused personnel resource on the work management system would be a fraction of the offshore resource that does not get allocated to maintenance activities.

The reserved resource would be a fraction of the unused resource of the work management system, reserved to the maintenance activity based on its ratio of resource requirement relative to other maintenance activities. The sum of the resource reservations of the maintenance activities determines the unused resource of the work management system. The allocated resource of a maintenance activity on the work management system would be the fraction of the work management system resource that is currently allocated and being used by the maintenance activity. When a maintenance activity is planned, an initial amount of resource would be reserved to it among all the available offshore resources, based on the minimum resource requirement of the maintenance activity that is known to the work management system initially. The overall resource of a maintenance activity among the resources in the work management system would be the sum of the allocated resource and reserved resource for the maintenance activity after the maintenance activity resource allocation and reservation update.

The resource utilisation and quality of service utility models could be used to check the utility checks of maintenance items and maintenance activities. In this work, the resource utilisation has been used to check if the allocated maintenance window for the maintenance activity is utilised. Also, resource utilisation would indicate the usage of the available maintenance window effectively for the maintenance activity, such that higher weighted sum of the task completion times at as short time as possible, would lead to higher resource utilisations and enables enhancement of FPSO conditions.

3.3.3 Degradation model

During the life of FPSO, the component considered for maintenance degrades as the time goes by until their failure. Modelling the time to failure t, of the component i, at random by employing the Weibull distribution with scale parameter σ, and shape parameter ϵ, the component probability density function $f_i(t)$, reliability function $R_i(t)$, and mean time to failure $MTTF_i$, could be expressed as follows as in the works of M. Li, et. al. 2021 [16].

$$f_i(t) \ = \ \frac{\epsilon_i}{\sigma_i} \, (\frac{t}{\sigma_i})^{\epsilon_i - 1} \, e^{-} (\frac{t}{\sigma_i})^{\epsilon_i} \tag{3.2}$$

$$R_i(t) \ = \ e^{-} (\frac{t}{\sigma_i})^{\epsilon_i} \tag{3.3}$$

$$MTTF_i \ = \ \int_0^{\infty} \ t f_i(t) \ = \ \sigma_i \, \Gamma \, (\frac{1}{\epsilon_i} \ + \ 1) \tag{3.4}$$

where, $\Gamma\left(\frac{1}{\epsilon_i} + 1\right)$ denotes the Gamma function.

3.3.4 Constraints

Similar to most literature, this work considers site constraints of access restrictions, condition of work, personnel availability, equipment availability, weather conditions, repair shifts, technician capabilities and impact on other activities. However, differing from the existing literature, this work considers the new important factor, the impact of time required to carry out offshore maintenance activities, to achieve the optimal personnel resource utilisations. Shadow areas and locations with accessibility issue, restricted access spaces that require additional risk assessment prior accessing, overside sections of the deck that need boat cover and additional risk assessment prior accessing, locations having presence of continuous water and need special equipment for carrying out maintenance, locations with accessibility issues during normal operations and need to be dealt during a pre-specified period such as plant shut down as an opportunistic work, are typical site constraints on a FPSO.

3.3.5 Decision variables

The decision variables considered in this work are the design features, operating conditions, deteriorations experienced and the consequences of not doing the maintenance activities.

3.3.5.1 Design features

The strength design of the FPSO hull ensures that the structure could withstand the von mises stresses experienced on the hull. The calculated von mises stresses determines whether the location would lead to a hot spot for deterioration and failures. The von mises could be evaluated by considering the stress unity check value, such that,

$$Stress\ Unity\ Check\ UC\ =\ \frac{von\ mises\ stress}{yield\ strength} \tag{3.5}$$

Stress Unity Check $\{x_1\}$, UC is the inverse of factor of safety. UC value high, means high stress locations and need to be prioritised for maintenance.

A fatigue design ensures that the FPSO hull structure has an adequate fatigue life. The calculated fatigue lives form the basis for the operational life of the FPSO hull. Fatigue could be evaluated by considering the fatigue damage ratio, such that,

$$Fatigue\ Damage\ ratio\ D\ =\ \frac{fatigue\ damage\ at\ considered\ no.\ of\ cycles}{fatigue\ life\ at\ constant\ amplitude\ loading} \tag{3.6}$$

Fatigue Damage ratio, $\{x_2\}$,D value high, means location has low fatigue life and need to be prioritised for maintenance.

3.3.5.2 Operating conditions

The bending moment experienced on the FPSO hull during operating conditions defines how much indicates the reaction in a cross-section of the hull due to the external forces and moments induced by the loads that the structure gets subjected to. The bending moment experienced could be evaluated by considering the bending moment ratio, such that,

The bending moment experienced on the FPSO hull during operating condition indicates the reaction in a cross-section of the hull due to the external forces and moments induced by the loads that the structure gets subjected to. The bending moment experienced could be evaluated by considering the bending moment ratio, such that,

$$Bending\ Moment\ ratio\ M \ = \ \frac{bending\ moment\ experienced\ in\ situ}{bending\ moment\ allowable} \tag{3.7}$$

Bending Moment ratio, $\{x_3\}$, M value high, means high bending moment experienced at the location and need to be prioritised for maintenance.

The shear force experienced on the FPSO hull during operating condition indicates the resultant shearing forces on the hull due to the external forces induced by the loads that the structure gets subjected to. The shear force experienced could be evaluated by considering the shear force ratio, such that,

$$Shear\ Force\ ratio\ S \ = \ \frac{shear\ force\ experienced\ in\ situ}{shear\ force\ allowable} \tag{3.8}$$

Shear Force ration,$\{x_4\}$, S value high, means high shear force experienced at the location and need to be prioritised for maintenance.

As the stresses in hull section induced by the bending moment and shear force are carried by hull girder structural members, namely strength deck plating and deck longitudinal, side shell plating and longitudinal, bottom shell plating and longitudinal, inner bottom plating and longitudinal, double bottom girders and bilge plating, any deterioration of these structural members during the life of the FPSO impacts the design envelopes of M and S, whereby reducing the still water bending moment and shear force allowable limits.

3.3.5.3 Deteriorations

The dominant deterioration mechanism expected on FPSO structures has been considered as the corrosion. The structures exposed to weather or sea water would be protected by paint coating and the expected lifetime of the coating would generally exceed that of the FPSO. The intact coating condition would be achieved when the coating has been applied to a clean surface with good surface preparation. The areas with degraded coating could become anodic compared with areas with intact coating and would lead to corrosion.
The coating breakdown and scattered corrosion in excess of approx. 8% of the area considered would generally be recommended for remedial action, while other minor blisters and coating breakdowns are classed as insignificant findings. The corrosion scale could be evaluated by considering the degree of corrosion scale, such that,

$$Degree\ of\ corrosion\ scale\ R_i = \frac{observed\ \%\ corrosion\ scale}{coating\ intact\ condition} \tag{3.9}$$

Degree of corrosion scale, $\{x_5\}$, R_i value high, means high corrosion scale at the location and need to be prioritised for maintenance.

The individual component thickness has to be maintained within the diminution allowances considered in the strength assessment. The corrosion would lead to metal loss of the original thickness and the resultant metal loss could be evaluated by the diminution ratio, such that,

$$Diminution\ ration\ C\ =\ Degree\ of\ metal\ loss\ =\ \frac{loss\ in\ plate\ thickness}{intact\ gross\ plate\ thickness} \tag{3.10}$$

Diminution ratio, $\{x_6\}$,C value high, means high degree of metal loss at the location and need to be prioritised for maintenance.

3.3.5.4 Consequences of not doing maintenance

TThe consequences of corrosion have significance on strength, operability, and operating life of the FPSO hull structures. The main consequences of hull structural failures could be the impacts on Safety and Financial aspects, resulting in the scenarios such as release of hydrocarbon gas to the atmosphere and a potential explosion; release of hydrocarbon oil to the environment; internal structural failure leading to contaminations between compartments; global Hull girder and local structural failures; and loss of stability, resulting in capsizes. The associated risks could be quantified as safety risks and financial risks of high, medium, and low severities, such that,

Safety risks, $\{x_7\}$,

$$Criticality\ Sa = 3\ High.\ Sa = 2\ Medium.\ Sa = 1\ Low \tag{3.11}$$

Safety risks, $\{x_7\}$, Sa value high, means high safety risks involved in case of not doing the maintenance, and hence need to be prioritised for maintenance.

Financial risks, $\{x_8\}$,

$$Criticality\ Fi = 3\ High.\ Fi = 2\ Medium.\ Fi = 1\ Low \tag{3.12}$$

Financial risks, $\{x_8\}$, Fi value high, means high financial risks involved in case of not doing the maintenance, and hence need to be prioritised for maintenance.

3.3.5.5 Personnel resource for activity completion

The personnel resource Time, $\{x_9\}$, required for each activity could be estimated based on the extent of coating breakdown observed at the FPSO locations. The time T required to complete the task, based on the coating breakdown, could be evaluated by considering the ratio of coating breakdown area, such that,

$$Ratio\ of\ coating\ breakdown\ area\ R\ = \frac{observed\ \%\ coating\ breakdown\ area}{total\ coating\ intact\ area} \tag{3.13}$$

R value high, means coating breakdown over a large area at the location and need more time to carry out maintenance.

$IF\ R \leq 0.2,\ return\ T = 2$

$IF\ R > 0.2\ but \leq 0.4,\ return\ T = 3$

$IF\ R > 0.4\ but \leq 0.6,\ return\ T = 4$

$IF\ R > 0.6,\ return\ T = 5$

3.3.6 Objective functions

The main objective of this work was to maximise the maintenance personnel resource utilisation and enable FPSO condition enhancement, considering the priorities with respect to design features, operating conditions, deteriorations, and the consequences of not doing the maintenance, taking into consideration the personnel resource time required for activity completion.

Objective Function,

$$F_i = \sum \left(\frac{P[i]}{T[i]} * C[i]\right) \tag{3.14}$$

where, $P[i]$ is the Priority based on the objectives, and $T[i]$ is the time required to complete a maintenance activity, and $C[i] = \sum T[j]$ the cumulative task completion time.

By aggregating the parameters, Priority P and Time T, into the single score of $\frac{P[i]}{T[i]}$, when the tasks are sorted from higher score to lower score, that would lead to optimal solution.

Higher priorities $\{P\}$ lead to a higher score for the Objective Function. More time $\{T\}$ required to complete the task, would decrease the score of the Objective Function.

The objective function corresponding to maintenance priorities with respect to design features of Stress Unity Check $\{x_1\}$ taking into consideration the personnel resource time required for activity completion has been termed as $F_1 = \sum (\frac{P[1]}{T[1]} * C[\ 1]$. The objective function corresponding to maintenance priorities with respect to design features of Fatigue Damage Ratio $\{x_2\}$ taking into consideration the personnel resource time required for activity completion has been termed as $F_2 = \sum (\frac{P[2]}{T[2]} * C[\ 2]$. The objective function corresponding to maintenance priorities with respect to operating conditions of Bending Moment Ratio $\{x_3\}$ taking into consideration the personnel resource time required for activity completion has been termed as $F_3 = \sum (\frac{P[3]}{T[3]} * C[\ 3]$. The objective function corresponding to maintenance priorities with respect to operating conditions of Shear Force Ratio $\{x_4\}$ taking into consideration the personnel resource time required for activity completion has been termed as $F_4 = \sum (\frac{P[4]}{T[4]} * C[\ 4]$. The objective function corresponding to maintenance priorities with respect to deteriorations of Degree of Corrosion Scale $\{x_5\}$ taking into consideration the personnel resource time required for activity completion has been termed as $F_5 = \sum (\frac{P[5]}{T[5]} * C[\ 5]$. The objective function corresponding to maintenance priorities with respect to deteriorations of Degree of Metal Loss $\{x_6\}$ taking into consideration the personnel resource time required for activity completion has been termed as $F_6 = \sum (\frac{P[6]}{T[6]} * C[\ 6]$. The objective function corresponding to maintenance priorities with respect to Safety Risks in the event of not doing maintenance $\{x_7\}$ taking into consideration the personnel resource time required for activity completion has been termed as $F_7 = \sum (\frac{P[7]}{T[7]} * C[\ 7]$. The objective function corresponding to maintenance priorities with respect to Financial Risks in the event of not doing maintenance $\{x_8\}$ taking into consideration the personnel resource time required for activity completion has been termed as $F_8 = \sum (\frac{P[8]}{T[8]} * C[\ 8]$.

3.3.7 Implementation of multi-objective problem formulation and optimisation model

To enable the problem formulation, a novel approach has been utilised such that the decision variables for each location on the FPSO have been normalised between the maximum and minimum values along the length of FPSO in order to bring the variables related to the functionality in proportion with that at other locations along the FPSO, and also to enable scaling all of the decision variables and whereby their respective objective functions to the same magnitude, such that,

$$Normalised\ \{x_i\}\ = \frac{Max.\ \{x_i\}\ at\ location\ -\ Min.\ \{x_i\}\ along\ length\ of\ FPSO}{Max.\ \{x_i\}\ along\ length\ of\ FPSO\ -\ Min.\ \{x_i\}\ along\ length\ of\ FPSO} \tag{3.15}$$

The FPSO main deck maintenance planning system problem has been implemented incorporating design features of stress unity check,x_1 and fatigue damage ratio, x_2; operating conditions of bending moment ratio, x_3 and shear force ratio, x_4; deteriorations of degree of corrosion scale, x_5 and degree of metal loss,x_6; safety and financial consequences of not doing maintenance, x_7, x_8 and the personnel resource to complete the activity, x_9 based on the ratio of coating breakdown area. It was estimated that there would be no coating breakdown on the main deck for the first 10 years of the FPSO life and thereafter an 8% annual coating breakdown deterioration is anticipated on the main deck structures for the next 3 years, if no maintenance is carried out.

The input data for the design values, x_1, x_2 were estimated from the real life experience of the Author, operating condition values, x_3, x_4 obtained from running various load cases on the geometrical model of the FPSO in commercially available loading calculator, deterioration values, x_5, x_6 developed employing the information from published literature of corrosion rates of ships from Tanker Structure Co-Operative Forum and the consequence values of not doing the tasks, x_7, x_8 were estimated from the real life experience of the Author. The time required to complete the task, x_9 was estimated based on the extent of coating breakdown considered at the main deck locations, dependent on the age of the FPSO.

The proposed FPSO main deck maintenance planning system problem has been shown in Figure 3.3.

To find the Pareto-optimal solution, an overall objective function has been developed as a linear combination of the multiple objective functions, similar to the approach proposed in the works of R E. Steuer 1986 [84].

The objective functions, $F_1,\ F_2,\ F_3,\ F_4,\ F_5,\ F_6,\ F_7,\ F_8$ corresponding to maintenance priorities with respect to normalised Stress Unity Check x_1, Fatigue Damage Ratio x_2 , Bending Moment Ratio x_3, Shear Force Ratio x_4, Degree of Corrosion Scale x_5 , Degree of Metal Loss x_6 , Safety Risks in the event of not doing maintenance x_7 and Financial Risks in the event of not doing maintenance x_8 respectively, taking into consideration the personnel resource time required for activity completion, were combined into an overall objective optimisation problem. Depending on the priority of the objective function when compared to other objective functions, a relative weight has been associated to the prioritised objective function, using the weighted sum approach, such that

$$\{y_i\} \ = \ \sum(\pm\alpha_i \ * \ F_i) \tag{3.16}$$

where, α_i indicate the relative weight of the prioritised objective function when com-

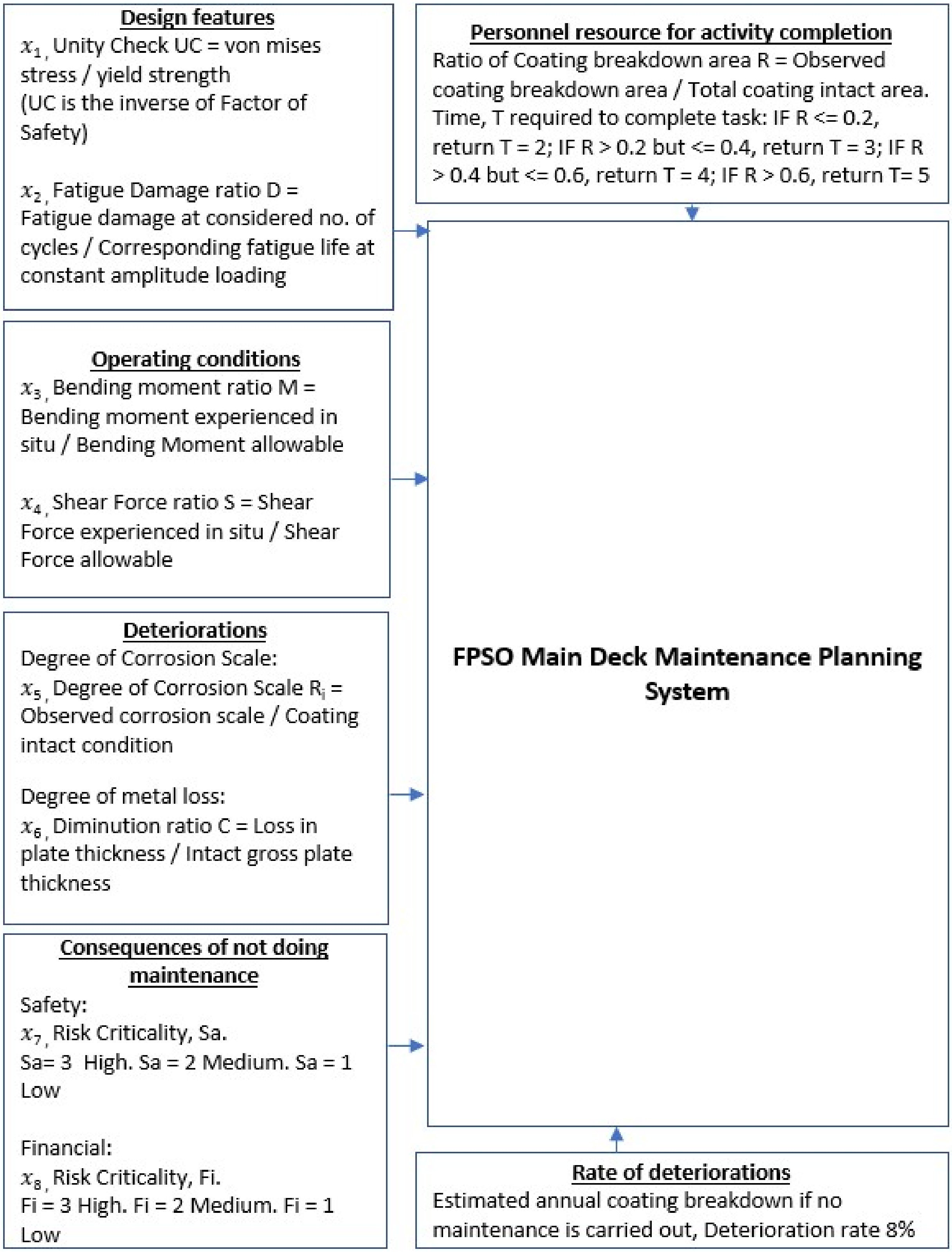

Figure 3.3: FPSO Main Deck maintenance planning system problem

pared with the priority of other objective functions. The positive weight, $Sign\ +$, means the corresponding objective function would be maximised, and negative weight, $Sign\ -$, means the corresponding objective function would be minimised. This formulation provides flexibility to direct the focus of the overall objective function, y_i, towards any one or more of the objective functions by adjusting their respective weight according to the maintenance strategy followed.

3.4 Conclusion

The main objective of this Chapter was to formulate a maintenance plan optimisation problem that maximise the maintenance personnel resource utilisation and enable FPSO condition enhancement, considering the priorities with respect to design features, operating conditions, deteriorations, and the consequences of not doing the maintenance, taking into consideration the personnel resource time required for activity completion.

This has been achieved by developing a FPSO main deck maintenance system model incorporating design features, operating conditions, deteriorations, consequences of not doing the maintenance and the personnel resource estimated to complete the activity. To enable the problem formulation, a novel approach has been utilised such that the decision variables for each location on the FPSO have been normalised between the maximum and minimum values along the length of FPSO in order to bring the variables related to the functionality in proportion with that at other locations along the FPSO, and also to enable scaling all of the decision variables and whereby their respective objective functions to the same magnitude.

Also, a novel approach has been employed for the multi-objective optimisation of FPSO main deck maintenance activities, such that to find the Pareto-optimal solution, an overall objective function has been developed as a linear combination of the multiple objective functions corresponding to maintenance priorities with respect to normalised Stress Unity

Check, Fatigue Damage Ratio, Bending Moment Ratio, Shear Force Ratio, Degree of Corrosion Scale, Degree of Metal Loss, Safety Risks in the event of not doing maintenance and Financial Risks in the event of not doing maintenance respectively, taking into consideration the personnel resource time required for activity completion. Depending on the priority of the objective function when compared to other objective functions, a relative weight has been associated to the prioritised objective function, using the weighted sum approach. Also, the formulation enables maximisation and minimisation of the objective functions and provides flexibility to direct the focus of the overall objective function towards any one or more of the objective functions by adjusting their respective weight according to the maintenance strategy followed.

Chapter4

Benchmarking and Analysis of Novel Greedy Algorithm for problem formulation of FPSO main deck maintenance

4.1 Introduction

Based on the formulation of multi-objective optimisation carried out in Chapter 4, a greedy algorithm has been proposed in Chapter 5 that incorporates the impact of time required to complete the activities on the optimisation objectives of FPSO design features, operating conditions, deteriorations, consequences of not doing the maintenance and the personnel resource availability for activity completion. Also, the benchmarking of the algorithm has been carried out by comparing the parameters, with and without considering the time required to complete the task, which reflects influence of the time required to carry out the activity, on the prioritisation of activities.

The performance of the greedy algorithm has been evaluated in terms of the personnel resource allocation and resource utilisation. To evaluate the satisfaction of resource allocation, the weighted sum of the task completion times based on the priorities have been considered. To evaluate the satisfaction of resource utilisation, it has been considered that the higher weighted sum of the completion times at as short time as possible, leads to higher resource utilisations.

In summary, the following contributions are made in this Chapter:

• A novel multi-objective optimisation of maintenance activities has been formulated whereby a greedy algorithm has been proposed that incorporates the impact of time required to complete the activities on the optimisation objectives of design features, operating conditions, deteriorations, consequences of not doing the maintenance and the personnel resource availability for activity completion.

• The benchmarking of the algorithm has been carried out by comparing the parameters, with and without considering the time required to complete the task, which reflects influence of the time required to carry out the activity, on the prioritisation of activities.

• The performance of the greedy algorithm has been evaluated in terms of the personnel resource allocation and resource utilisation. To evaluate the satisfaction of resource allocation, the weighted sum of the task completion times based on the priorities have been considered. To evaluate the satisfaction of resource utilisation, it has been considered that the higher weighted sum of the completion times at as short time as possible, leads to higher resource utilisations.

• Also, for multi-objective optimisation, the overall objective optimisation problem has been proposed by linear combinations of the multiple objective functions, using the weighted sum approach.

4.2 Novel Greedy Algorithm for formulation of FPSO main deck maintenance

The novelty of this work is that a greedy algorithm approach, which follows the problem-solving pattern of making the locally optimal choice at each step with the hope of finding the globally optimal solution has been employed in this work, for the problem formulation of FPSO main deck maintenance. The greedy algorithm was chosen for this work, as it works step by step looking at the immediate situation and chooses the steps that provide immediate benefits. This in turn enables achieving the most feasible solution immediately. In the FPSO main deck maintenance optimisation problem, if more activities could be done before completing the ongoing activity, these activities could be performed within the same time. Also, the greedy algorithm enables dividing the problem iteratively based on a condition and makes one greedy choice after another and reduces the problem, without need to combine all the solutions.

In this problem formulation, the greedy algorithm makes greedy choices to get the optimum overall objective function, developed as a linear combination of the multiple objective functions. The objective function $\{F_i = \sum (\frac{P[i]}{T[i]} * C[\, i]\}$ is the weighted sum of the completion times based on the priorities with respect to design features, operating conditions, deteriorations, and the consequences of not doing the maintenance, and the objective is to have higher weighted sum of the completion times at as short time as possible.

The following algorithm returns the optimal value of the objective functions:

Algorithm 1 Greedy Algorithm:

$Algorithm(P,\ T,\ N)$

$\{$

$Minimum\ x_i;\ Maximum\ x_i.$

$Normalised\ x_i\ =\ (Max\ x_i\ -\ Min\ x_i\ value\ along\ the\ FPSO)\ /$

$(Max\ x_i\ value\ along\ FPSO\ -\ Max\ x_i\ value\ along\ the\ FPSO)$

$Priority\ for\ the\ task,\ P,\ assigned\ based\ on\ Offshore\ Operational\ practices:$

$IF\ x_i\ \leq\ 0.25,\ return\ 2,\ Priority\ P4;$

$IF\ x_i\ >\ 0.25\ but\ \leq\ 0.5,\ return\ 3,\ Priority\ P3;$

$IF\ x_i\ >\ 0.5\ but\ \leq\ 0.75,\ return\ 4,\ Priority\ P2;$

$IF\ x_i\ >\ 0.75\ return\ 5,\ Priority\ P1;$

$Ratio\ of\ Coating\ breakdown\ area\ R\ =$

$Observed\ \%\ coating\ breakdown\ area\ /\ Total\ \%\ coating\ intact\ area.$

$Estimated\ annual\ coating\ breakdown\ if\ no\ maintenance\ is\ carried\ out\ -$

$Deterioration\ rate\ 8\%.$

$Time,\ T\ required\ to\ complete\ the\ task:$

$IF\ R\ \leq\ 0.2,\ return\ T\ =\ 2$

$IF\ R\ >\ 0.2\ but\ \leq\ 0.4,\ return\ T\ =\ 3$

$IF\ R\ >\ 0.4\ but\ \leq\ 0.6,\ return\ T\ =\ 4$

$IF\ R\ >\ 0.6,\ return\ T\ =\ 5$

$Algorithm:\ (P[i]\,/\,T[i])$

$Aggregating\ the\ parameters\ (Priority\ P\ and\ Time\ T)\ into\ a\ single\ score,\ such\ that$

$when\ the\ tasks\ are\ sorted\ from\ higher\ to\ lower\ score,\ lead\ to\ optimal\ solution.$

$*\ Higher\ priorities\ (P)\ lead\ to\ a\ higher\ score\ for\ the\ Objective\ Function$

$*\ More\ time\ (T)\ required\ to\ complete\ the\ task,\ would\ decrease\ the\ score\ of\ the\ -$

$Objective\ Function$

$Algorithm:\ Order\ the\ tasks\ by\ decreasing\ value\ of\ (P[i]\,/\,T[i])$

$Time,\ T_j\ ,\ estimated\ shifts\ required\ to\ complete\ the\ task,\ as\ per\ the\ new\ order\ of$

$tasks\ by\ decreasing\ value\ of\ (P[i]\,/\,T[i]).$

$Algorithm:\ Cumulative\ Task\ Completion\ time\ C\ (i)\ =\ \sum\ T\ [j]\ =\ T\ [1]\ +\ T\ [2]\ +$

$...T\ [j]$

$Algorithm:\ Weighted\ completion\ times,$

$\sum\ P[i]\,/\,T[i]\ *\ C\ (i)\ =\ P[i]\,/\,T[i]\ *\ C\ (i)\ ,\ ...,\ P[N]\,/\,T[N]\ *\ C\ (N)$

$Algorithm:\ Objective\ function\ F_i:\ Weighted\ sum\ of\ the\ completion\ times\ based\ on$

$priorities\ to\ address\ locations\ with\ high\ x_i$

$P[1]\,/\,T[1]\ *\ C\ (1)\ +\ P[2]\,/\,T[2]\ *\ C\ (2)\ +\ ...\ P[N]\,/\,T[N]\ *\ C\ (N)$

}

The FPSO main deck maintenance planning system problem has been implemented incorporating design features of stress unity check,x_1 and fatigue damage ratio, x_2; operating conditions of bending moment ratio, x_3 and shear force ratio, x_4; deteriorations of degree of corrosion scale, x_5 and degree of metal loss,x_6; safety and financial consequences of not doing maintenance, x_7, x_8 and the personnel resource to complete the activity, x_9 based on the ratio of coating breakdown area. It was estimated that there would be no coating breakdown on the main deck for the first 10 years of the FPSO life and thereafter an 8% annual coating breakdown deterioration is anticipated on the main deck structures for the next 3 years, if no maintenance is carried out.

The input data for the design values, x_1, x_2 were estimated from the real life experience of the Author, operating condition values, x_3, x_4 obtained from running various load cases on the geometrical model of the FPSO in commercially available loading calculator, deterioration values, x_5, x_6 developed employing the information from published literature of corrosion rates of ships from Tanker Structure Co-Operative Forum and the consequence values of not doing the tasks, x_7, x_8 were estimated from the real life experience of the Author. The time required to complete the task, x_9 was estimated based on the extent of coating breakdown considered at the main deck locations, dependent on the age of the FPSO.

The proposed problem formulation for FPSO main deck maintenance planning has been shown in Figure 4.1.

4.3 Benchmarking and Evaluation of Greedy Algorithm for FPSO main deck maintenance

The benchmarking of the algorithm has been carried out by comparing the parameters, with and without considering the time required to complete the task, which reflects influence of the time required to carry out the activity, on the prioritisation of activities. In the simula-

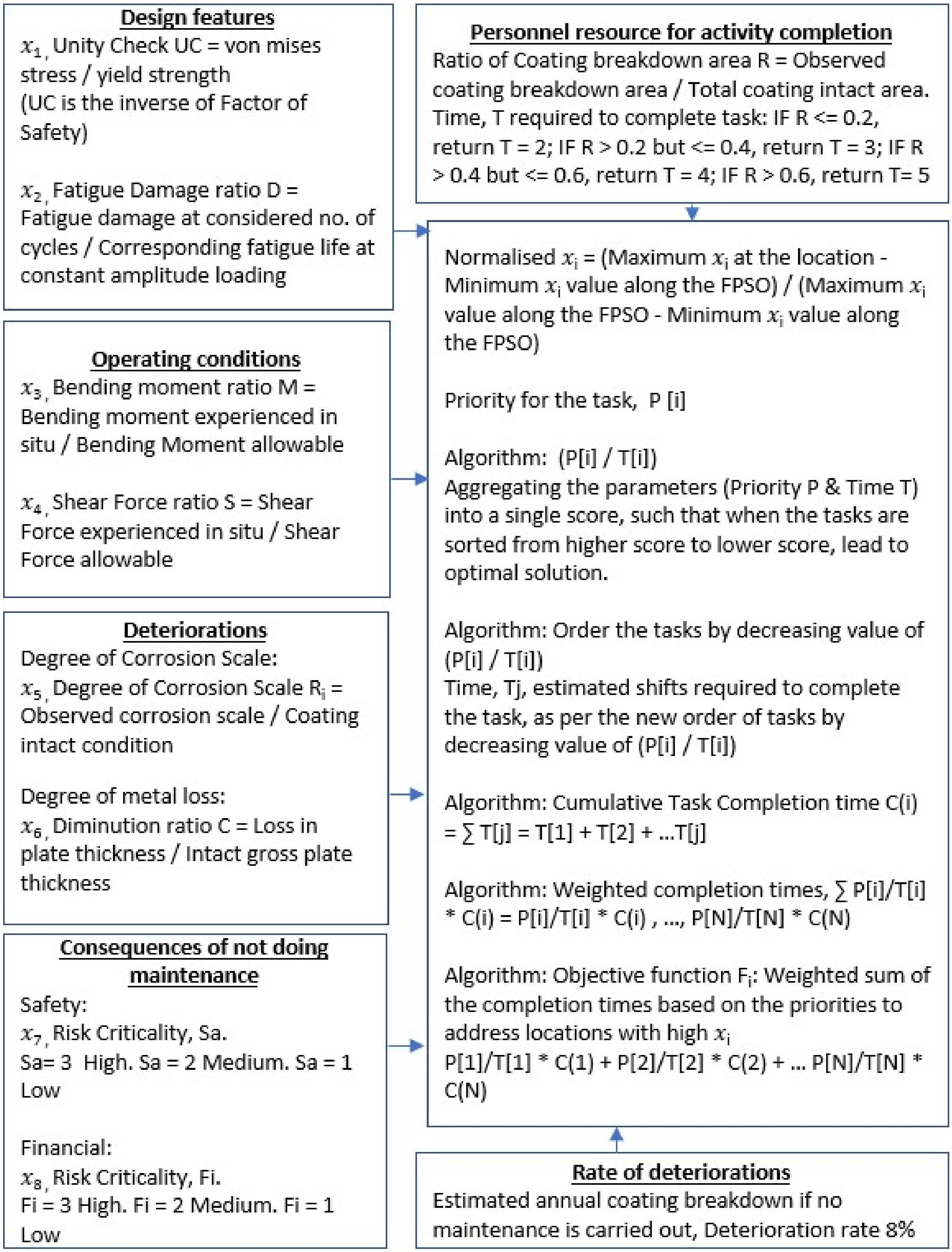

Figure 4.1: Problem formulation of FPSO main deck maintenance planning

tions, the performance of the greedy algorithm has been evaluated in terms of the personnel resource allocation and resource utilisation.

To evaluate the satisfaction of resource allocation, the weighted sum of the task completion times based on the priorities have been considered. To evaluate the satisfaction of resource utilisation, it has been considered that the higher weighted sum of the completion times at as short time as possible, would lead to higher resource utilisations and enable FPSO condition enhancement.

The evaluation of the model has been carried out by comparing the parameters based on three different loading conditions of the FPSO – light, medium and full load conditions.

The schematic representation of the FPSO system optimisation problem has been shown in Figure 4.2.

The graphs shown in the Figures 4.3 to 4.18 in the following sections indicate three different loading conditions of the FPSO such that, yellow coloured graph corresponds to the full load condition of the FPSO, grey coloured graph corresponds to the light load condition of the FPSO, and the orange and blue coloured graph corresponds to the medium load condition of the FPSO. It was observed that the priorities remain almost identical for full load and light load conditions of the FPSO, and hence a single plot of yellow colour corresponds to the full and light loading conditions in the Figures 4.3 to 4.18.

The bending moment experienced on the hull girder would always be maximum at the midship region of the FPSO, which extends one fourth length of the FPSO forward and aft of the midship. The bending stress reach a peak at this region, irrespective of the loading condition the FPSO is subjected to in its lifetime. This makes the midship region vulnerable to exceed the threshold of bending strength of the material in the event of an improper loading and any eventual failures affecting the ability to control the FPSO stability during a damage event leading to Safety risks. Also, any excessive corrosion at the midships region of the FPSO could result in overstressed and buckled primary and secondary structures, requiring

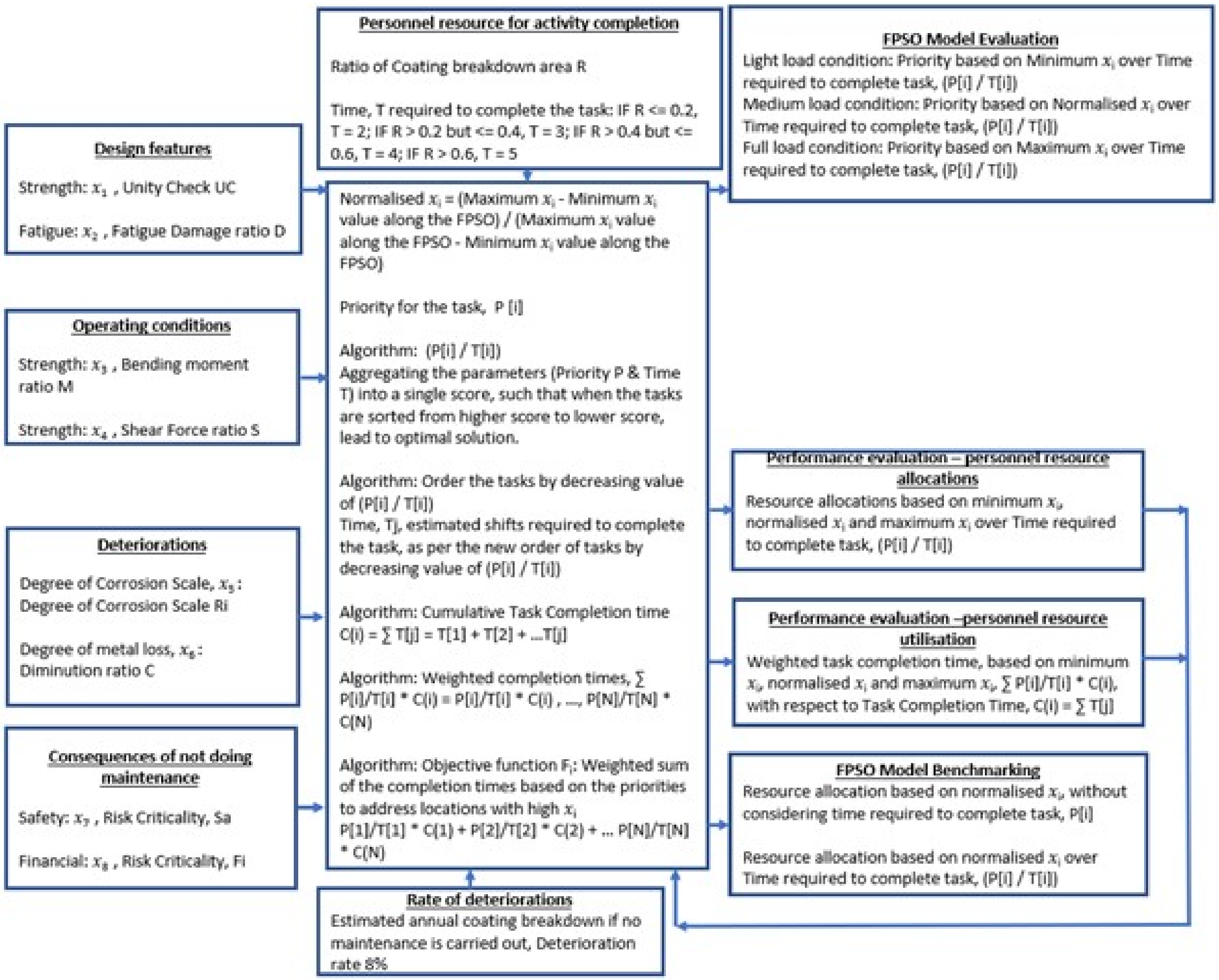

Figure 4.2: FPSO system optimisation problem

in situ or dry-docking steel repairs leading to financial impacts.

The Figures in the following sections show that the midship region need to be prioritised for maintenance and the relative order of execution at this region has become clearer from the plots, which leads to condition enhancement of the FPSO.

4.3.1 Resource allocation based on design features – Stress Unity Check over Time required to complete task

In this simulation in Figure 4.3, the performance of the greedy algorithm is being evaluated in terms of the personnel resource allocation, in terms of the priorities based on Stress Unity Check over Time required to complete tasks, $(P[i]/T[i])$.

The simulation results obtained for the priority based on Stress Unity Check over Time required to complete task are shown is figure 4.3.

It could be observed in Figure 4.3 that when the maintenance activities are prioritised solely based on the design feature of von mises stress, the highest priority is to allocate resources to the locations on the FPSO at a distance of $161 - 209m$ from the Aft Peak of FPSO, followed by locations $150 - 208.9m, 209.1 - 231m$.

When the time required to complete the maintenance activities have been considered along with the priorities based on the design feature of Stress Unity Check for Full load condition of the FPSO, it could be observed that the highest priority is to allocate resources to the locations on the FPSO at a distance of 0m and 209m from the Aft Peak of FPSO, followed by locations $0.1 - 20m, 190 - 208.9m, 209.1 - 231m$, and so on.

When the time required to complete the maintenance activities have been considered along with the priorities based on the design feature of Stress Unity Check for Medium load condition of the FPSO, it could be observed that the highest priority is to allocate resources to the locations on the FPSO at a distance of 209m from the Aft Peak of FPSO, followed by

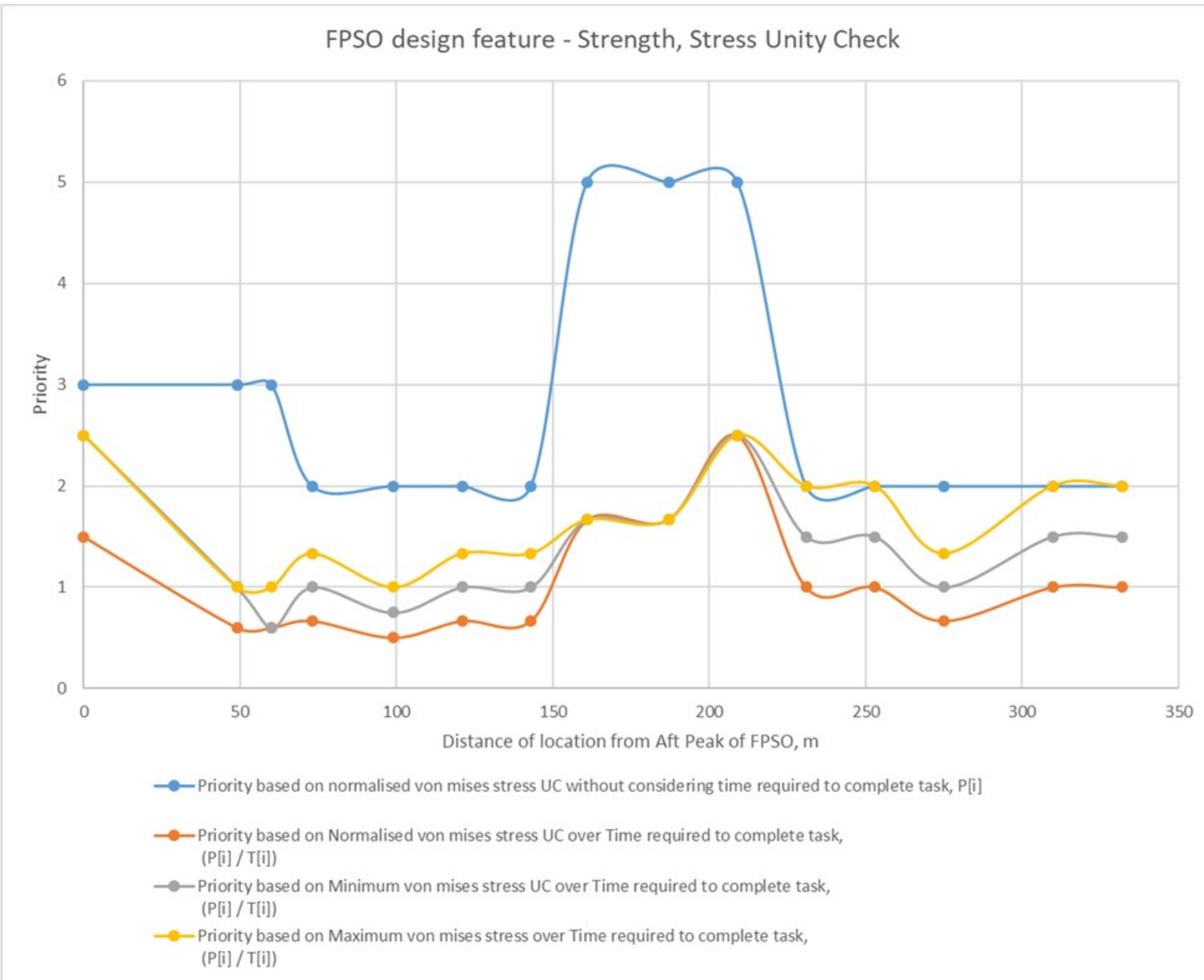

Figure 4.3: Resource allocation based on design feature - Stress Unity Check over Time required to complete task, (P[i] / T[i])

locations $187 - 208.9m, 209.1 - 225m$, and so on.

When the time required to complete the maintenance activities have been considered along with the priorities based on the design feature of Stress Unity Check for Light load condition of the FPSO, it could be observed that the highest priority is to allocate resources to the locations on the FPSO at a distance of 0m and 209m from the Aft Peak of FPSO, followed by locations $0.1 - 20m, 190 - 208.9m, 209.1 - 225m$, and so on.

The benchmarking of the algorithm has been carried out by comparing the resource allocations, with and without considering the time required to complete the task, which reflects influence of the time required to carry out the activity, on the prioritisation of activities.

The evaluation of the model carried out by comparing the resource allocations based on 3 different loading conditions of the FPSO – Full load, Medium load, and Light load conditions, as indicated in Figure 4.3, demonstrates the performance of the greedy algorithm, in terms of the personnel resource allocation based on Stress Unity Check over the time required to complete tasks.

In this simulation in Figure 4.4, the performance of the greedy algorithm is being evaluated in terms of the personnel resource utilisation, in terms of the weighted task completion time, based on design feature of Stress Unity Check over Time required to complete tasks,

$\sum \; P[i] \, / \, T[i] \, * \, C\,(i)$,

where, Task Completion Time, $C(i) \; = \; \sum \; T[\,j\,]$.

The benchmarking of the algorithm has been carried out by comparing the resource utilisations, with and without considering the time required to complete the task, which reflects influence of the time required to carry out the activity, on the prioritisation of activities.

To evaluate the satisfaction of resource utilisation, it could be observed that the higher weighted sum of the completion times at as short time as possible, would lead to higher resource utilisations. The evaluation of the model carried out by comparing the resource

Figure 4.4: Weighted task completion time, based on design feature - Stress Unity Check over Time required to complete task, $\sum P[i] / T[i] * C(i)$

utilisations based on 3 different loading conditions of the FPSO – Full load, Medium load, and Light load conditions, as indicated in Figure 4.4, demonstrates the performance of the greedy algorithm, in terms of the variation in personnel resource utilisation, based on Stress Unity Check over the time required to complete tasks.

4.3.2 Resource allocation based on design features – Fatigue Damage Ratio over Time required to complete task

In this simulation in Figure 4.5, the performance of the greedy algorithm is being evaluated in terms of the personnel resource allocation, in terms of the priorities based on fatigue damage ratio over Time required to complete tasks, ($P[i]$ / $T[i]$).
The simulation results obtained for the priority based on Fatigue Damage Ratio over Time required to complete task are shown is figure 4.5.

It could be observed in Figure 4.5 that when the maintenance activities are prioritised solely based on the design feature of fatigue damage ratio, the highest priority is to allocate resources to the locations on the FPSO at a distance of $161 - 209m$ from the Aft Peak of FPSO, followed by locations $150 - 208.9m, 209.1 - 225m$.
When the time required to complete the maintenance activities have been considered along with the priorities based on the design feature of fatigue damage ratio for Full load condition of the FPSO, it could be observed that the highest priority is to allocate resources to the locations on the FPSO at a distance of $209 - 253m$ from the Aft Peak of FPSO, followed by locations $195 - 208.9m, 253.1 - 265m$, and so on.
When the time required to complete the maintenance activities have been considered along with the priorities based on the design feature of fatigue damage ratio for Medium load condition of the FPSO, it could be observed that the highest priority is to allocate resources to the locations on the FPSO at a distance of 253m from the Aft Peak of FPSO, followed

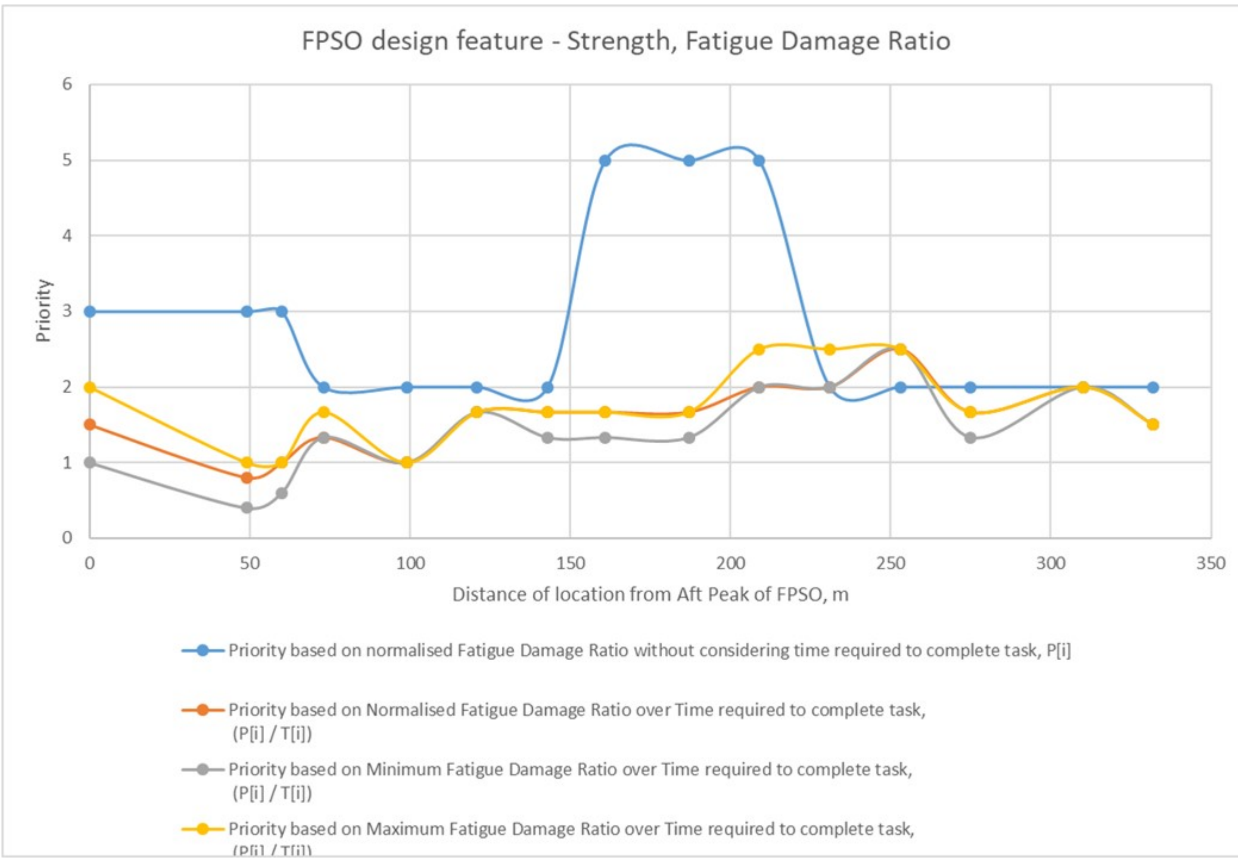

Figure 4.5: Resource allocation based on design feature – Fatigue Damage Ratio over Time required to complete task, $P[i] \,/\, T[i]$

by locations $230 - 252.9m, 253.1 - 265m$, and so on.

When the time required to complete the maintenance activities have been considered along with the priorities based on the design feature of fatigue damage ratio for Light load condition of the FPSO, it could be observed that the highest priority is to allocate resources to the locations on the FPSO at a distance of 253m from the Aft Peak of FPSO, followed by locations $231 - 252.9m, 253.1 - 260m$, and so on.

The benchmarking of the algorithm has been carried out by comparing the resource allocations, with and without considering the time required to complete the task, which reflects influence of the time required to carry out the activity, on the prioritisation of activities.

The evaluation of the model carried out by comparing the resource allocations based on 3 different loading conditions of the FPSO – Full load, Medium load and Light load conditions, as indicated in Figure 4.5, demonstrates the performance of the greedy algorithm, in terms of the personnel resource allocation based on fatigue damage ratio over the time required to complete tasks.

In this simulation in Figure 4.6, the performance of the greedy algorithm is being evaluated in terms of the personnel resource utilisation, in terms of the weighted task completion time, based on design feature of Fatigue Damage Ratio over Time required to complete tasks,

$\sum P[i] \,/\, T[i] * C\,(i)$,

where, Task Completion Time, $C(i) = \sum T[\,j\,]$.

The benchmarking of the algorithm has been carried out by comparing the resource utilisations, with and without considering the time required to complete the task, which reflects influence of the time required to carry out the activity, on the prioritisation of activities.

To evaluate the satisfaction of resource utilisation, it could be observed that the higher weighted sum of the completion times at as short time as possible, would lead to higher

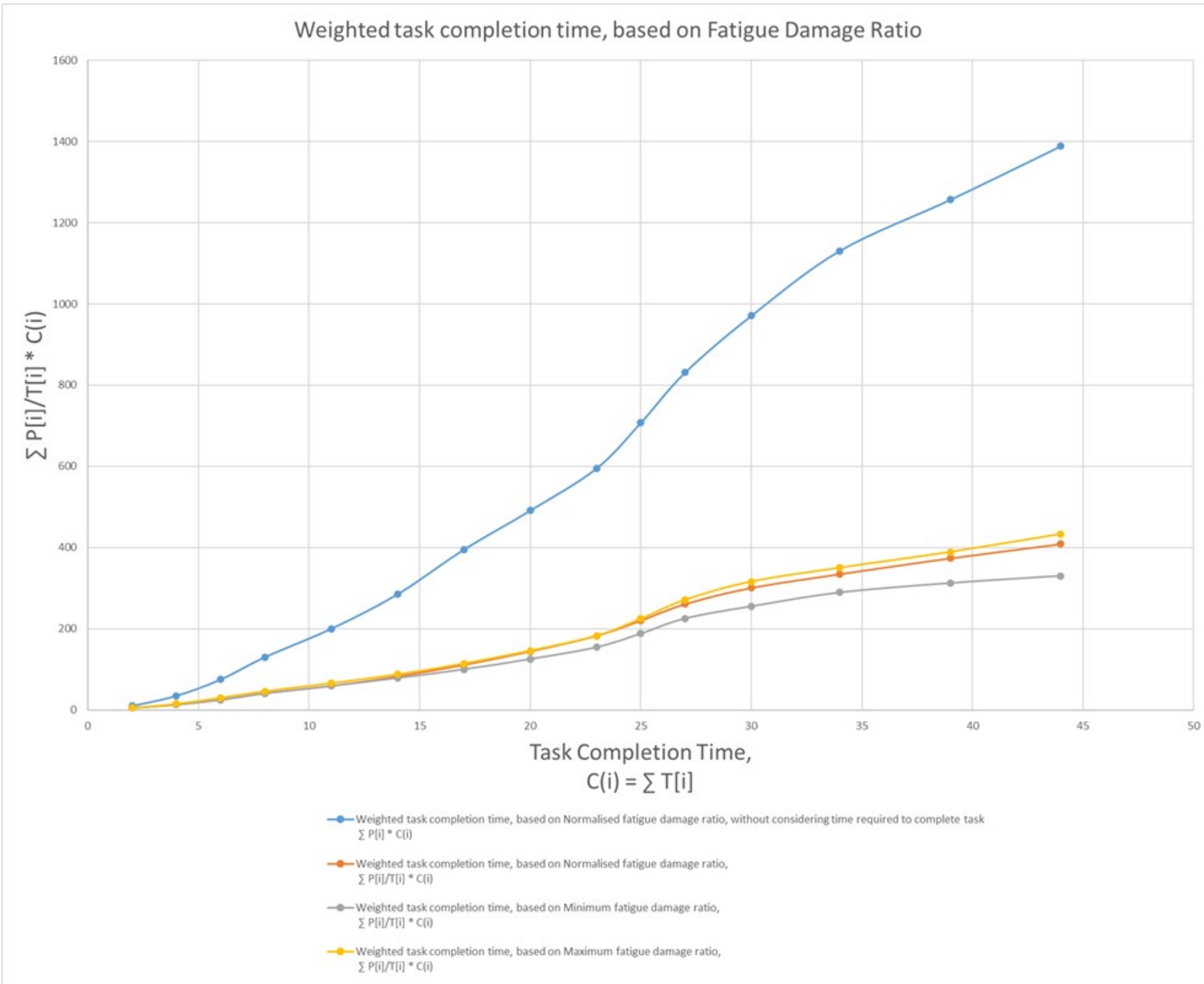

Figure 4.6: Weighted task completion time, based on design feature - Fatigue Damage Ratio over Time required to complete task, $\sum P[i] / T[i] * C(i)$

resource utilisations. The evaluation of the model carried out by comparing the resource utilisations based on 3 different loading conditions of the FPSO – Full load, Medium load, and Light load conditions, as indicated in Figure 4.6, demonstrates the performance of the greedy algorithm, in terms of the variation in personnel resource utilisation, based on Fatigue Damage Ratio over the time required to complete tasks.

4.3.3 Resource allocation based on operating conditions – Strength, Bending Moment Ratio over Time required to complete task

In this simulation in Figure 4.7, the performance of the greedy algorithm is being evaluated in terms of the personnel resource allocation, in terms of the priorities based on strength, Bending Moment Ratio over Time required to complete tasks, ($P[i]$ / $T[i]$).
. The simulation results obtained for the priority based on Strength, Bending Moment Ratio over Time required to complete task are shown is figure 4.7.

It could be observed in Figure 4.7 that when the maintenance activities are prioritised solely based on the operating conditions – Strength, Bending Moment Ratio, the highest priority is to allocate resources to the locations on the FPSO at a distance of $73 - 332m$ from the Aft Peak of FPSO, followed by locations $60 - 72.9m$, and so on.
When the time required to complete the maintenance activities have been considered along with the priorities based on the operating conditions – Strength, Bending Moment Ratio for Full load condition of the FPSO, it could be observed that the highest priority is to allocate resources to the locations on the FPSO at a distance of 310-332m from the Aft Peak of FPSO, followed by locations $295 - 309.9m$, and so on.
When the time required to complete the maintenance activities have been considered along with the priorities based on the operating conditions – Strength, Bending Moment Ratio for Medium load condition of the FPSO, it could be observed that the highest priority is to allocate resources to the locations on the FPSO at a distance of $209-253m$ and $310-332m$ from

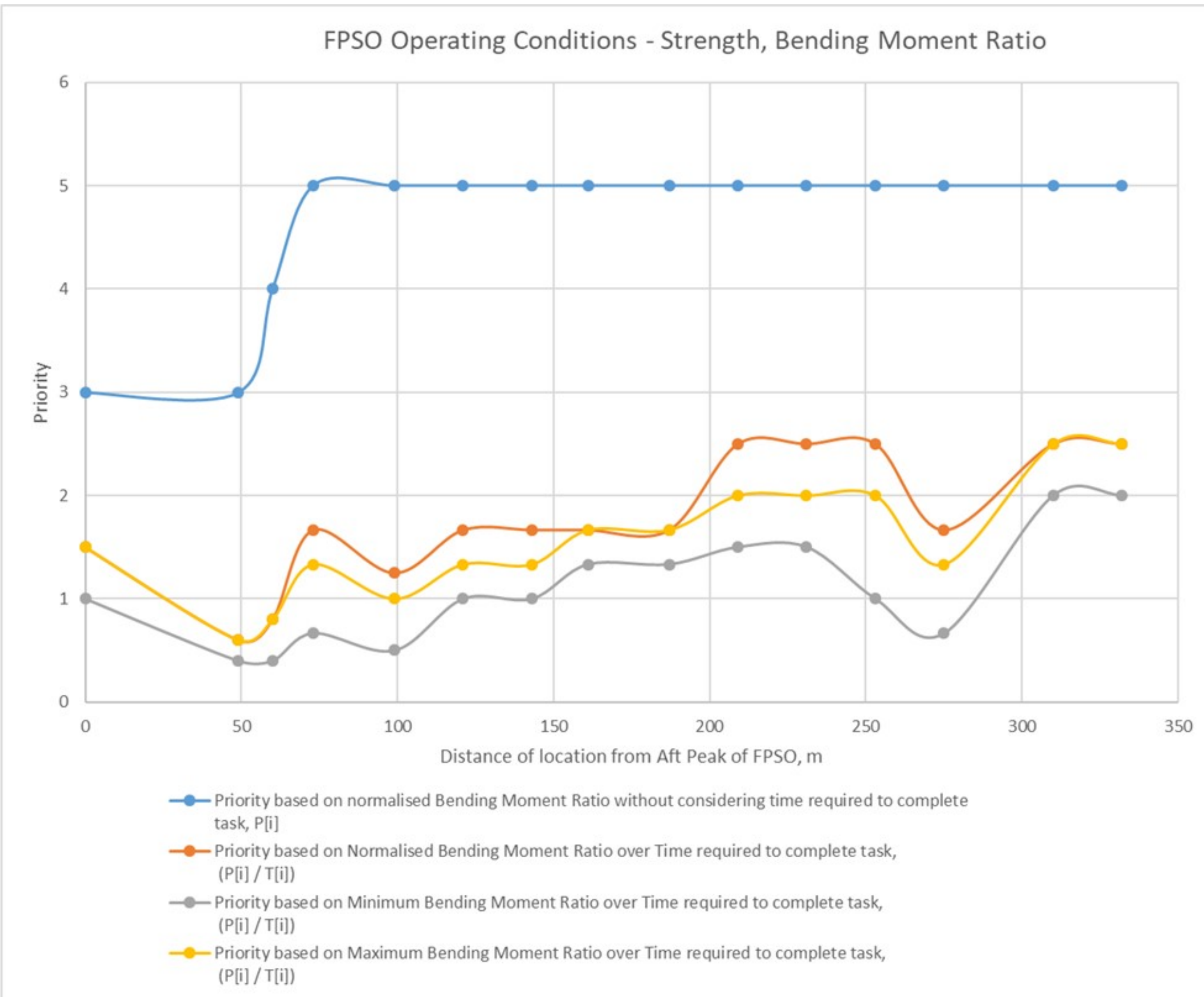

Figure 4.7: Resource allocation based on operating conditions – Strength, Bending Moment Ratio over Time required to complete task,$P[i]\,/\,T[i]$

the Aft Peak of FPSO, followed by locations $187 - 208.9m, 253.1 - 274.9m, 275.1 - 309.9m$ and so on.

When the time required to complete the maintenance activities have been considered along with the priorities based on the operating conditions – Strength, Bending Moment Ratio for Light load condition of the FPSO, it could be observed that the highest priority is to allocate resources to the locations on the FPSO at a distance of $310 - 332m$ from the Aft Peak of FPSO, followed by locations $290 - 309.9m$, and so on.

The benchmarking of the algorithm has been carried out by comparing the resource allocations, with and without considering the time required to complete the task, which reflects influence of the time required to carry out the activity, on the prioritisation of activities.

The evaluation of the model carried out by comparing the resource allocations based on 3 different loading conditions of the FPSO – Full load, Medium load and Light load conditions, as indicated in Figure 4.7, demonstrates the performance of the greedy algorithm, in terms of the personnel resource allocation based on Strength, Bending Moment Ratio over the time required to complete tasks.

In this simulation in Figure 4.8, the performance of the greedy algorithm is being evaluated in terms of the personnel resource utilisation, in terms of the weighted task completion time, based on operating conditions of Strength, Bending Moment Ratio over Time required to complete tasks , $\sum\ P[i] \,/\, T[i] \,*\, C\ (i)$,

where, Task Completion Time, $C(i)\ =\ \sum\ T[\,j\,]$.

The benchmarking of the algorithm has been carried out by comparing the resource utilisations, with and without considering the time required to complete the task, which reflects influence of the time required to carry out the activity, on the prioritisation of activities.

To evaluate the satisfaction of resource utilisation, it could be observed that the higher weighted sum of the completion times at as short time as possible, would lead to higher

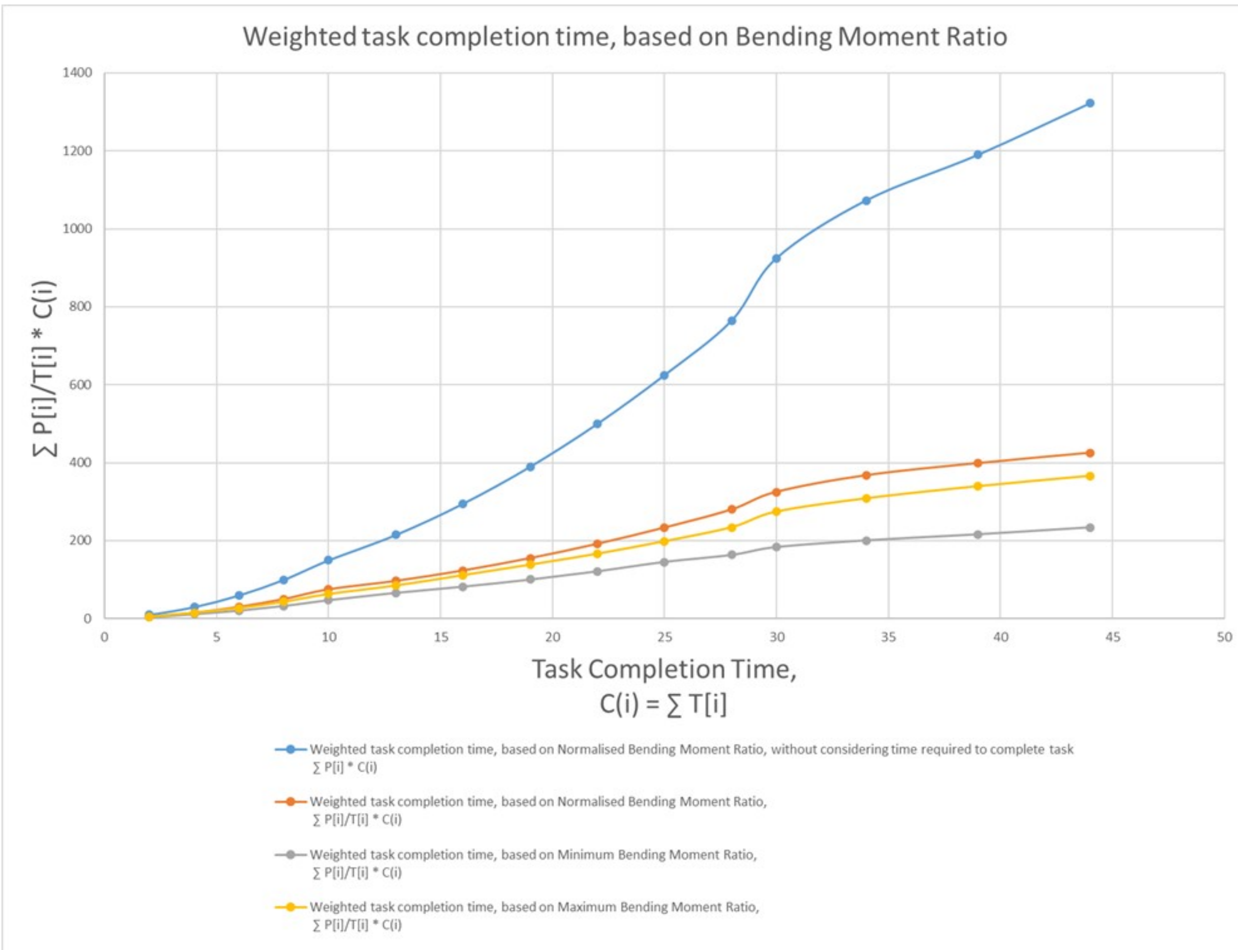

Figure 4.8: Weighted task completion time, based on operating conditions – Strength, Bending Moment Ratio over Time required to complete task, $\sum\ P[\,i]\,/\,T[\,i]\,*\,C\,(i)$

resource utilisations. The evaluation of the model carried out by comparing the resource utilisations based on 3 different loading conditions of the FPSO – Full load, Medium load, and Light load conditions, as indicated in Figure 4.8, demonstrates the performance of the greedy algorithm, in terms of the variation in personnel resource utilisation, based on Bending Moment Ratio over the time required to complete tasks.

4.3.4 Resource allocation based on operating conditions – Strength, Shear Force Ratio over Time required to complete task

In this simulation in Figure 4.9, the performance of the greedy algorithm is being evaluated in terms of the personnel resource allocation, in terms of the priorities based on Strength, Shear Force Ratio over Time required to complete tasks, ($P[i] / T[i]$).
The simulation results obtained for the priority based on Strength, Shear Force Ratio over Time required to complete task are shown is figure 4.9.

It could be observed in Figure 4.9 that when the maintenance activities are prioritised solely based on the operating conditions – Strength, Shear Force Ratio, the highest priority is to allocate resources to the locations on the FPSO at a distance of $143m, 275m$ from the Aft Peak of FPSO, followed by locations $121 - 142.9m, 143.1 - 155m, 253 - 274.9m, 275.1 - 290m$ and so on.
When the time required to complete the maintenance activities have been considered along with the priorities based on the operating conditions – Strength, Shear Force Ratio for Full load condition of the FPSO, it could be observed that the highest priority is to allocate resources to the locations on the FPSO at a distance of $143m$ and $275m$ from the Aft Peak of FPSO, followed by locations $135 - 142.9m, 143.1 - 150m, 253 - 274.9m, 275.1 - 310m$and so on.
When the time required to complete the maintenance activities have been considered along

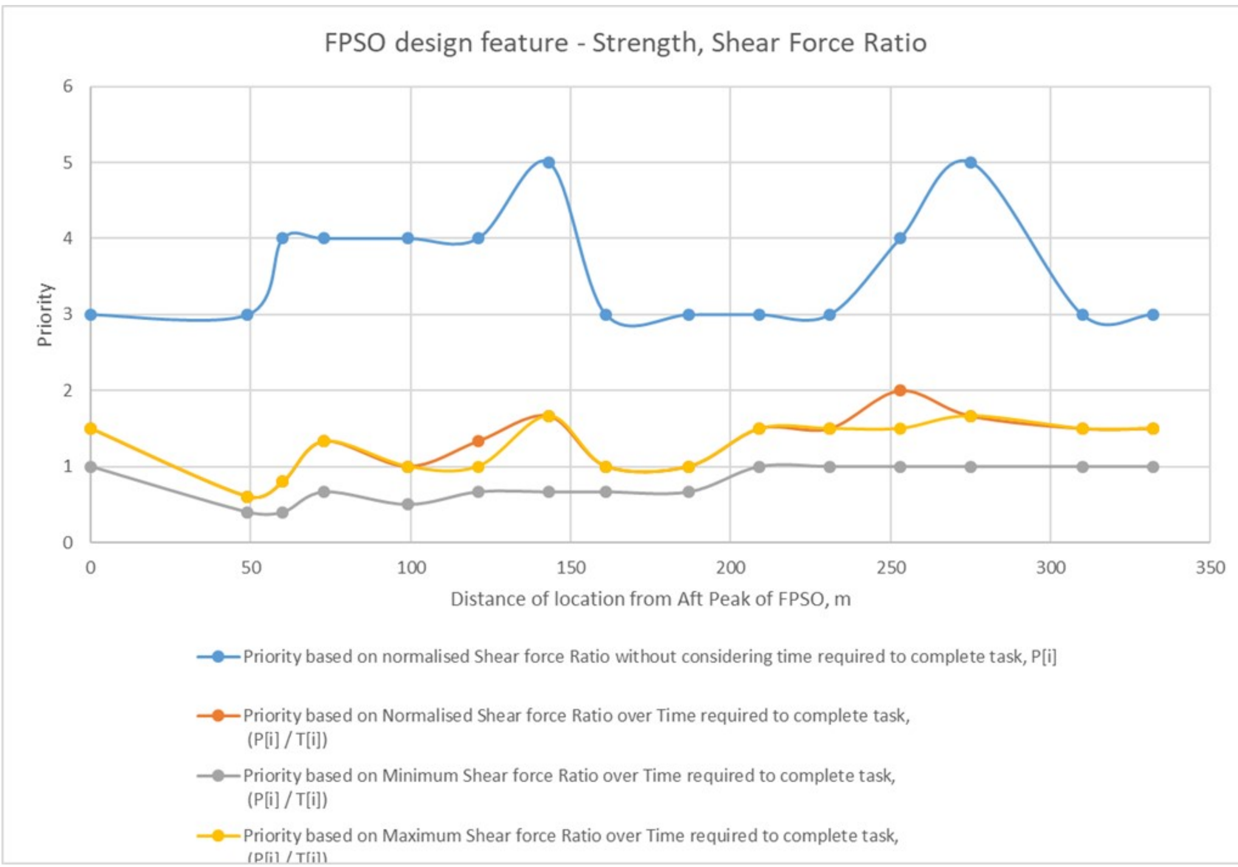

Figure 4.9: Resource allocation based on operating conditions – Strength, Shear Force Ratio over Time required to complete task, $P[i] \, / \, T[i]$

with the priorities based on the operating conditions – Strength, Shear Force Ratio for Medium load condition of the FPSO, it could be observed that the highest priority is to allocate resources to the locations on the FPSO at a distance of $253m$ from the Aft Peak of FPSO, followed by locations $240 - 252.9m, 253.1 - 275m$, and so on.

When the time required to complete the maintenance activities have been considered along with the priorities based on the operating conditions – Strength, Shear Force Ratio for Light load condition of the FPSO, it could be observed that the highest priority is to allocate resources to the locations on the FPSO at a distance of $0m$ and $209 - 332m$ from the Aft Peak of FPSO, followed by locations $0.1 - 40m, 187 - 208.9m$ and so on.

The benchmarking of the algorithm has been carried out by comparing the resource allocations, with and without considering the time required to complete the task, which reflects influence of the time required to carry out the activity, on the prioritisation of activities.

The evaluation of the model carried out by comparing the resource allocations based on 3 different loading conditions of the FPSO – Full load, Medium load, and Light load conditions, as indicated in Figure 4.9, demonstrates the performance of the greedy algorithm, in terms of the personnel resource allocation based on Strength, Shear Force Ratio over the time required to complete tasks.

In this simulation in Figure 4.10, the performance of the greedy algorithm is being evaluated in terms of the personnel resource utilisation, in terms of the weighted task completion time, based on operating conditions of Strength, Shear Force Ratio over Time required to complete tasks , $\sum\ P[\,i]\,/\,T[\,i] \,*\, C\ (i)$,

where, Task Completion Time, $C(i)\ =\ \sum\ T[\,j\ ]$.

The benchmarking of the algorithm has been carried out by comparing the resource utilisations, with and without considering the time required to complete the task, which reflects influence of the time required to carry out the activity, on the prioritisation of activities.

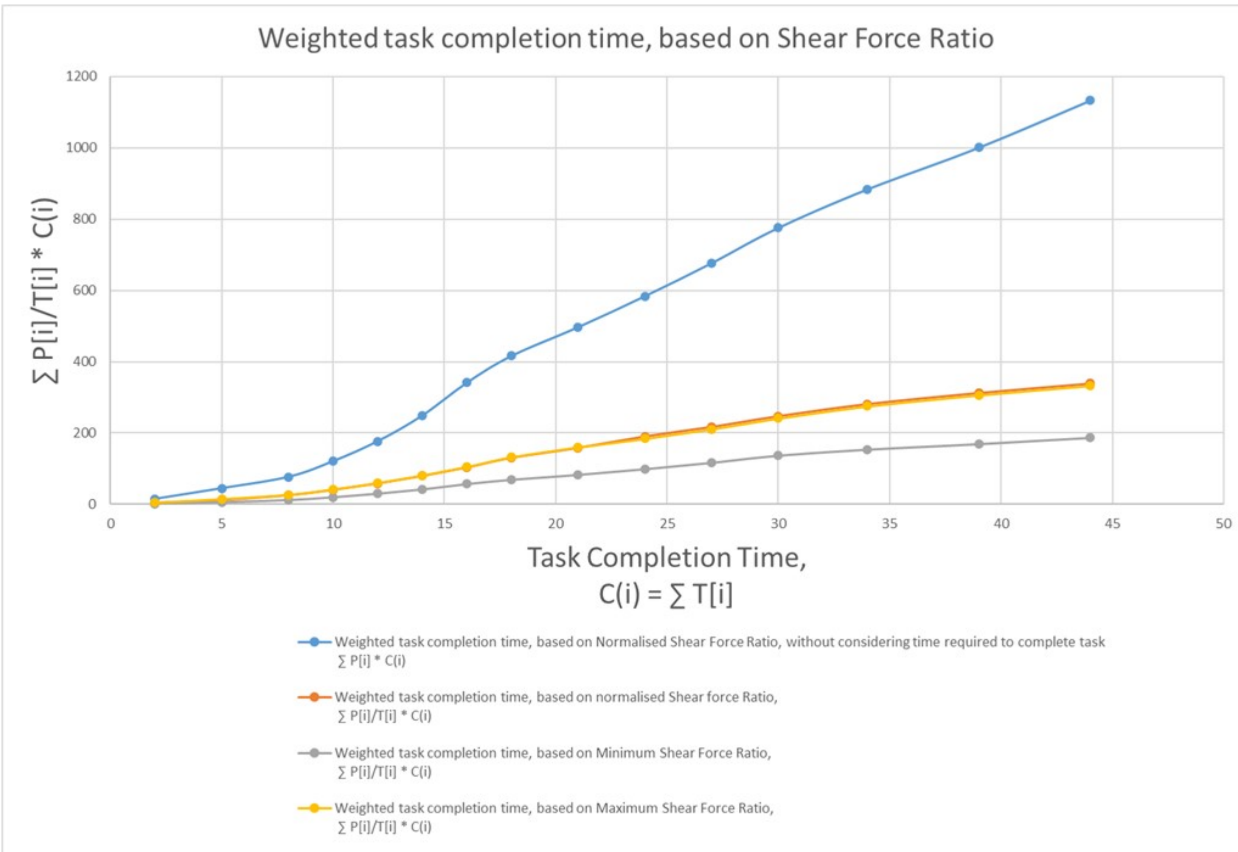

Figure 4.10: Weighted task completion time, based on operating conditions – Strength, Shear Force Ratio over Time required to complete task, $\sum P[i] \,/\, T[i] \, * \, C\,(i)$

To evaluate the satisfaction of resource utilisation, it could be observed that the higher weighted sum of the completion times at as short time as possible, would lead to higher resource utilisations. The evaluation of the model carried out by comparing the resource utilisations based on 3 different loading conditions of the FPSO – Full load, Medium load, and Light load conditions, as indicated in Figure 4.10, demonstrates the performance of the greedy algorithm, in terms of the variation in personnel resource utilisation, based on Shear Force Ratio over the time required to complete tasks.

4.3.5 Resource allocation based on deterioration mechanisms – Degree of Corrosion Scale over Time required to complete task

In this simulation in Figure 4.11, the performance of the greedy algorithm is being evaluated in terms of the personnel resource allocation, in terms of the priorities based on Degree of Corrosion Scale over Time required to complete tasks, ($P[\,i]\,/\,T[\,i]$).

The simulation results obtained for the priority based on Degree of Corrosion Scale over Time required to complete task are shown is figure 4.11.

It could be observed in Figure 4.11 that when the maintenance activities are prioritised solely based on the deterioration mechanisms – Degree of Corrosion Scale, the highest priority is to allocate resources to the locations on the FPSO at a distance of $49 - 73m, 121 - 161m, 253m, 310m$ from the Aft Peak of FPSO, followed by locations $30 - 48.9m, 73.1 - 98.9, 99.1 - 120.9, 161.1 - 170m, 231 - 252.9, 253.1 - 265m, 295 - 309.9, 310.1 - 325m$ and so on.

When the time required to complete the maintenance activities have been considered along with the priorities based on the deterioration mechanisms – Degree of Corrosion Scale for

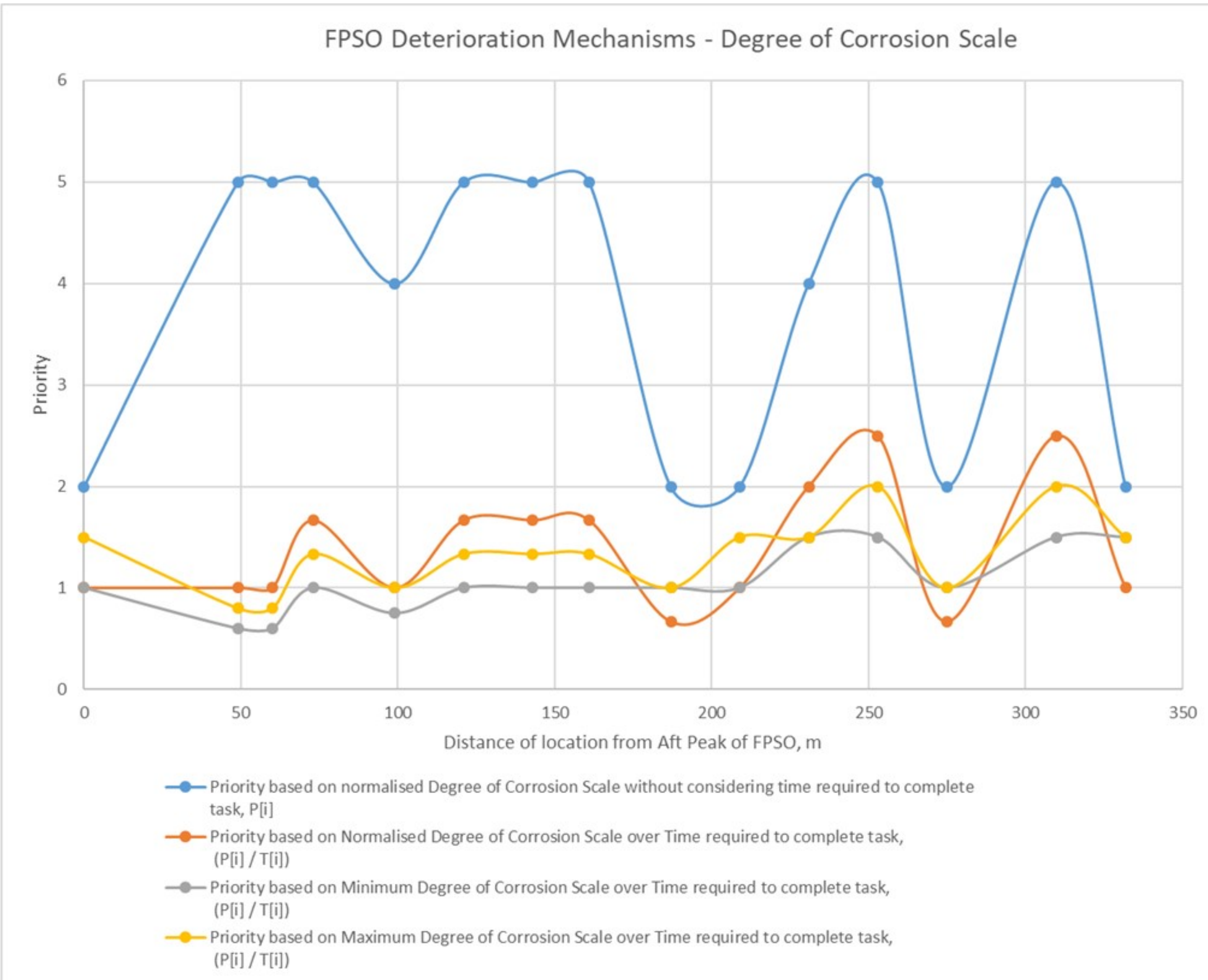

Figure 4.11: Resource allocation based on deterioration mechanisms – Degree of Corrosion Scale over Time required to complete task, $P[i] \,/\, T[i]$

Full load condition of the FPSO, it could be observed that the highest priority is to allocate resources to the locations on the FPSO at a distance of $253m$ and $310m$ from the Aft Peak of FPSO, followed by locations $243 - 252.9m, 253.1 - 265m, 285 - 309.9, 310.1 - 332m$ and so on.

When the time required to complete the maintenance activities have been considered along with the priorities based on the deterioration mechanisms – Degree of Corrosion Scale for Medium load condition of the FPSO, it could be observed that the highest priority is to allocate resources to the locations on the FPSO at a distance of $253m$ and $310m$ from the Aft Peak of FPSO, followed by locations $220 - 252.9m, 253.1 - 270m, 285 - 309.9, 310.1 - 325m$ and so on.

When the time required to complete the maintenance activities have been considered along with the priorities based on the deterioration mechanisms – Degree of Corrosion Scale for Light load condition of the FPSO, it could be observed that the highest priority is to allocate resources to the locations on the FPSO at a distance of $231 - 253m, 310 - 332m$ from the Aft Peak of FPSO, followed by locations $209 - 230.9m, 253.1 - 275m, 275.1 - 309.9m$, and so on.

The benchmarking of the algorithm has been carried out by comparing the resource allocations, with and without considering the time required to complete the task, which reflects influence of the time required to carry out the activity, on the prioritisation of activities.

The evaluation of the model carried out by comparing the resource allocations based on 3 different loading conditions of the FPSO – Full load, Medium load, and Light load conditions, as indicated in Figure 4.11, demonstrates the performance of the greedy algorithm, in terms of the personnel resource allocation based on von mises stress over the time required to complete tasks.

In this simulation in Figure 4.12, the performance of the greedy algorithm is being evaluated in terms of the personnel resource utilisation, in terms of the weighted task completion

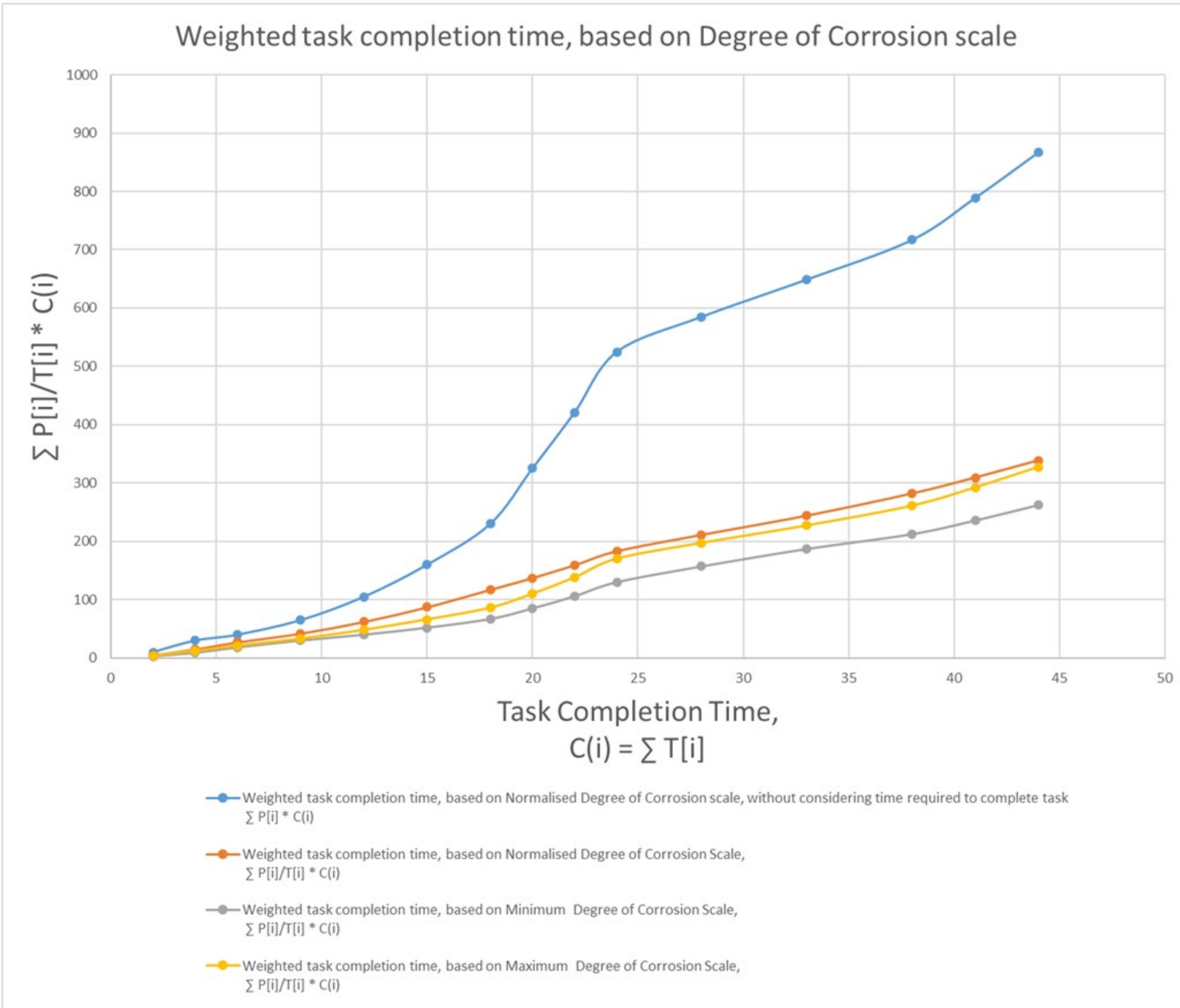

Figure 4.12: Weighted task completion time, based on deterioration mechanisms – Degree of Corrosion Scale over Time required to complete task, $\sum P[i] / T[i] * C(i)$

time, based on deterioration mechanisms of Degree of Corrosion Scale over Time required to complete tasks, $\sum P[i] \,/\, T[i] * C\,(i)$,
where, Task Completion Time, $C(i) = \sum T[\,j\,]$.

The benchmarking of the algorithm has been carried out by comparing the resource utilisations, with and without considering the time required to complete the task, which reflects influence of the time required to carry out the activity, on the prioritisation of activities.
To evaluate the satisfaction of resource utilisation, it could be observed that the higher weighted sum of the completion times at as short time as possible, would lead to higher resource utilisations. The evaluation of the model carried out by comparing the resource utilisations based on 3 different loading conditions of the FPSO – Full load, Medium load, and Light load conditions, as indicated in Figure 4.12, demonstrates the performance of the greedy algorithm, in terms of the variation in personnel resource utilisation, based on Degree of Corrosion Scale over the time required to complete tasks.

4.3.6 Resource allocation based on deterioration mechanisms – Degree of Metal Loss over Time required to complete task

In this simulation in Figure 4.13, the performance of the greedy algorithm is being evaluated in terms of the personnel resource allocation, in terms of the priorities based on Degree of Metal Loss over Time required to complete tasks, ($P[i] \,/\, T[i]$).
The simulation results obtained for the priority based on Degree of Metal Loss over Time required to complete task are shown is figure 4.13.

It could be observed in Figure 4.13 that when the maintenance activities are prioritised solely based on the deterioration mechanisms – Degree of Metal Loss, the highest priority is to allocate resources to the locations on the FPSO at a distance of $49-161m$ and $310m$ from the

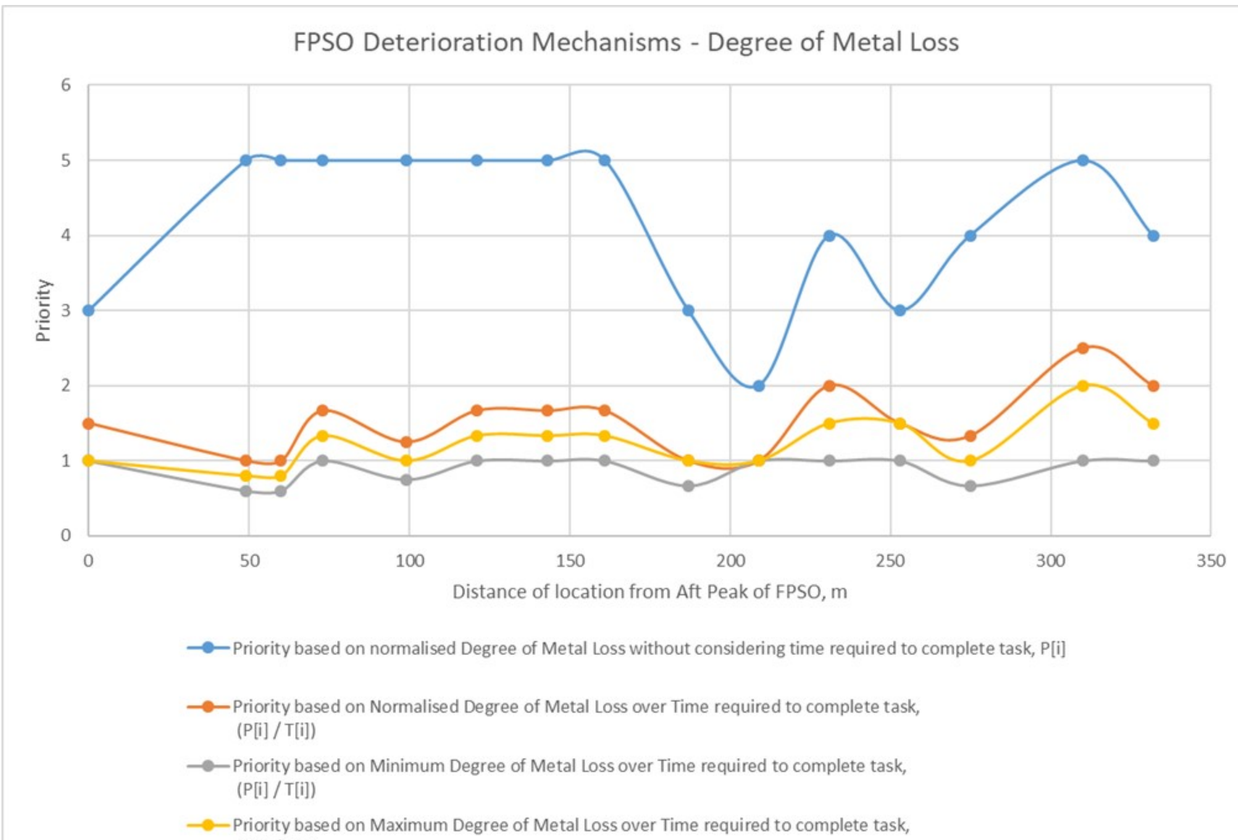

Figure 4.13: Resource allocation based on deterioration mechanisms – Degree of Metal Loss over Time required to complete task,$P[i]$ / $T[i]$

Aft Peak of FPSO, followed by locations $25-48.9m, 161.1-175m, 275-309.9, 310.1-332m$ and so on.

When the time required to complete the maintenance activities have been considered along with the priorities based on the deterioration mechanisms – Degree of Metal Loss for Full load condition of the FPSO, it could be observed that the highest priority is to allocate resources to the locations on the FPSO at a distance of $310m$ from the Aft Peak of FPSO, followed by locations $285-309.9, 310.1-332m$ and so on.

When the time required to complete the maintenance activities have been considered along with the priorities based on the deterioration mechanisms – Degree of Metal Loss for Medium load condition of the FPSO, it could be observed that the highest priority is to allocate resources to the locations on the FPSO at a distance of 310m from the Aft Peak of FPSO, followed by locations $290-309.9m, 310.1-332m$ and so on.

When the time required to complete the maintenance activities have been considered along with the priorities based on the deterioration mechanisms – Degree of Metal Loss for Light load condition of the FPSO, it could be observed that the highest priority is to allocate resources to the locations on the FPSO at a distance of $0m, 73m, 121-161m, 209-253m, 310-332m$ from the Aft Peak of FPSO, followed by locations $0.1-25m, 65-72.9, 73.1-85m, 115-120.9, 161.1-170m, 195-208.9, 253.1-265m, 290-309.9m$ and so on.

The benchmarking of the algorithm has been carried out by comparing the resource allocations, with and without considering the time required to complete the task, which reflects influence of the time required to carry out the activity, on the prioritisation of activities.

The evaluation of the model carried out by comparing the resource allocations based on 3 different loading conditions of the FPSO – Full load, Medium load, and Light load conditions, as indicated in Figure 4.13, demonstrates the performance of the greedy algorithm, in terms of the personnel resource allocation based on Degree of Metal Loss over the time required to complete tasks.

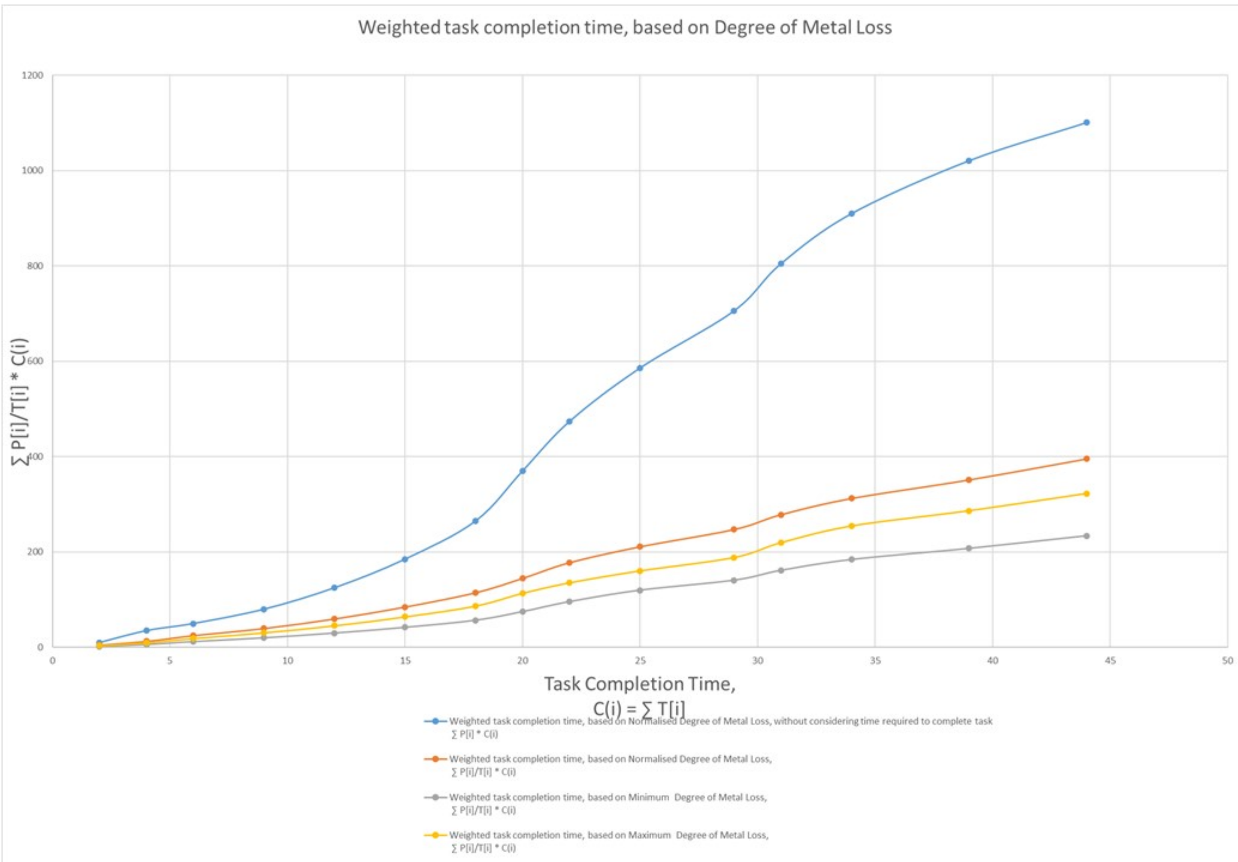

Figure 4.14: Weighted task completion time, based on deterioration mechanisms – Degree of Metal Loss over Time required to complete task, $\sum\ P[\,i]\,/\,T[\,i]\,*\,C\,(i)$

In this simulation in Figure 4.14, the performance of the greedy algorithm is being evaluated in terms of the personnel resource utilisation, in terms of the weighted task completion time, based on deterioration mechanisms of Degree of Metal Loss over Time required to complete tasks, $\sum\ P[\,i]\,/\,T[\,i]\,*\ C\ (i)$,
where, Task Completion Time, $C(i)\ =\ \sum\ T[\,j\ ]$.

The benchmarking of the algorithm has been carried out by comparing the resource utilisations, with and without considering the time required to complete the task, which reflects influence of the time required to carry out the activity, on the prioritisation of activities.
To evaluate the satisfaction of resource utilisation, it could be observed that the higher weighted sum of the completion times at as short time as possible, would lead to higher resource utilisations. The evaluation of the model carried out by comparing the resource utilisations based on 3 different loading conditions of the FPSO – Full load, Medium load, and Light load conditions, as indicated in Figure 4..14, demonstrates the performance of the greedy algorithm, in terms of the variation in personnel resource utilisation, based on Degree of Metal Loss over the time required to complete tasks.

4.3.7 Resource allocation based on Consequences of not doing the tasks – Safety Risk over Time required to complete task

In this simulation in Figure 4.15, the performance of the greedy algorithm is being evaluated in terms of the personnel resource allocation, in terms of the priorities based on Safety Risk over Time required to complete tasks, ($P[\,i]\,/\,T[\,i]$).
The simulation results obtained for the priority based on Consequences of not doing the tasks – Safety Risk over Time required to complete task are shown is figure 4.15.

It could be observed in Figure 4.15 that when the maintenance activities are prioritised

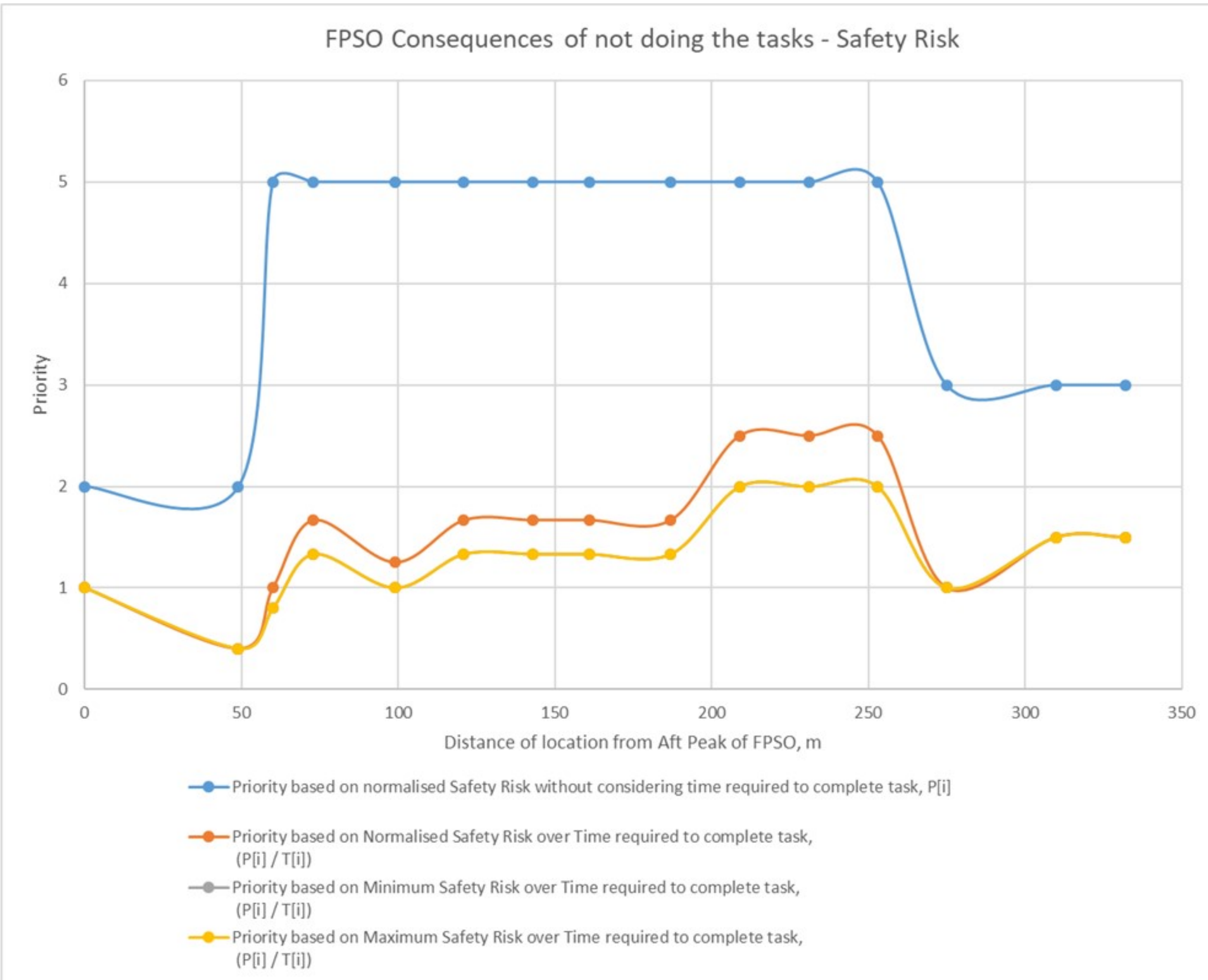

Figure 4.15: Resource allocation based on Consequences of not doing the tasks – Safety Risk over Time required to complete task, $P[i] \,/\, T[i]$

solely based on the Consequences of not doing the tasks – Safety Risk, the highest priority is to allocate resources to the locations on the FPSO at a distance of $60 - 253m$ from the Aft Peak of FPSO, followed by locations $50 - 59.9m, 253.1 - 275m$ and so on.

When the time required to complete the maintenance activities have been considered along with the priorities based on the Consequences of not doing the tasks – Safety Risk for Full load condition of the FPSO, it could be observed that the highest priority is to allocate resources to the locations on the FPSO at a distance of $209 - 253m$ from the Aft Peak of FPSO, followed by locations $195 - 208.9m, 253.1 - 270m$ and so on.

When the time required to complete the maintenance activities have been considered along with the priorities based on the Consequences of not doing the tasks – Safety Risk for Medium load condition of the FPSO, it could be observed that the highest priority is to allocate resources to the locations on the FPSO at a distance of $209 - 253m$ from the Aft Peak of FPSO, followed by locations $187 - 208.9m, 253.1 - 275m$ and so on.

When the time required to complete the maintenance activities have been considered along with the priorities based on the Consequences of not doing the tasks – Safety Risk for Light load condition of the FPSO, it could be observed that the highest priority is to allocate resources to the locations on the FPSO at a distance of $209 - 253m$ from the Aft Peak of FPSO, followed by locations $195 - 208.9m, 253.1 - 270m$ and so on.

The benchmarking of the algorithm has been carried out by comparing the resource allocations, with and without considering the time required to complete the task, which reflects influence of the time required to carry out the activity, on the prioritisation of activities.

The evaluation of the model carried out by comparing the resource allocations based on 3 different loading conditions of the FPSO – Full load, Medium load and Light load conditions, as indicated in Figure 4.15, demonstrates the performance of the greedy algorithm, in terms of the personnel resource allocation based on Consequences of not doing the tasks – Safety Risk over the time required to complete tasks.

Figure 4.16: Weighted task completion time, based on Consequences of not doing the tasks – Safety Risk over Time required to complete task, $\sum\ P[i]\,/\,T[i]\,*\,C\,(i)$

In this simulation in Figure 4.16, the performance of the greedy algorithm is being evaluated in terms of the personnel resource utilisation, in terms of the weighted task completion time, based on Consequences of not doing the tasks – Safety Risk over Time required to complete tasks, $\sum P[i] / T[i] * C(i)$,
where, Task Completion Time, $C(i) = \sum T[j]$.

The benchmarking of the algorithm has been carried out by comparing the resource utilisations, with and without considering the time required to complete the task, which reflects influence of the time required to carry out the activity, on the prioritisation of activities.
To evaluate the satisfaction of resource utilisation, it could be observed that the higher weighted sum of the completion times at as short time as possible, would lead to higher resource utilisations. The evaluation of the model carried out by comparing the resource utilisations based on 3 different loading conditions of the FPSO – Full load, Medium load, and Light load conditions, as indicated in Figure 4.16, demonstrates the performance of the greedy algorithm, in terms of the variation in personnel resource utilisation, based on Safety Risk over the time required to complete tasks.

4.3.8 Resource allocation based on Consequences of not doing the tasks – Financial Risk over Time required to complete task

In this simulation in Figure 4.17, the performance of the greedy algorithm is being evaluated in terms of the personnel resource allocation, in terms of the priorities based on Financial Risk over Time required to complete tasks, ($P[i] / T[i]$).
The simulation results obtained for the priority based on Consequences of not doing the tasks – Financial Risk over Time required to complete task are shown is figure 4.17.

It could be observed in Figure 4.17 that when the maintenance activities are prioritised

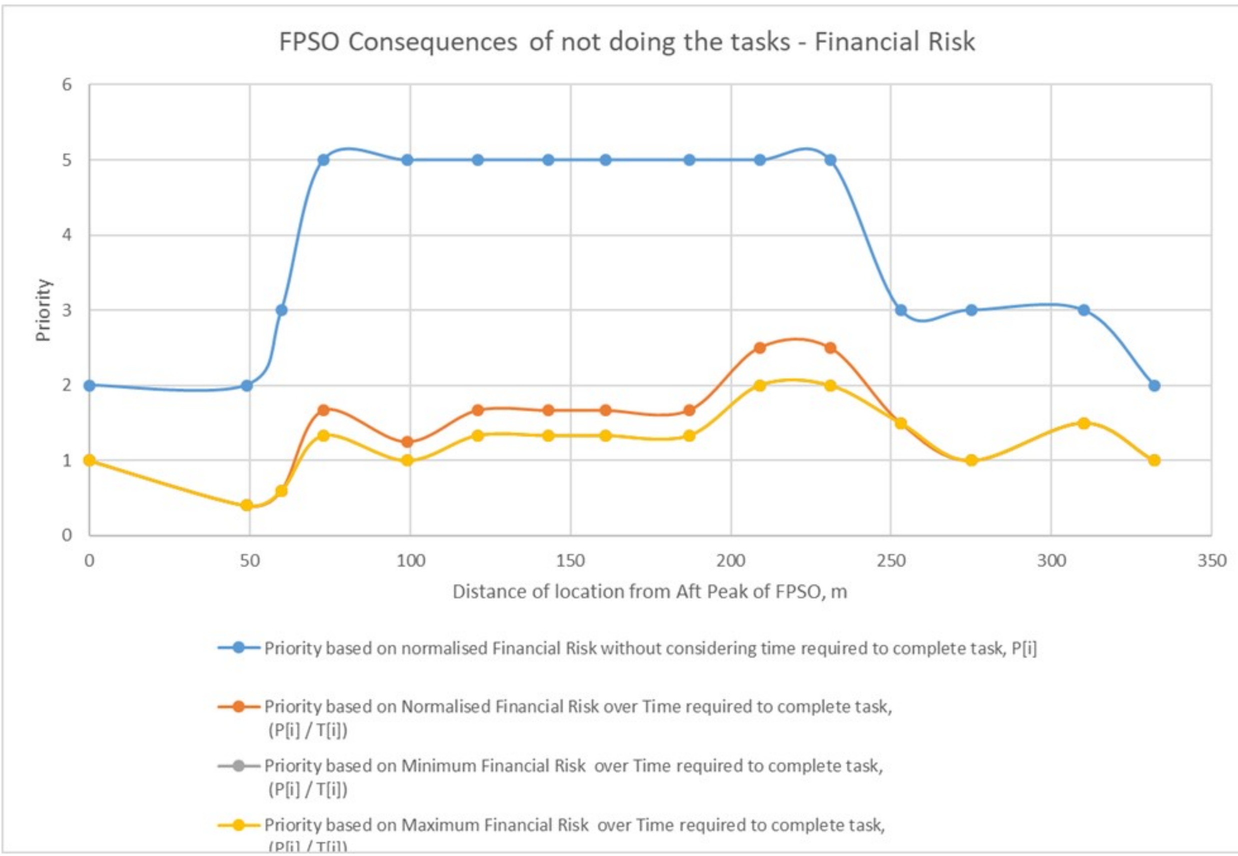

Figure 4.17: Resource allocation based on Consequences of not doing the tasks – Financial Risk over Time required to complete task,$P[i] \, / \, T[i]$

solely based on the Consequences of not doing the tasks – Financial Risk, the highest priority is to allocate resources to the locations on the FPSO at a distance of $73 - 231m$ from the Aft Peak of FPSO, followed by locations $60 - 72.9m, 231.1 - 250m$ and so on.

When the time required to complete the maintenance activities have been considered along with the priorities based on the Consequences of not doing the tasks – Financial Risk for Full load condition of the FPSO, it could be observed that the highest priority is to allocate resources to the locations on the FPSO at a distance of $209 - 231m$ from the Aft Peak of FPSO, followed by locations $195 - 208.9m, 231.1 - 253m$ and so on.

When the time required to complete the maintenance activities have been considered along with the priorities based on the Consequences of not doing the tasks – Financial Risk for Medium load condition of the FPSO, it could be observed that the highest priority is to allocate resources to the locations on the FPSO at a distance of $209 - 231m$ from the Aft Peak of FPSO, followed by locations $187 - 208.9m, 231.1 - 253m$, and so on.

When the time required to complete the maintenance activities have been considered along with the priorities based on the Consequences of not doing the tasks – Financial Risk for Light load condition of the FPSO, it could be observed that the highest priority is to allocate resources to the locations on the FPSO at a distance of $209 - 231m$ from the Aft Peak of FPSO, followed by locations $195 - 208.9m, 231.1 - 253m$ and so on.

The benchmarking of the algorithm has been carried out by comparing the resource allocations, with and without considering the time required to complete the task, which reflects influence of the time required to carry out the activity, on the prioritisation of activities.

The evaluation of the model carried out by comparing the resource allocations based on 3 different loading conditions of the FPSO – Full load, Medium load, and Light load conditions, as indicated in Figure 4.17, demonstrates the performance of the greedy algorithm, in terms of the personnel resource allocation based on Financial Risk over the time required to complete tasks.

Figure 4.18: Weighted task completion time, based on Consequences of not doing the tasks – Financial Risk over Time required to complete task, $\sum\ P[\,i]\,/\,T[\,i]\,*\,C\,(i)$

In this simulation in Figure 4.18, the performance of the greedy algorithm is being evaluated in terms of the personnel resource utilisation, in terms of the weighted task completion time, based on Consequences of not doing the tasks – Financial Risk over Time required to complete tasks, $\sum P[i] \,/\, T[i] * C\,(i)$,
where, Task Completion Time, $C(i) = \sum T[\,j\,]$.

The benchmarking of the algorithm has been carried out by comparing the resource utilisations, with and without considering the time required to complete the task, which reflects influence of the time required to carry out the activity, on the prioritisation of activities.
To evaluate the satisfaction of resource utilisation, it could be observed that the higher weighted sum of the completion times at as short time as possible, would lead to higher resource utilisations. The evaluation of the model carried out by comparing the resource utilisations based on 3 different loading conditions of the FPSO – Full load, Medium load, and Light load conditions, as indicated in Figure 4.18, demonstrates the performance of the greedy algorithm, in terms of the variation in personnel resource utilisation, based on Financial Risk over the time required to complete tasks.

4.4 Analysis on maintenance priorities and productivity if no maintenance is carried out

This section evaluates the proposed Greedy Algorithm, to optimise maintenance personnel resources based on knowledge of the design, equipment condition, operating condition, deterioration mechanisms involved, rate of deteriorations, inspection and maintenance history, involved risks. Towards this, the changes in maintenance priorities and productivity if no maintenance is carried out within a period - years' time and two years' time - have been simulated and compared with the present planned priorities and productivities.

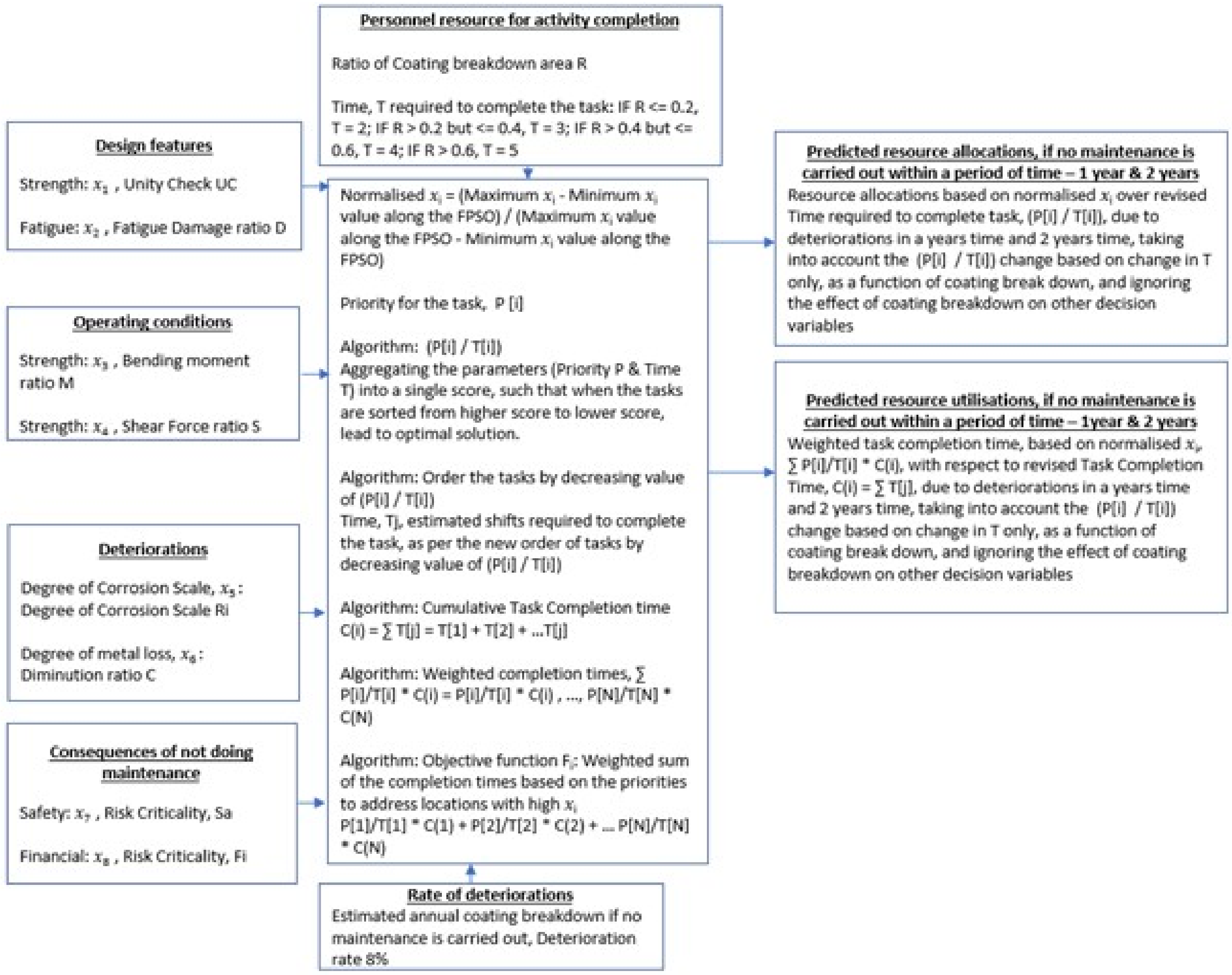

Figure 4.19: FPSO system evaluation on maintenance priorities and productivities over a period of time

The schematic representation of the FPSO system evaluation on maintenance priorities and productivities over a period of time has been shown in Figure 4.19.

4.4.1 Resource allocation based on design features – Stress Unity Check over Time required to complete task

In this simulation in Figure 4.20, the performance of the greedy algorithm is being evaluated in terms of the personnel resource allocation, in terms of the priorities based on Stress Unity Check over Time required to complete tasks, ($P[i] \,/\, T[i]$).

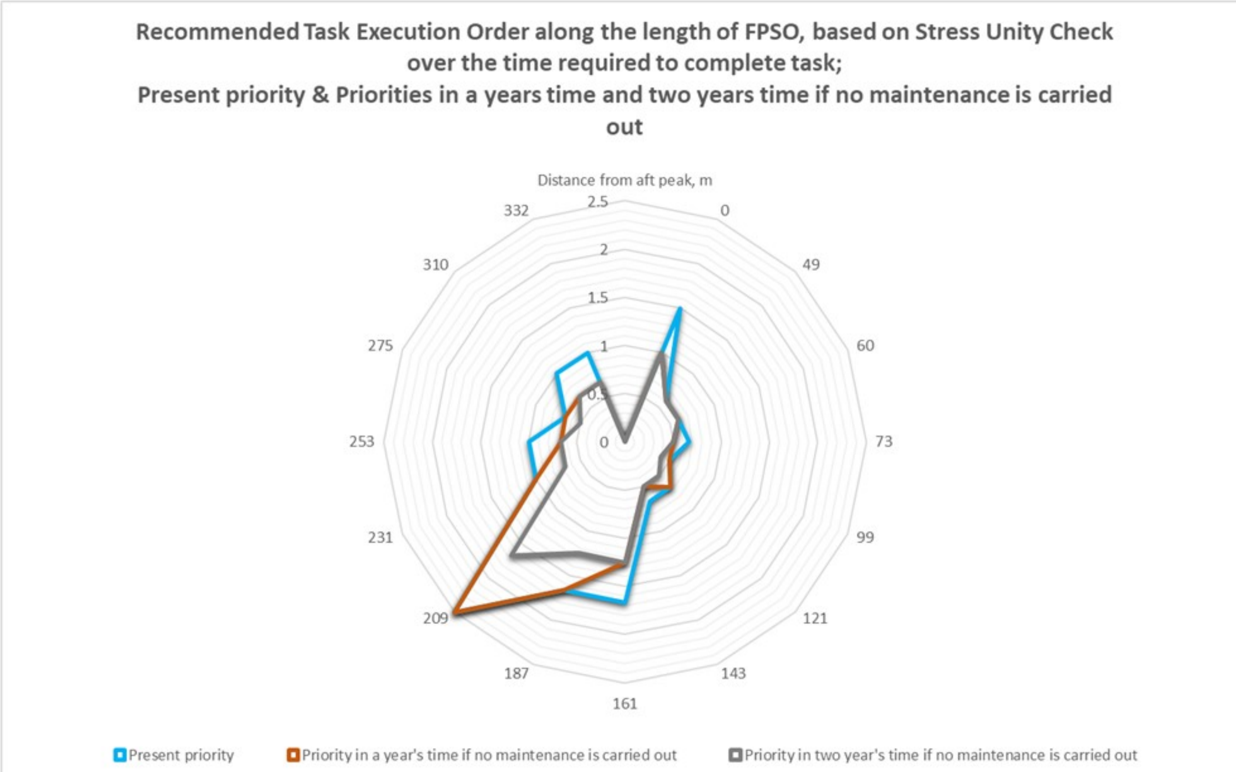

Figure 4.20: Changes in resource allocations if no maintenance is carried out, based on normalised Stress Unity Check over the time required to complete task

The recommended resource allocation order along the length of FPSO, based on design feature – normalised Stress Unity Check over the time required to complete task has been indicated in Figure 4.20. The resource allocation priority with reference to the distance from the aft peak of the FPSO has been shown.

The simulation of predicted changes in priorities for resource allocations in a year's time and in two years' time if no maintenance is carried out has also been indicated in Figure 4.20. This is based on an estimated annual deterioration rate of 8% on the coating breakdown and the corresponding impact on the resource required for completion of activity, taking into account the ($P[i]\,/\,T[i]$) change based on change in T only, as a function of coating break down, and ignoring the effect of coating breakdown on other decision variables.

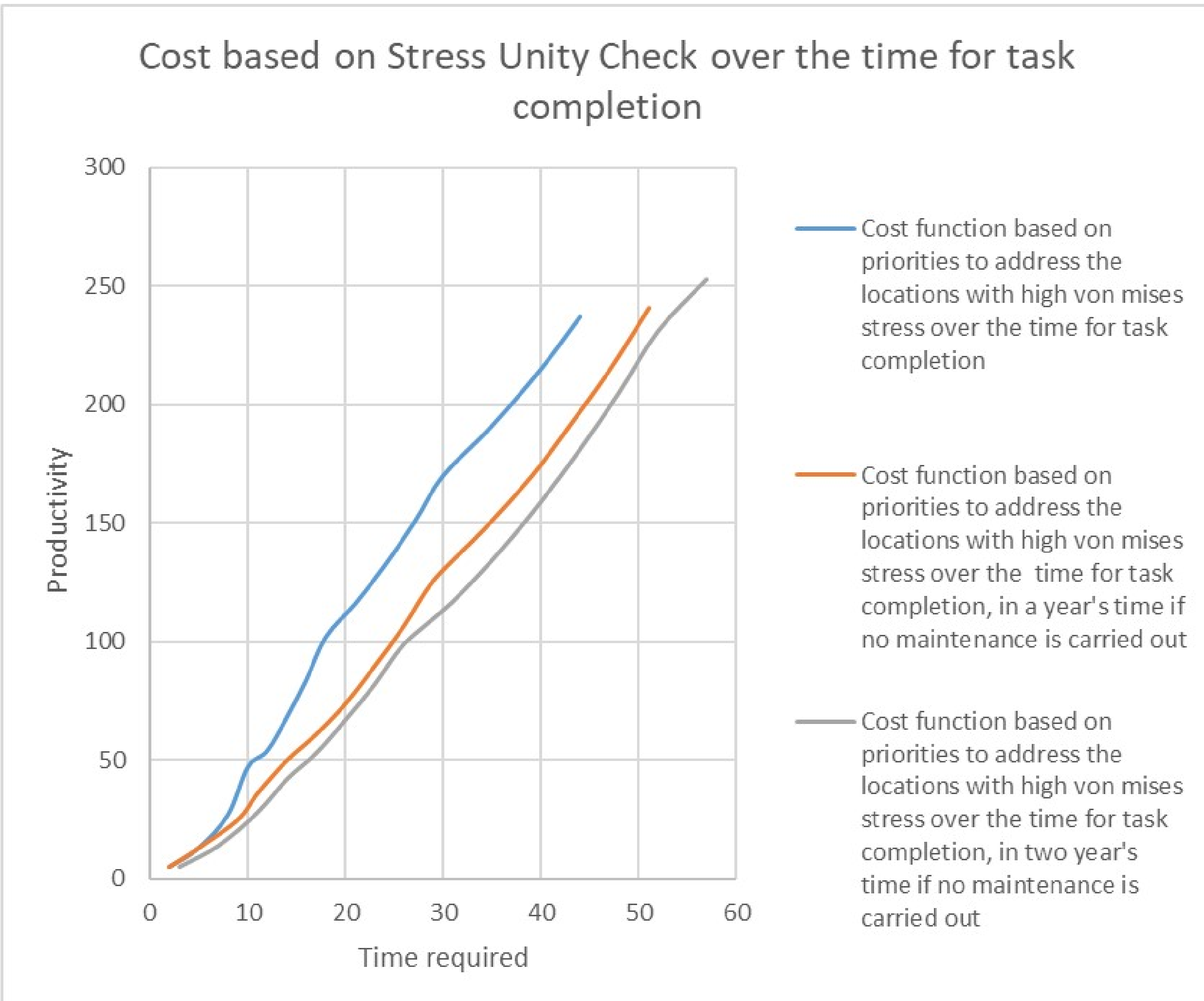

Figure 4.21: Changes in resource utilisations if no maintenance is carried out, based on normalised Stress Unity Check over the time required to complete task

The changes in resource allocations and resource utilisations, if no maintenance is carried out in a years' time and two years' time has been simulated and compared with the present planned priorities and productivities based on normalised Stress Unity Check over the time for task completion, as indicated in Figure 4.21.

The simulation of predicted changes in cost functions by way of productivity and the corresponding resource utilisations in a year's time and in two years' time if no maintenance is carried out has also been indicated in Figure 4.21. This is based on an estimated annual deterioration rate of 8% on the coating breakdown and the corresponding impacts on the weighted sum of the completion times based on the priorities, taking into account the ($P[i] / T[i]$) change based on change in T only, as a function of coating break down, and ignoring the effect of coating breakdown on other decision variables.

4.4.2 Resource allocation based on design features – Fatigue Damage Ratio over Time required to complete task

In this simulation in Figure 4.22, the performance of the greedy algorithm is being evaluated in terms of the personnel resource allocation, in terms of the priorities based on fatigue damage ratio over Time required to complete tasks, ($P[i] / T[i]$).

The recommended resource allocation order along the length of FPSO, based on design feature – normalised fatigue damage ratio over the time required to complete task has been indicated in Figure 4.22. The execution priority with reference to the distance from the aft peak of the FPSO has been shown.

The simulation of predicted changes in priorities for resource allocations in a year's time and in two years' time if no maintenance is carried out has also been indicated in Figure 4.22. This is based on an estimated annual deterioration rate of 8% on the coating breakdown and the corresponding impact on the resource required for completion of activity,

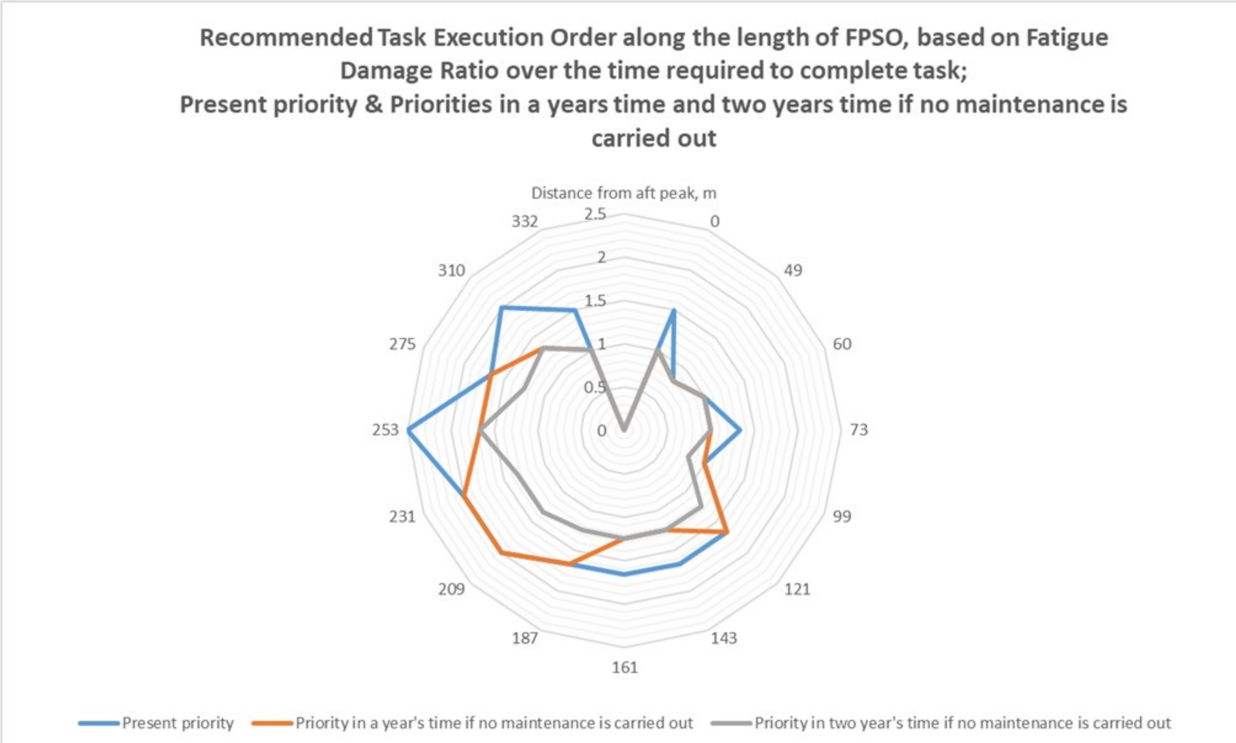

Figure 4.22: Changes in resource allocations if no maintenance is carried out, based on Fatigue Damage Ratio over the time required to complete task

taking into account the ($P[i] / T[i]$) change based on change in T only, as a function of coating break down, and ignoring the effect of coating breakdown on other decision variables.

The changes in resource allocations and resource utilisations, if no maintenance is carried out in a years' time and two years' time has been simulated and compared with the present planned priorities and productivities based on normalised fatigue damage ratio over the time for task completion, as indicated in Figure 4.23.

The simulation of predicted changes in cost functions by way of productivity and the corresponding resource utilisations in a year's time and in two years' time if no maintenance is carried out has also been indicated in Figure 4.23. This is based on an estimated annual deterioration rate of 8% on the coating breakdown and the corresponding impacts on the weighted sum of the completion times based on the priorities, taking into account the ($P[i] / T[i]$) change based on change in T only, as a function of coating break down, and

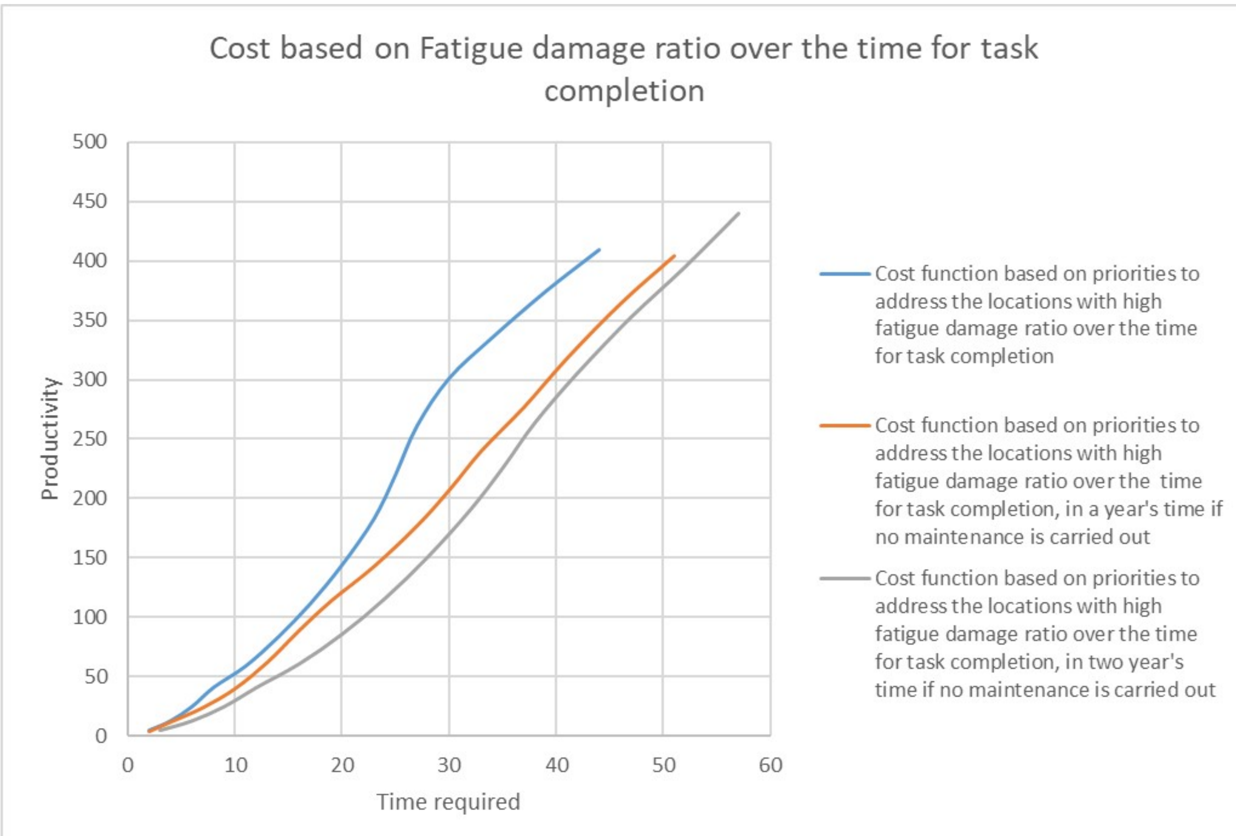

Figure 4.23: Changes in resource utilisations if no maintenance is carried out, based on Fatigue Damage Ratio over the time required to complete task

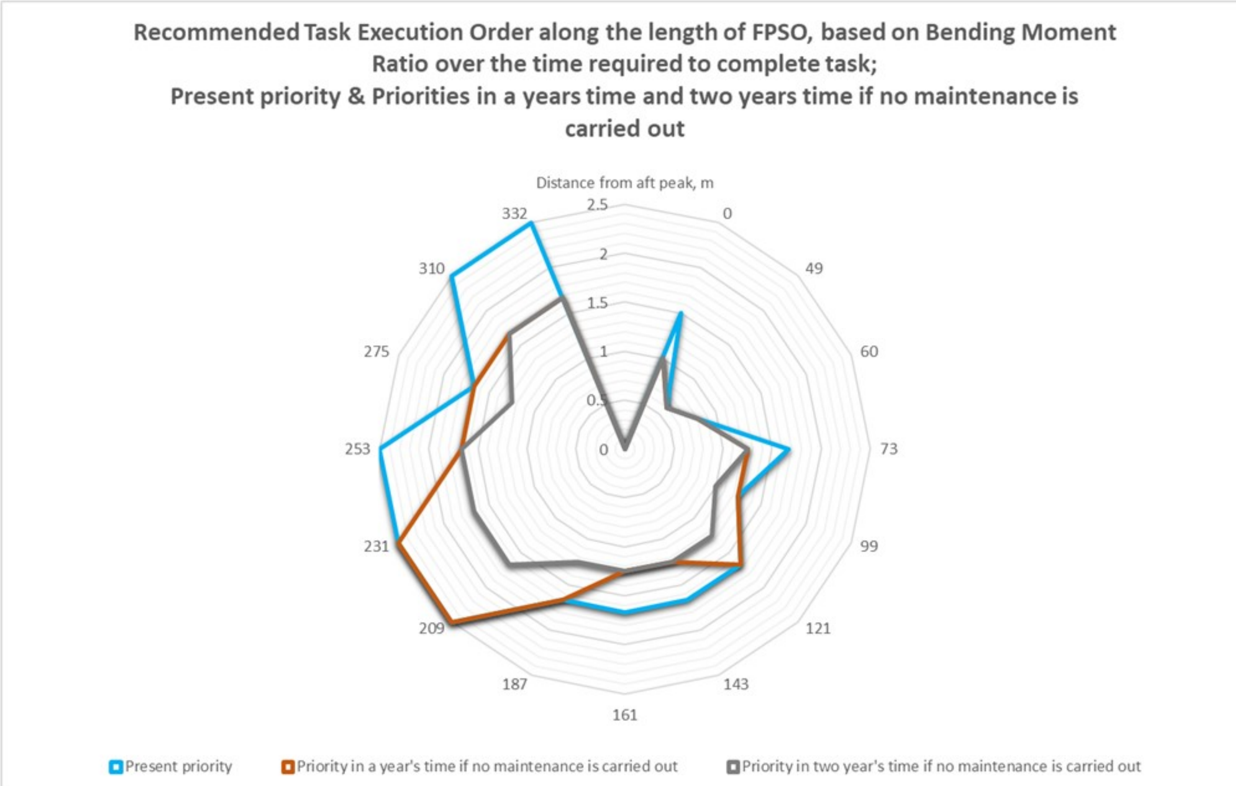

Figure 4.24: Changes in resource allocations if no maintenance is carried out, based on Strength, Bending Moment Ratio over the time required to complete task

ignoring the effect of coating breakdown on other decision variables.

4.4.3 Resource allocation based on operating conditions – Strength, Bending Moment Ratio over Time required to complete task

In this simulation in Figure 4.24, the performance of the greedy algorithm is being evaluated in terms of the personnel resource allocation, in terms of the priorities based on strength, Bending Moment Ratio over Time required to complete tasks, ($P[i] / T[i]$).

The recommended resource allocation order along the length of FPSO, based on Strength, normalised Bending Moment Ratio over the time required to complete task has been indicated in Figure 4.24. The execution priority with reference to the distance from the aft peak

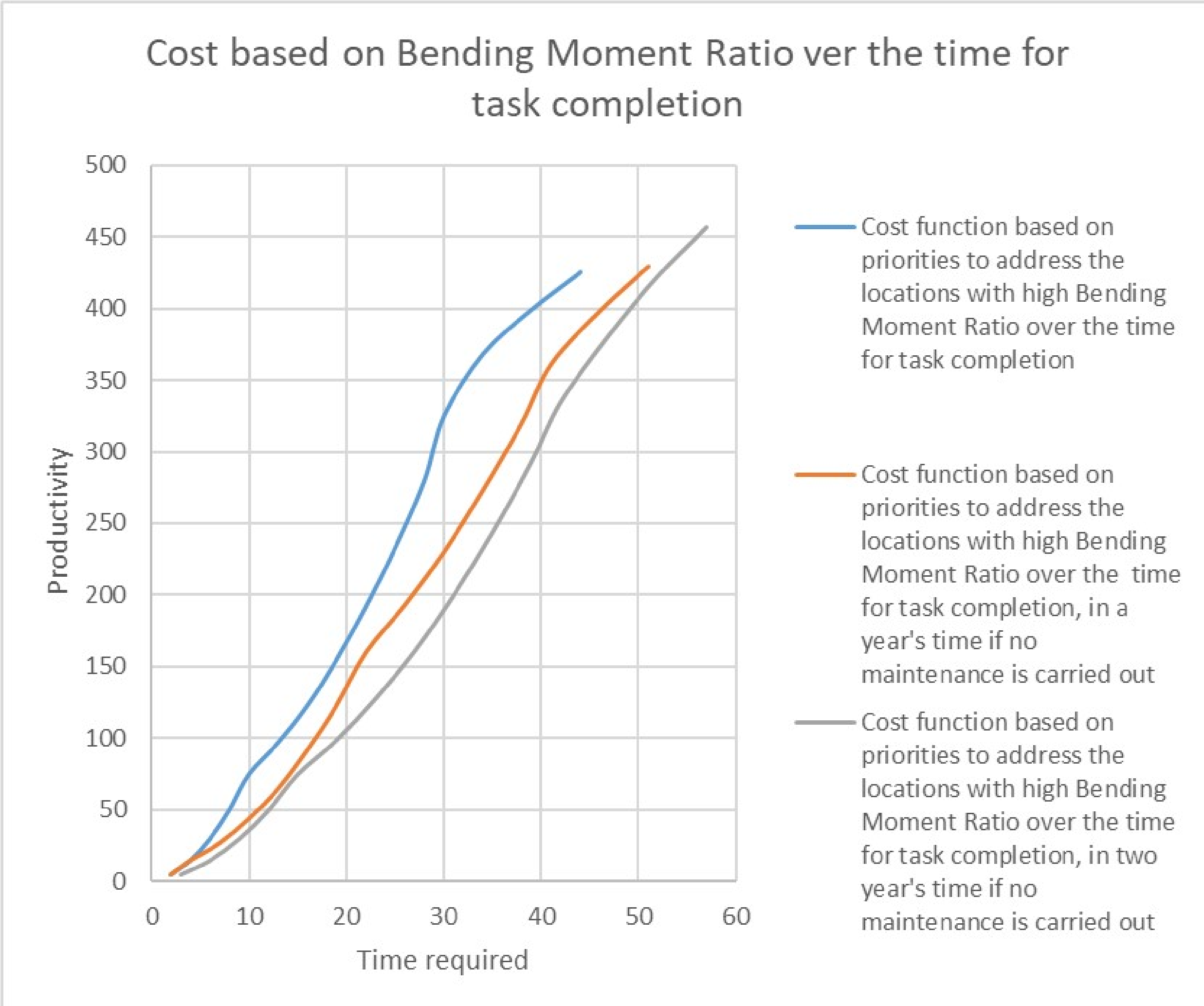

Figure 4.25: Changes in resource utilisations if no maintenance is carried out, based on Strength, Bending Moment Ratio over the time required to complete task

of the FPSO has been shown.

The simulation of predicted changes in priorities for resource allocations in a year's time and in two years' time if no maintenance is carried out has also been indicated in Figure 4.24. This is based on an estimated annual deterioration rate of 8% on the coating breakdown and the corresponding impact on the resource required for completion of activity, taking into account the ($P[i] \,/\, T[i]$) change based on change in T only, as a function of coating break down, and ignoring the effect of coating breakdown on other decision variables.

The changes in resource allocations and resource utilisations, if no maintenance is carried out in a years' time and two years' time has been simulated and compared with the present planned priorities and productivities based on normalised Bending Moment Ratio over the time for task completion, as indicated in Figure 4.25.

The simulation of predicted changes in cost functions by way of productivity and the corresponding resource utilisations in a year's time and in two years' time if no maintenance is carried out has also been indicated in Figure 4.25. This is based on an estimated annual deterioration rate of 8% on the coating breakdown and the corresponding impacts on the weighted sum of the completion times based on the priorities, taking into account the ($P[i] / T[i]$) change based on change in T only, as a function of coating break down, and ignoring the effect of coating breakdown on other decision variables.

4.4.4 Resource allocation based on operating conditions – Strength, Shear Force Ratio over Time required to complete task

In this simulation in Figure 4.26, the performance of the greedy algorithm is being evaluated in terms of the personnel resource allocation, in terms of the priorities based on Strength, Shear Force Ratio over Time required to complete tasks, ($P[i] / T[i]$).

The recommended resource allocation order along the length of FPSO, based on operating condition – normalised Strength, Shear Force Ratio over the time required to complete task has been indicated in Figure 4.26. The execution priority with reference to the distance from the aft peak of the FPSO has been shown.

The simulation of predicted changes in priorities for resource allocations in a year's time and in two years' time if no maintenance is carried out has also been indicated in Figure 4.26. This is based on an estimated annual deterioration rate of 8% on the coating breakdown and the corresponding impact on the resource required for completion of activity,

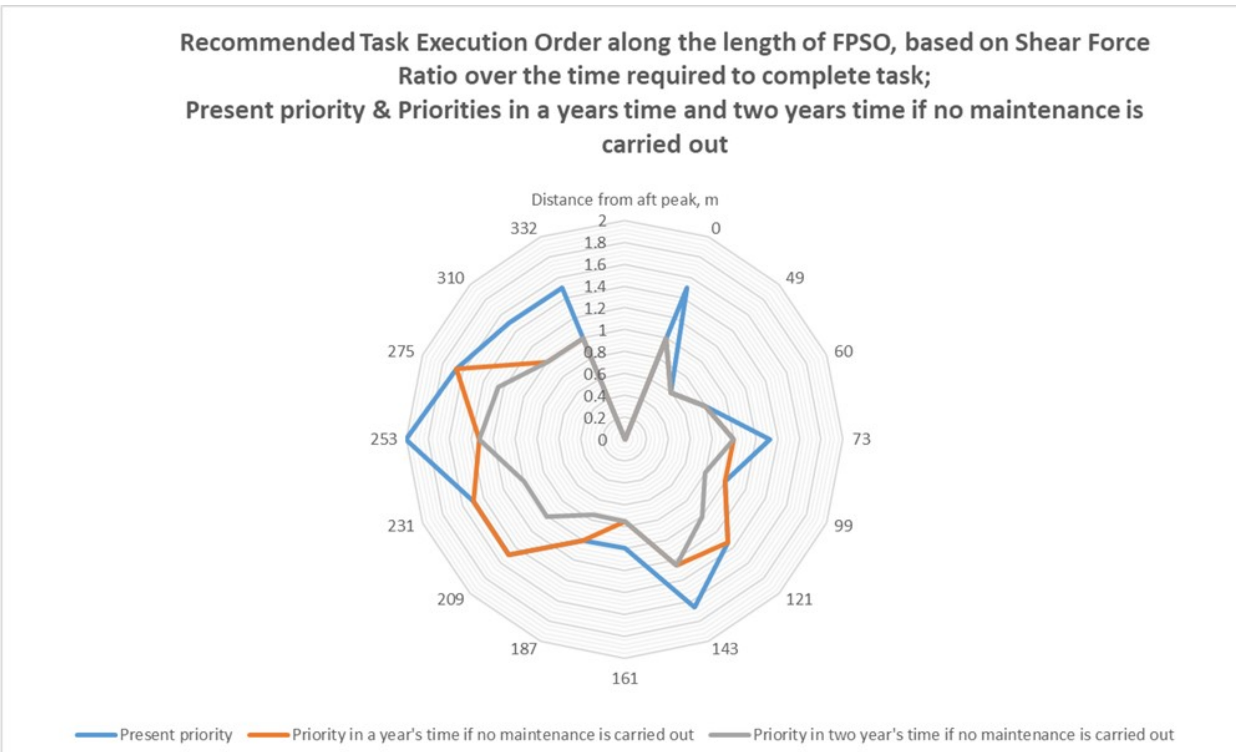

Figure 4.26: Changes in resource allocations if no maintenance is carried out, based on normalised Strength, Shear Force Ratio over the time required to complete task

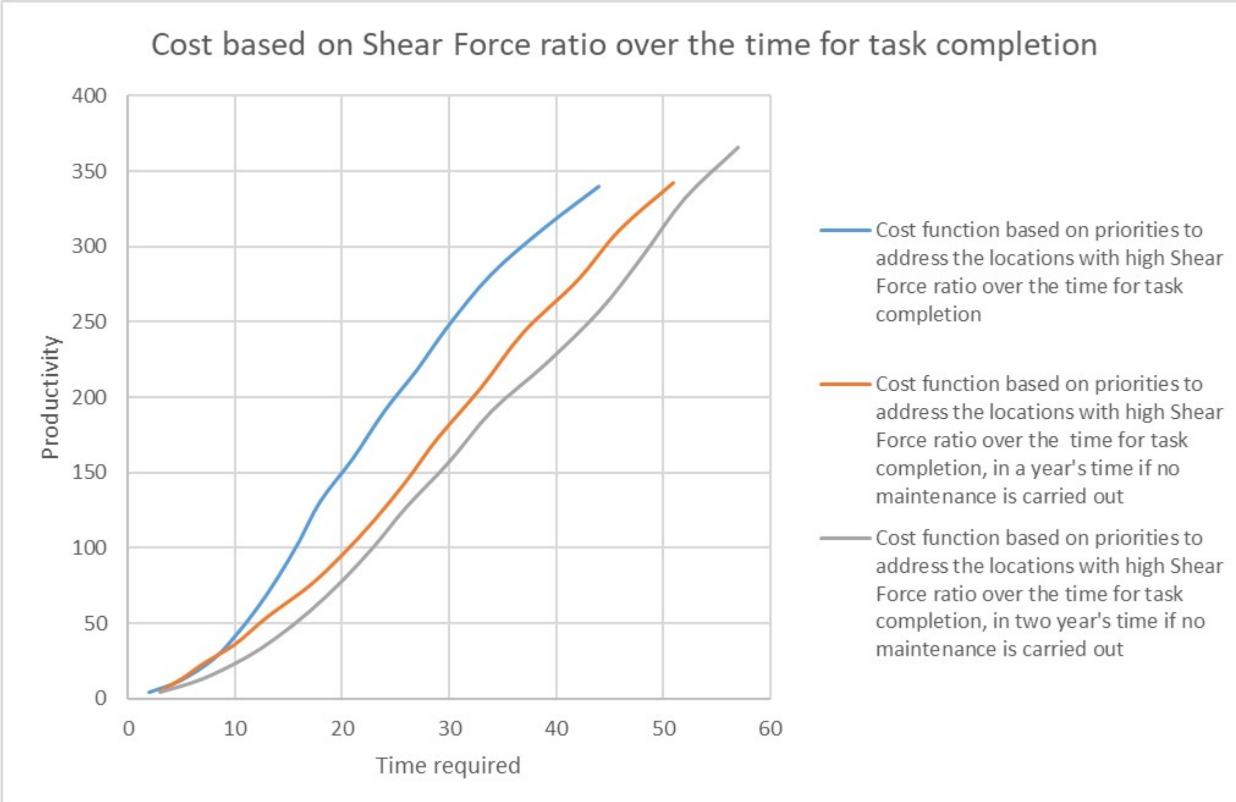

Figure 4.27: Changes in resource utilisations if no maintenance is carried out, based on Strength, Shear Force Ratio over the time required to complete task

taking into account the ($P[i] / T[i]$) change based on change in T only, as a function of coating break down, and ignoring the effect of coating breakdown on other decision variables.

The changes in resource allocations and resource utilisations, if no maintenance is carried out in a years' time and two years' time has been simulated and compared with the present planned priorities and productivities based on normalised Strength, Shear Force Ratio over the time for task completion, as indicated in Figure 4.27.

The simulation of predicted changes in cost functions by way of productivity and the corresponding resource utilisations in a year's time and in two years' time if no maintenance is carried out has also been indicated in Figure 4.27. This is based on an estimated annual deterioration rate of 8% on the coating breakdown and the corresponding impacts on the weighted sum of the completion times based on the priorities, taking into account the

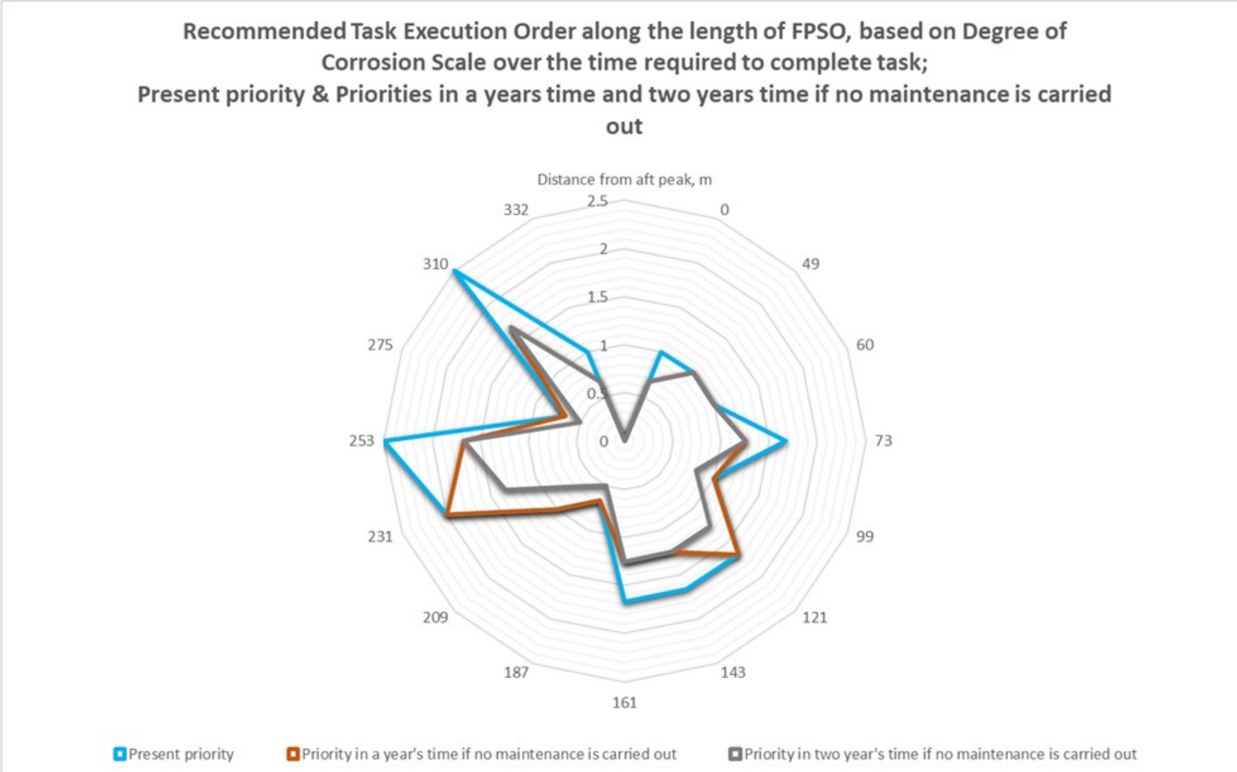

Figure 4.28: Changes in resource allocations if no maintenance is carried out, based on Degree of Corrosion Scale over the time required to complete task

($P[i] / T[i]$) change based on change in T only, as a function of coating break down, and ignoring the effect of coating breakdown on other decision variables.

4.4.5 Resource allocation based on deterioration mechanisms – Degree of Corrosion Scale over Time required to complete task

In this simulation in Figure 4.28, the performance of the greedy algorithm is being evaluated in terms of the personnel resource allocation, in terms of the priorities based on Degree of Corrosion Scale over Time required to complete tasks, ($P[i] / T[i]$).

The recommended resource allocation order along the length of FPSO, based on deterioration mechanisms – normalised Degree of Corrosion Scale over the time required to complete task has been indicated in Figure 4.28. The execution priority with reference to the distance from the aft peak of the FPSO has been shown.

The simulation of predicted changes in priorities for resource allocations in a year's time and in two years' time if no maintenance is carried out has also been indicated in Figure 4.28. This is based on an estimated annual deterioration rate of 8% on the coating breakdown and the corresponding impact on the resource required for completion of activity, taking into account the ($P[i] / T[i]$) change based on change in T only, as a function of coating break down, and ignoring the effect of coating breakdown on other decision variables.

The changes in resource allocations and resource utilisations, if no maintenance is carried out in a years' time and two years' time has been simulated and compared with the present planned priorities and productivities based on normalised Degree of Corrosion Scale over the time for task completion, as indicated in Figure 4.29.

The simulation of predicted changes in cost functions by way of productivity and the corresponding resource utilisations in a year's time and in two years' time if no maintenance is carried out has also been indicated in Figure 4.29. This is based on an estimated annual deterioration rate of 8% on the coating breakdown and the corresponding impacts on the weighted sum of the completion times based on the priorities, taking into account the ($P[i] / T[i]$) change based on change in T only, as a function of coating break down, and ignoring the effect of coating breakdown on other decision variables.

4.4.6 Resource allocation based on deterioration mechanisms – Degree of Metal Loss over Time required to complete task

In this simulation in Figure 4.30, the performance of the greedy algorithm is being evaluated in terms of the personnel resource allocation, in terms of the priorities based on Degree of

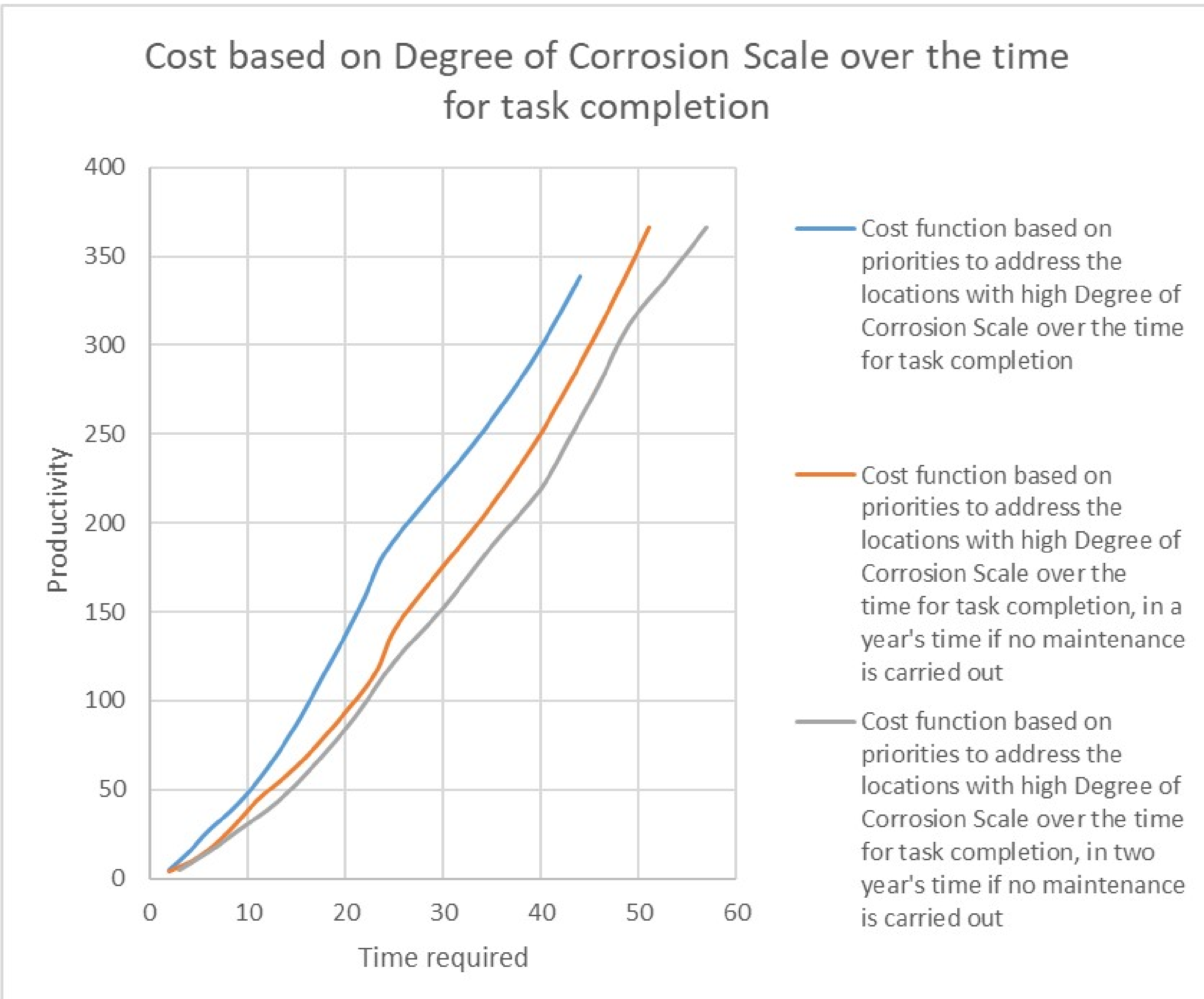

Figure 4.29: Changes in resource utilisations if no maintenance is carried out, based on Degree of Corrosion Scale over the time required to complete task

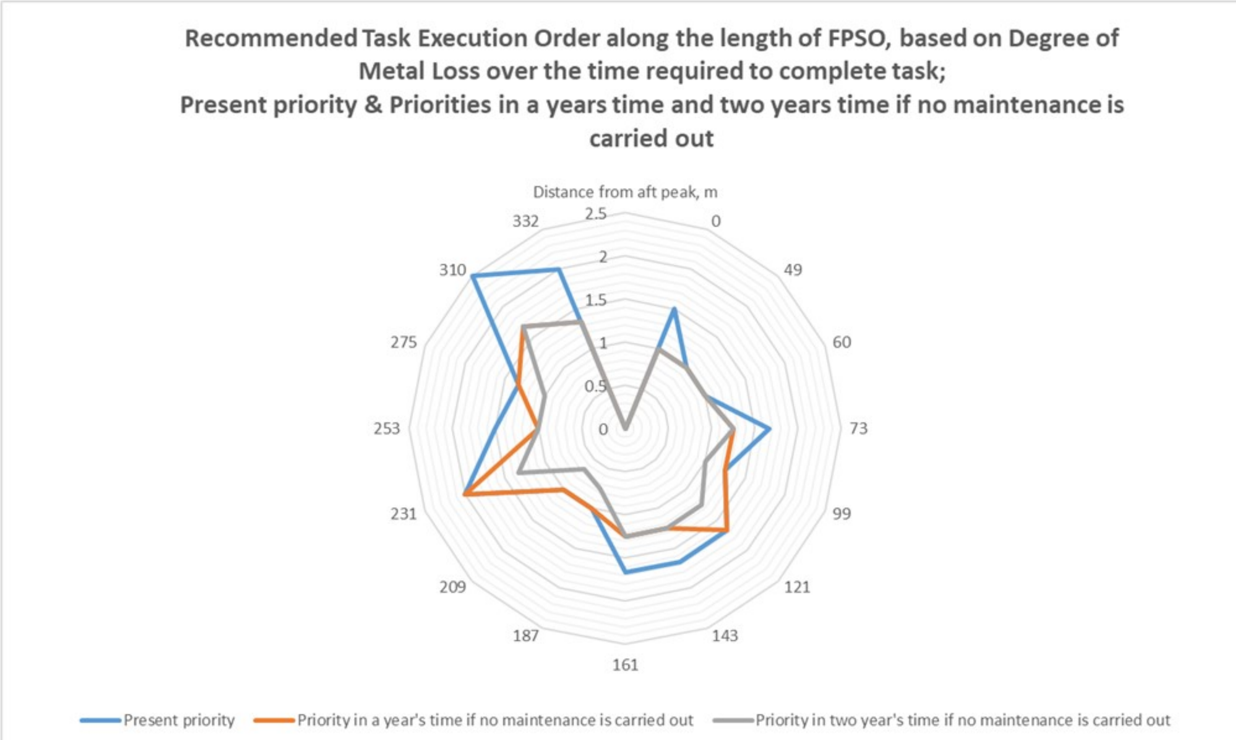

Figure 4.30: Changes in resource allocations if no maintenance is carried out, based on Degree of Metal Loss over the time required to complete task

Metal Loss over Time required to complete tasks, ($P[i] \,/\, T[i]$).

The recommended resource allocation order along the length of FPSO, based on deterioration mechanisms – normalised Degree of Metal Loss over the time required to complete task has been indicated in Figure 4.30. The execution priority with reference to the distance from the aft peak of the FPSO has been shown.

The simulation of predicted changes in priorities for resource allocations in a year's time and in two years' time if no maintenance is carried out has also been indicated in Figure 4.30. This is based on an estimated annual deterioration rate of 8% on the coating breakdown and the corresponding impact on the resource required for completion of activity, taking into account the ($P[i] \,/\, T[i]$) change based on change in T only, as a function of coating break down, and ignoring the effect of coating breakdown on other decision variables.

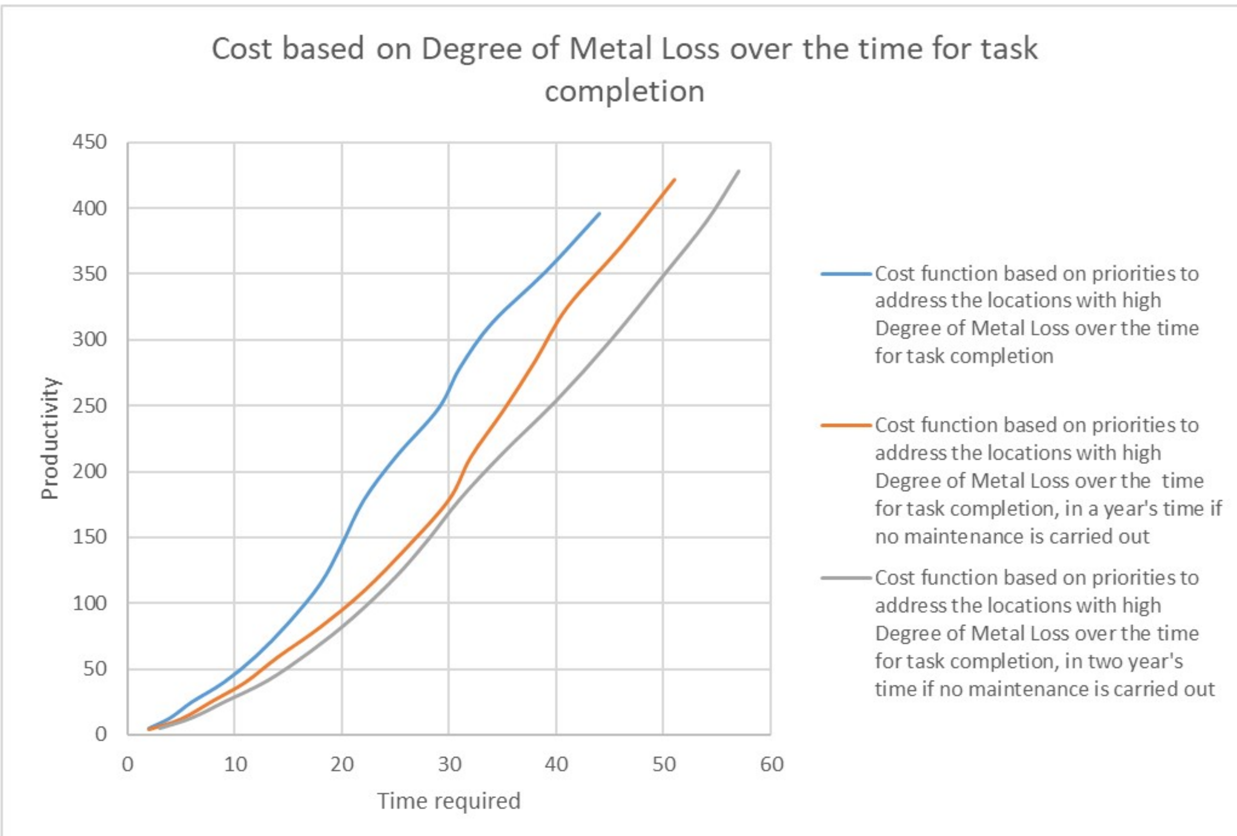

Figure 4.31: Changes in resource utilisations if no maintenance is carried out, based on Degree of Metal Loss over the time required to complete task

The changes in resource allocations and resource utilisations, if no maintenance is carried out in a years' time and two years' time has been simulated and compared with the present planned priorities and productivities based on normalised Degree of Metal Loss over the time for task completion, as indicated in Figure 4.31.

The simulation of predicted changes in cost functions by way of productivity and the corresponding resource utilisations in a year's time and in two years' time if no maintenance is carried out has also been indicated in Figure 4.31. This is based on an estimated annual deterioration rate of 8% on the coating breakdown and the corresponding impacts on the weighted sum of the completion times based on the priorities, taking into account the ($P[i] / T[i]$) change based on change in T only, as a function of coating break down, and ignoring the effect of coating breakdown on other decision variables.

4.4.7 Resource allocation based on Consequences of not doing the tasks – Safety Risk over Time required to complete task

In this simulation in Figure 4.32, the performance of the greedy algorithm is being evaluated in terms of the personnel resource allocation, in terms of the priorities based on Safety Risk over Time required to complete tasks, ($P[i] / T[i]$).

The recommended resource allocation order along the length of FPSO, based on Consequences of not doing the tasks – normalised Safety Risk over the time required to complete task has been indicated in Figure 4.32. The execution priority with reference to the distance from the aft peak of the FPSO has been shown.

The simulation of predicted changes in priorities for resource allocations in a year's time and in two years' time if no maintenance is carried out has also been indicated in Figure 4.32. This is based on an estimated annual deterioration rate of 8% on the coating breakdown and the corresponding impact on the resource required for completion of activity,

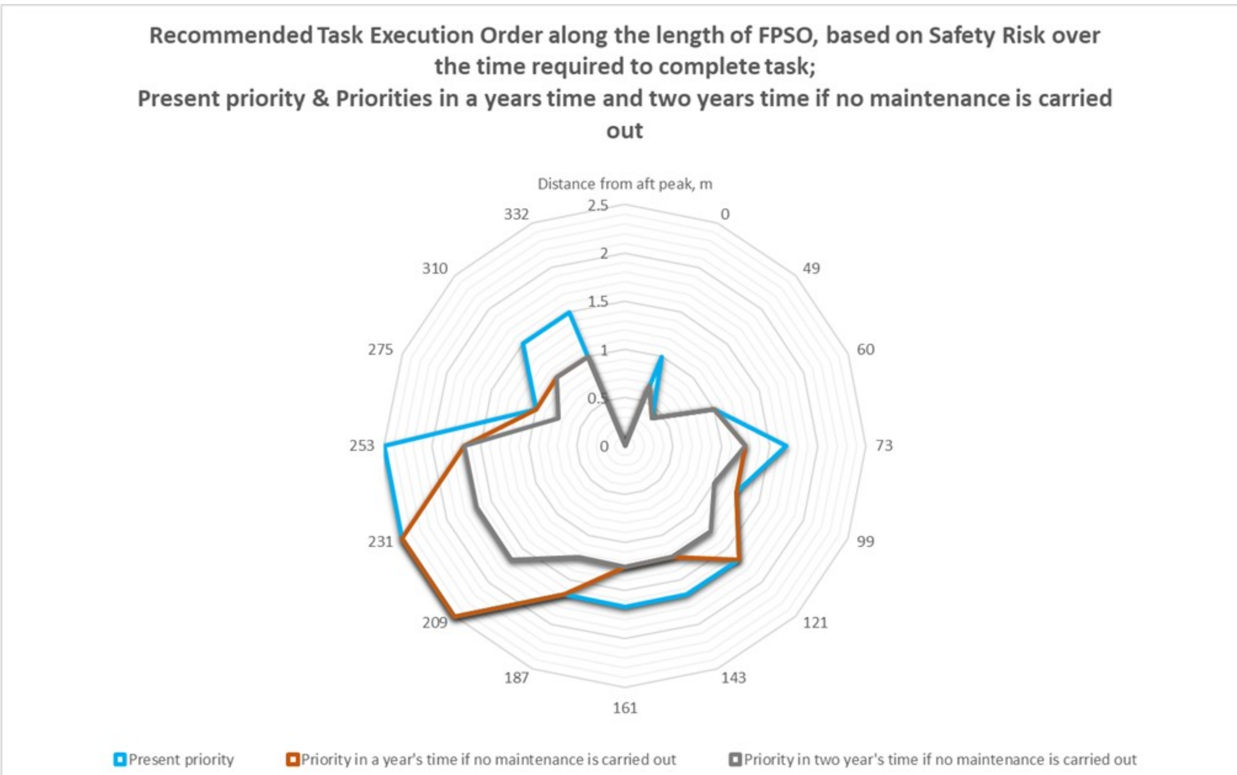

Figure 4.32: Changes in resource allocations if no maintenance is carried out, based on Consequences of not doing tasks–normalised Safety Risk over time required to complete task

Figure 4.33: Changes in resource utilisations if no maintenance is carried out, based on Consequences of not doing the tasks – Safety Risk over the time required to complete task

taking into account the ($P[i] \,/\, T[i]$) change based on change in T only, as a function of coating break down, and ignoring the effect of coating breakdown on other decision variables.

The changes in resource allocations and resource utilisations, if no maintenance is carried out in a years' time and two years' time has been simulated and compared with the present planned priorities and productivities based on normalised Safety Risk over the time for task completion, as indicated in Figure 4.33.

The simulation of predicted changes in cost functions by way of productivity and the corresponding resource utilisations in a year's time and in two years' time if no maintenance is carried out has also been indicated in Figure 4.33. This is based on an estimated annual deterioration rate of 8% on the coating breakdown and the corresponding impacts on the weighted sum of the completion times based on the priorities, taking into account the ($P[i]$ / $T[i]$) change based on change in T only, as a function of coating break down, and ignoring the effect of coating breakdown on other decision variables.

4.4.8 Resource allocation based on Consequences of not doing the tasks – Financial Risk over Time required to complete task

In this simulation in Figure 4.34, the performance of the greedy algorithm is being evaluated in terms of the personnel resource allocation, in terms of the priorities based on Financial Risk over Time required to complete tasks, ($P[i]$ / $T[i]$).

The recommended resource allocation order along the length of FPSO, based on design feature – normalised Financial Risk over the time required to complete task has been indicated in Figure 4.34. The execution priority with reference to the distance from the aft peak of the FPSO has been shown.

The simulation of predicted changes in priorities for resource allocations in a year's time and in two years' time if no maintenance is carried out has also been indicated in Figure 4.34. This is based on an estimated annual deterioration rate of 8% on the coating breakdown and the corresponding impact on the resource required for completion of activity, taking into account the ($P[i]$ / $T[i]$) change based on change in T only, as a function of coating break down, and ignoring the effect of coating breakdown on other decision variables.

The changes in resource allocations and resource utilisations, if no maintenance is carried out in a years' time and two years' time has been simulated and compared with the present

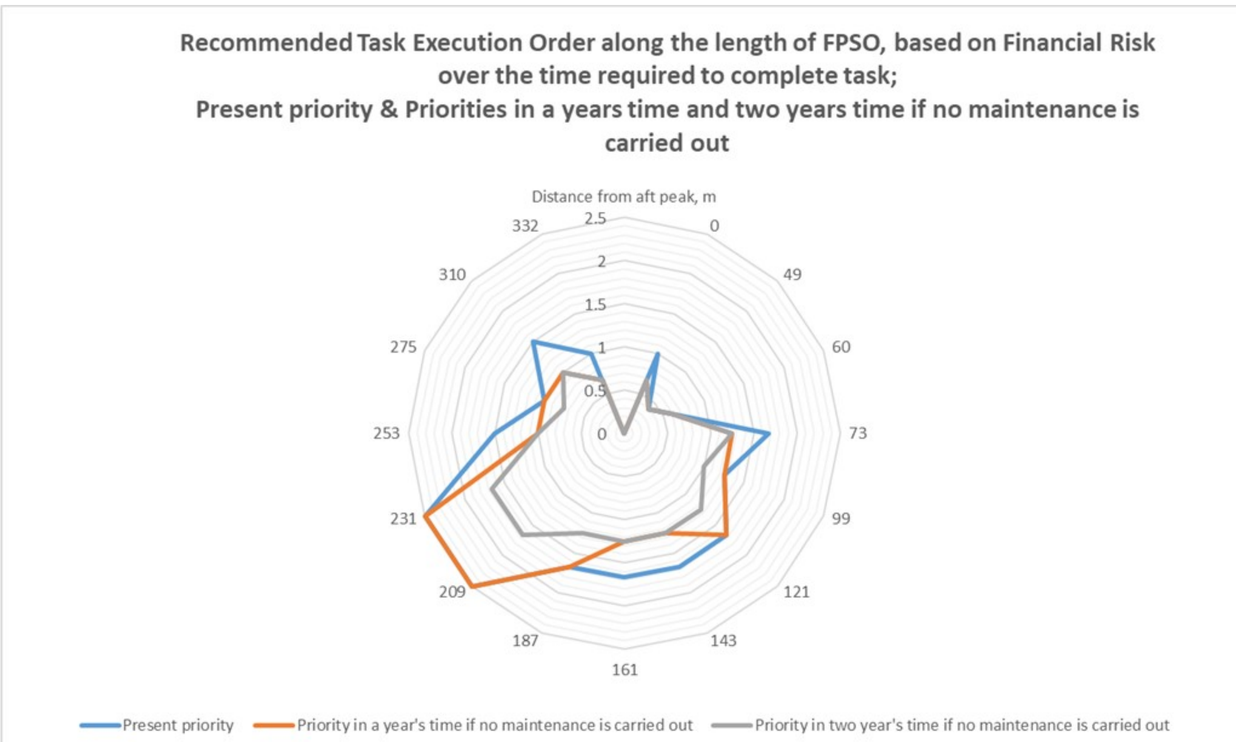

Figure 4.34: Changes in resource allocations if no maintenance is carried out, based on Consequences of not doing tasks– normalised Financial Risk over the time required to complete task

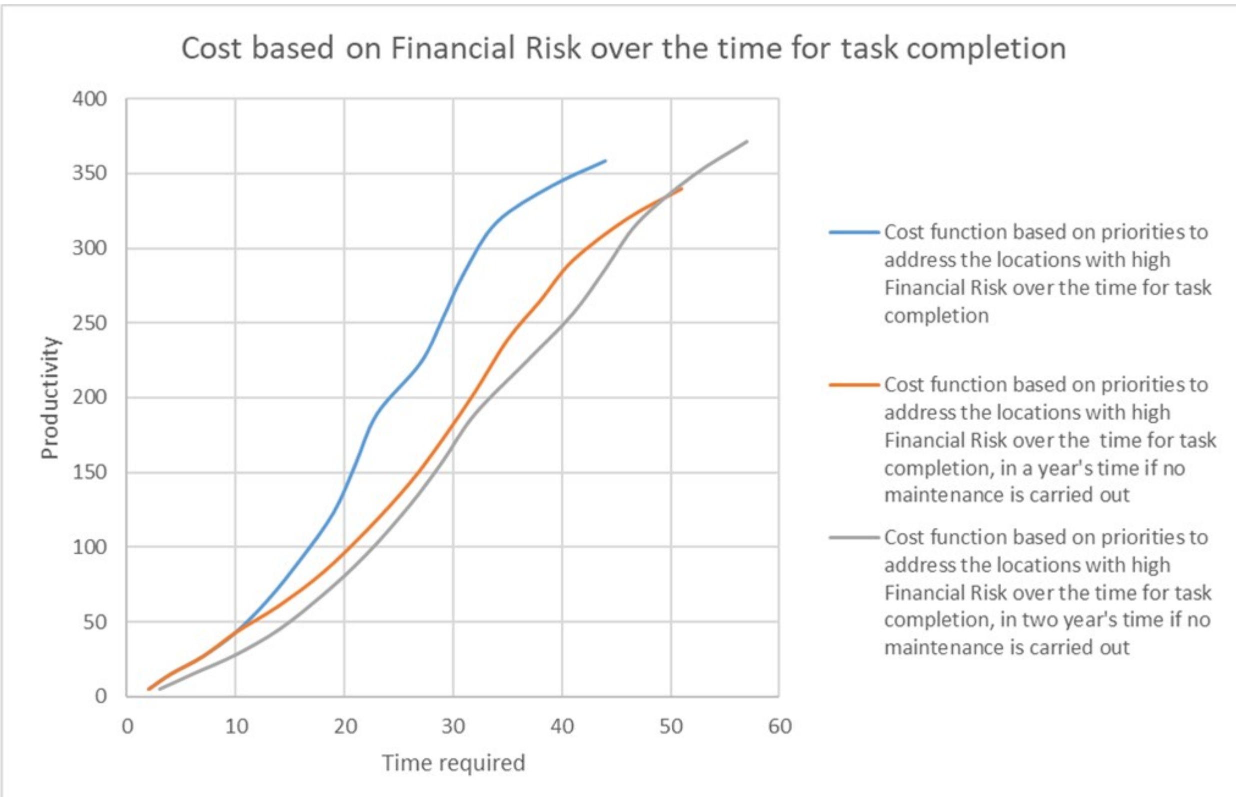

Figure 4.35: Changes in resource utilisations if no maintenance is carried out, based on Consequences of not doing the tasks – normalised Financial Risk over the time required to complete task

planned priorities and productivities based on normalised Financial Risk over the time for task completion, as indicated in Figure 4.35.

The simulation of predicted changes in cost functions by way of productivity and the corresponding resource utilisations in a year's time and in two years' time if no maintenance is carried out has also been indicated in Figure 4.35. This is based on an estimated annual deterioration rate of 8% on the coating breakdown and the corresponding impacts on the weighted sum of the completion times based on the priorities, taking into account the ($P[i] \,/\, T[i]$) change based on change in T only, as a function of coating break down, and ignoring the effect of coating breakdown on other decision variables.

4.5 Overall objective maintenance optimisation

The main objective of this work was to maximise the maintenance personnel resource utilisation and enable FPSO condition enhancement, considering the priorities with respect to design features, operating conditions, deteriorations, and the consequences of not doing the maintenance, taking into consideration the personnel resource time required for activity completion.

Objective Function,

$$F_i \;=\; \sum \left(\frac{P[i]}{T[i]} \,*\, C[i]\right) \tag{4.1}$$

where, $P[i]$ is the Priority based on the objectives, and $T[i]$ is the time required to complete a maintenance activity, and $C[i] \;=\; \sum T[j]$ the cumulative task completion time.

The objective functions, $F_1,\ F_2,\ F_3,\ F_4,\ F_5,\ F_6,\ F_7,\ F_8$ corresponding to maintenance priorities with respect to normalised Stress Unity Check x_1, Fatigue Damage Ratio x_2 , Bending Moment Ratio x_3, Shear Force Ratio x_4, Degree of Corrosion Scale x_5 , Degree of Metal Loss x_6 , Safety Risks in the event of not doing maintenance x_7 and Financial Risks in the event of not doing maintenance x_8 respectively, taking into consideration the personnel resource time required for activity completion, were combined into an overall objective optimisation problem. Depending on the priority of the objective function when compared to other objective functions, a relative weight has been associated to the prioritised objective function, using the weighted sum approach, such that

$$\{y_i\} = \sum(\pm\alpha_i * F_i) \tag{4.2}$$

where, α_i indicate the relative weight of the prioritised objective function when compared with the priority of other objective functions. The positive weight, $Sign\ +$, means the corresponding objective function would be maximised, and negative weight, $Sign\ -$, means the corresponding objective function would be minimised. This formulation provides flexibility to direct the focus of the overall objective function, y_i, towards any one or more of the objective functions by adjusting their respective weight according to the maintenance strategy followed.

The schematic representation of the FPSO system overall multi-objective optimisation problem has been shown in Figure 4.36.

In the simulation in Figure 4.37, the performance of the greedy algorithm is being evaluated in terms of the personnel resource utilisation, based on an overall objective function developed by linear combinations of the multiple objective functions.

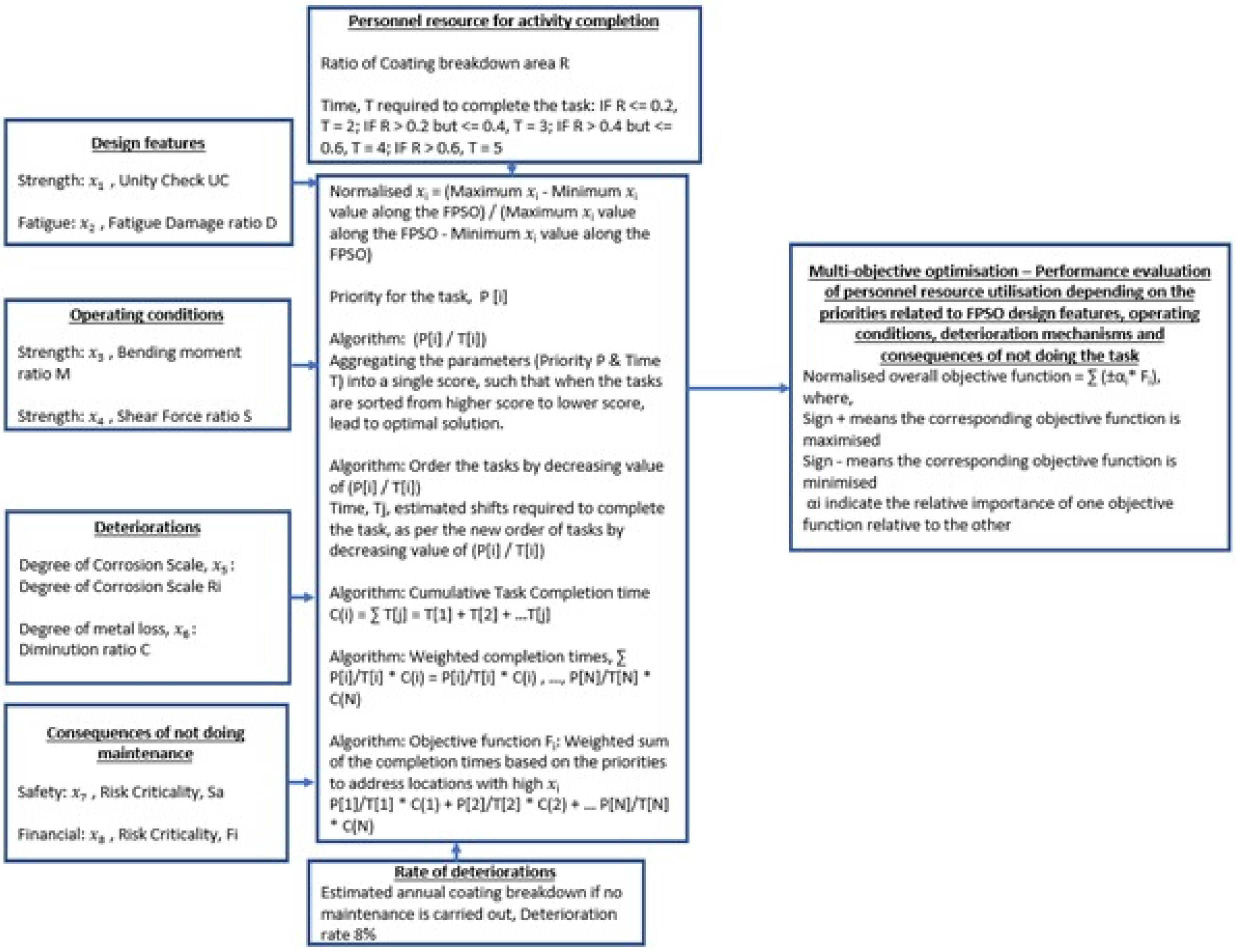

Figure 4.36: FPSO system overall multi-objective optimisation problem

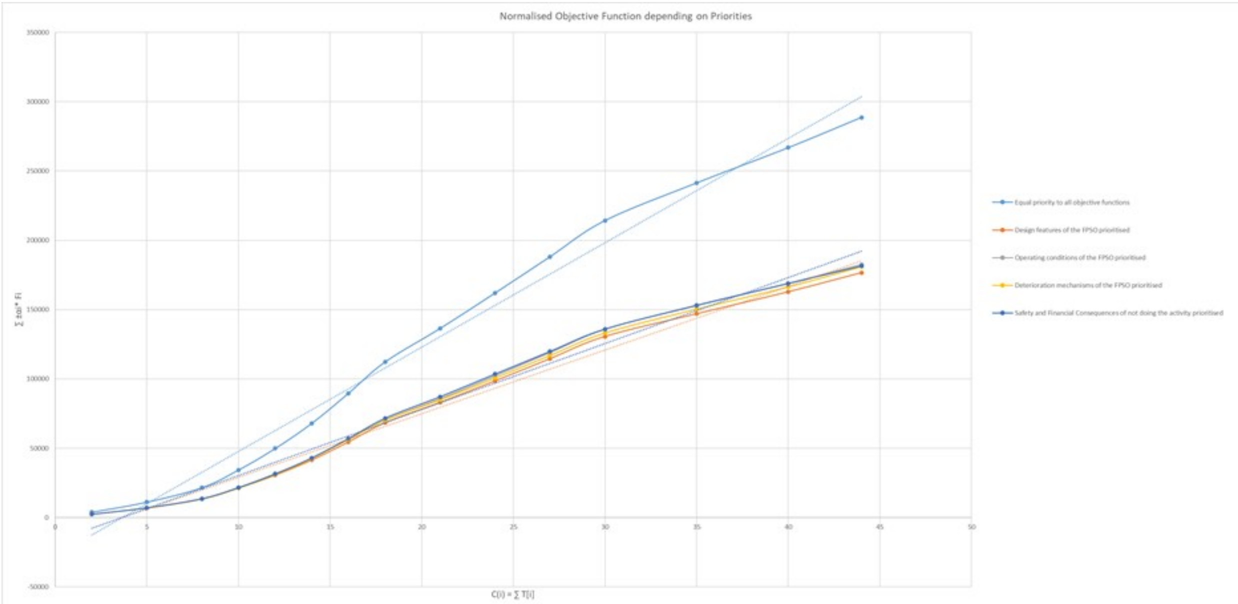

Figure 4.37: Overall objective optimisation depending on Priorities

The optimisation simulation results obtained for the various scenarios of priorities have been presented in figure 4.37.

In the simulation Figure 4.37, the performance of the greedy algorithm has been demonstrated in terms of the personnel resource utilisation, based on an overall objective function developed by linear combinations of the multiple objective functions $\sum(\pm\alpha_i * F_i)$. This simulation demonstrates the performance evaluation of proposed multi-objective optimisation employing weighted sum approach for maintenance planning, in terms of personnel resource utilisation.

The Objective functions of the design features, operating conditions, deteriorations, consequences of not doing the maintenance have been combined in into a single objective maximisation problem using the weighted sum approach, such that depending on the priority of the objective function when compared to other objective functions, a weighting factor has been associated to the prioritised objective function. The higher weighted sum of the completion times at as short time as possible, would lead to higher resource utilisation.

It could be observed from the gradient of the simulations, when equal priorities are provided to all the objective functions, the resource utilisation is much higher than that for individual prioritisation of objective functions. Also, no significant changes to the resource utilisations have been noted when the objective functions were prioritised individually.

4.6 Conclusion

Based on the formulation of multi-objective optimisation carried out in Chapter 3, a novel greedy algorithm has been proposed in this Chapter that incorporate the impact of time required to complete the activities on the optimisation objectives of FPSO design features, operating conditions, deteriorations, consequences of not doing the maintenance and the personnel resource availability for activity completion. Also, the benchmarking of the algorithm has been carried out by comparing the parameters, with and without considering the time required to complete the task, which reflects influence of the time required to carry out the activity, on the prioritisation of activities.

The evaluation of the model has been carried out by comparing the priorities for each scenario based on 3 different loading conditions of the FPSO – Light load condition, Medium load condition and Full Load condition. The performance of the greedy algorithm has been evaluated in terms of the personnel resource allocation and resource utilisation. To evaluate the satisfaction of resource allocation, the weighted sum of the task completion times based on the priorities have been considered. To evaluate the satisfaction of resource utilisation, it has been considered that the higher weighted sum of the completion times at as short time as possible, leads to higher resource utilisations.

The changes in priorities and productivity, if no maintenance is carried out in 1 years' time and 2 years' time has been simulated and compared with the present planned resource allocations and resource utilisations, taking into account the (P[i] / T[i]) change based on change in T only, as a function of coating break down, and ignoring the effect of coating breakdown on other decision variables.

Also, an overall objective optimisation problem has been proposed in this paper, by linear combinations of the multiple objective functions, using the weighted sum approach. This formulation provides flexibility to direct the focus of the overall objective function towards any one or more of the objective functions by adjusting their respective weight according to the maintenance strategy followed, which would supplement the Regulatory oversight requirements of the FPSO.

Chapter5

Novel Multi-objective Optimisation with Deep Q-Reinforcement Learning (DQN) for Maintenance Activities of Floating Production Storage and Offloading Facilities

5.1 Introduction

Through an extensive literature survey carried out, it has been identified that the current state-of-the-art literature does not incorporate site constraints of the asset related to offshore resource availability for the maintenance activity, the impact of time required to carry out activities and its impact on other activities due to this maintenance. There exists scope for further research works that addresses the afore-mentioned gaps by examining machine learning and Deep Q- reinforcement learning (DQN) network based artificial intelligence approach, considering the design features, actual condition of the component, site constraints, deterioration factors, consequences of not doing the activities, time required to complete the activities and investigating the impact on key maintenance performance indicators regarding resource allocations and resource utilisations.

In summary, the following contributions are made in this Chapter:

• A novel work management framework has been proposed that comprises of DQN problem formulation as a solution to multi-objective optimisation problem, to enable carrying out activities that have minimal site constraints, considering the design features, operating conditions, deteriorations, consequences of not doing the activities and time required to complete the activities, to get higher weighted sum of the completion times at short time as possible, whereby achieving higher resource utilisations. The goal is to achieve the best trade-off between the turnaround time for the activities and liquidating the risks to the asset's performance, based on completion of activities in the work management system.

• A greedy algorithm benchmarks the performances of DQN model and a hybrid model comprising of greedy and DQN parameters, with respect to average number of timesteps per episode – the smaller number of timesteps per episode means agent take minimum steps/shortest path to reach the target; average rewards per timestep – the larger the reward means the agent is doing the right thing; the solution provides execution of maintenance activities having minimal site constraints leading to better resource utilisation and completion of activities; average number of penalties per episode – the smaller the number, the better performance of agent. It has been noted that overall, the hybrid and the DQN models achieve better results when compared with the Greedy model, towards task completion time and liquidating the risks to the asset's performance.

5.2 Related work

The current state-of-the-art literature related to analyses techniques to develop the maintenance strategies for various systems have been reviewed and the highlights in the literature have been summarised in Table 5.1.

Table 5.1: Analyses techniques to develop maintenance strategies

Ref. / Year	**Equipment**	**Analyses**			
		Modelling/ Optimisation technique	**Objective functions**	**Decision variables**	**Constraints**
W. Zhu et al. 2019	Offshore wind turbine	Bayesian Network/ Monte-Carlo simulations	Ensure performance of the wind turbine, maximise short- and long-term profits, and optimise maintenance grouping, minimise logistic cost and downtime loss.	Failure modes, Logistic delays, Weather conditions	Uncertainties related to logistic delays and weather conditions
Z. Lin et al. 2020	Offshore wind turbine	Linear and Non-linear models			
A. Mentes and O. Turan. 2019	Offshore wind turbine	Resilience Engineering	Ability to learn, anticipate, monitor and respond to emergency	Human and organizational factors	Maintenance failures

Y. Li and Z. Hu. 2021	Offshore oil and gas facilities	Regression and Multi-criteria Decision Analysis	Asset retirement obligations of liabilities and expenses to be settled	Features of Environmental, Health and Safety, Technic/ Feasibility, Socio-economic and Financial	Potential ecosystem impacts, and gain or damage to hydrodynamic state
M N. Scheu et al. 2019	Offshore wind turbine	Risk-based model	Minimise operational expenditure, Downtime reduction	Failure modes of the components	System criticality
M. Zagorowska et al. 2020	Offshore turbomachinery	Linear and exponential non-linear regression in an expanding moving window framework	Additional operational profits and reduced energy consumption	Degradation indicator	Detection window
M. Li et al. 2020	Offshore wind turbine	Non-homogeneous Continuous-Time Markov Process	Minimise the total maintenance cost	Maintenance cost per unit of time, Degradations	Maintenance schedule

M.P. Asuquo et al. 2019	Marine and offshore machinery	Fuzzy-TOPSIS	Identify the best, most appropriate and acceptable maintenance strategy to be adopted	Reliability, Equipment and Labour Cost Effectiveness, Safety, Availability and Downtime	Costs and benefits for their subsequent implementation
A. Jamshidi et al. 2019	Offshore wind turbine	FMEA, FMECA, RBI, FCM (Fuzzy Cognitive Maps), Bayesian Network			
H N. Teixeira et al. 2020	Industrial applications	Big Data analytics and Internet of Things (IoT)			
Y. Lu et al. 2018	Offshore wind turbine	Artificial Neural Network life percentage prediction model	Determining optimal maintenance interval value to minimise the total maintenance cost	Conditional failure probabilities	Defined inspection intervals

R d O. Werneck et al. 2021	Well production	Recurrent Neural Networks	Well production and pressure forecasting	Production data, Injection data, Well's pressure	Production impacts
H. Seiti et al. 2019	Process Units	D-Fuzzy Axiomatic Design (D-FAD) method, is a combination of fuzzy axiomatic design and D numbers	Evaluate the alternatives for replacement intervals with respect to criteria with the associated risks. Cost function	Best Replacement Time	Expected cost function, Availability, Safety
O. Ahmadi et al. 2020	Atmospheric storage tanks	Fuzzy Decision-making trial and evaluation laboratory (DEMATEL) outputs in Bayesian network	Determination of leading indicators validity, importance and practicability	Failures, Hot work	Risk influence factors
M. Yazdi et al. 2019	Process facilities	Non-linear model / Bi-objective fuzzy structure optimization model	Minimise the safety investment and accident probability	Health & Safety importance, Time allocation, Cost, Environment	Budget limitation, Safety factors

				al enhancement , Reputation importance	
D. Fan et al. 2021	Subsea Equipment	Reliability model with stochastic dependency / Collaborative particle swarm optimization algorithm	Optimal group maintenance plan	Maintenance Cost, PM duration, PM interval, Corrective maintenance duration	System availability, Failure rate
N N. Ferreira et al. 2020	Exploration & Production (E&P) platforms in oil and gas industry	Structuring the process in stages			
J. Matias et al. 2020	Gas lift oil well	Remaining Useful Life (RUL) estimation model	Maximise production and economic objectives	Equipment health indicators, Plant data	System dynamics, Safety constraints, Operational constraints
Y. Han et al. 2021	Safety Critical Equipment on Offshore Installations	Hybrid dynamic risk modelling methodology that	Provide dynamic real time risk profile predictions	Dynamic variables	Human errors, Functional failures

		combines dynamic Bayesian network (DBN) technique and support vector regression (SVR) algorithm			
Y. Han et al. 2019	Offshore installations	Dynamic data model, Classificatio n model, Maintenance decision model	Minimise the total risk level while reducing the maintenance cost	Observed Samples, Observed failures, Maintenance time intervals	Degradation rate, Parameter uncertainty
E U. Olugu et al. 2021	Offshore Oil and Gas industry	Spherical fuzzy sets modified-Delphi Model	Technical performance, environmental performance, economic performance and social performance	Maintenance improvement , maintenance efficiency, management of resources, waste management, responsibilit y & Regulations, cost-effectiveness ,	

				investments, indirect economic impacts, skill improvement, occupational health & safety, maintenance employee, and social responsibility & Regulations	
M. Ibrion et al. 2020	Offshore installations	Learning from accidents			
B. Yeter et al. 2022	Offshore wind turbines	Structural integrity analysis employing Gaussian kernel for denoising, followed by a time-domain crack growth analysis / Unsupervise	Techno-economic feasibility of life extension	Environmental and operational parameters, operational expenditures, Structural design data, Wind load data, Material properties	Life extension duration and appropriate discount rate

		d machine learning			
T N. Schouten et al. 2021	Offshore wind turbine	Mixed integer linear programmin g model	Maintenance optimisation	Time-varying costs, Power outputs	Cost fluctuations
A L. Ramirez-Ledesma and J A. Juarez-Islas. 2022	Offshore oil platforms	Statistical predictive model	Remaining useful life	Mechanical properties, Chemical composition, hardness and tensile test properties	Component's interaction with atmospheric gases, Non-metallic inclusions associated with localised corrosion by pitting corrosion mechanism
S. Adumene et al. 2021	Marine pipelines	Copula-based Monte Carlo (CMC) simulation / Bayesian Network with Copula-	Microbial corrosion rate prediction, considering the interrelationshi ps between physio-	Geometry of Corrosion parameters, physio-chemical parameters, pipe variables and	Failure mode probabilities

		based Monte Carlo (BN-CMC) simulation	chemical parameters	mechanical properties	
Z. Ren et al. 2021	Offshore wind turbine	Big data and machine learning			
Y. Liu et al. 2018	Coal Transportatio n	Saddle point approximati on / Tailored ant colony optimisation algorithm	Maximize the probability of a system successfully completing the next mission, Optimal maintenance actions	Maintenance budget, Duration of break, Durations of maintenance actions	Duration Uncertainties of the maintenance actions and breaks
C. Zhang et al. 2019	Wind turbines	Markov chain model, Weibull distribution & mathematica l models	Minimise the total maintenance and inventory cost over the life cycle horizon, optimal opportunistic maintenance reliability threshold, reorder stock level	Life cycle Maintenance costs, Inventory costs	Maintenance budget, wait time owing to weather restrictions

C. Zhang and T. Yang. 2021	Wind turbines	Mathematical models / Nondominated sorting genetic algorithm (NSGA)	Efficient maintenance planning and resource allocation, prevent unnecessary downtime and reduce operational costs	Maintenance costs	Maintenance budget, weather restrictions

Table 5.1 references:

[10], [12], [13], [16], [18], [20], [23], [26], [27], [81], [29], [31], [33], [34], [40], [41], [68], [43], [44], [49], [50], [69], [54], [55], [57], [61], [70], [62], [64], [19].

5.3 DQN solution for FPSO main deck maintenance

Q-learning allow the agent to use the environment's rewards to learn, over time, the best action to take in a given state. In the Work Management System (WMS), we have the reward table, P, from which the agent will learn from. The agent does things by receiving a reward for taking an action in the current state, then updating a Q-value to remember if that action was beneficial. The values store in the Q-table are termed Q-values, and then map to a ($state$, $action$) combination.

A Q-value for a particular ($state$, $action$) combination is representative of the Quality of an action taken from that state. Better Q-values imply better chances of getting greater rewards.

Q-values are initialised to an arbitrary value, and as the agent exposes itself to the environment and receives different rewards by executing different actions, the Q-values are updated using the equation:

$$Q(state, action) \leftarrow (1-\alpha)\ Q\ (state,\ action) + \alpha\ (reward + \Gamma\ max_a\ Q\ (next\ state,\ all\ actions)\ ) \tag{5.1}$$

where:

α is the learning rate ($0 < \alpha \leq 1$). This is the extent to which the Q-values are being updated in every iteration.

γ is the discount factor ($0 \leq \gamma \leq 1$). This determines how much importance we want to give to future rewards. A high value for the discount factor, nearer to 1, captures the long-term effective award, whereas a discount factor nearer to zero makes the agent consider only immediate reward, hence making it greedy. In the algorithm, a γ value of 0.1 has been used for the iterations considered as Greedy, a γ value of 0.6 has been used for Hybrid model of Greedy and DQN, and a γ value of 1.0 for DQN model.

ϵ is the randomness factor ($0 < \epsilon \leq 1$). This determines how much exploration we want to have, to prevent the action from possible overfitting. Lower ϵ value would result in more exploring and making random decisions.

The Q-value of the agent's current state would be updated by first taking a weight $(1 - \alpha)$ of the old Q-value, then adding the learned value. The learned value is a combination of the reward for taking the current action in the current state, and the discounted maximum reward from the next state would be in, once the current action has been taken. Thus, the agent is learning the proper action to take in the current state by looking at the reward for the current $(state, action)$ combination, and the maximum rewards for the next state. This would eventually cause the WMS to consider the path with the best rewards strung together. The Q-value of a $(state, action)$ combination is the sum of the instant reward and the discounted future reward of the resulting state. The way we store the Q-values for each $(state, action)$ combination would be through the Q-table.

The Q-table is a matrix where we have a Row for every state and a Column for every action. It's first initialised to zero, and then values are updated during training to values that optimise the agent's travel through the environment for maximum rewards.

For training the agent, first, the Q-table has been initialised to a $500x6$ matrix of zeroes.

The training algorithm would update this Q-table as the agent explores the environment over thousands of episodes. In the first part of *while not done*, it is decided whether to pick a random action or to exploit the already computed Q-values. This is done using the ϵ value and comparing it to the $random.uniform$ (0, 1) function, which returns an arbitrary number between 0 and 1. The chosen action would be executed in the environment to obtain the *next state* and the *reward* from performing the action. Thereafter, the maximum Q-value has been calculated for the actions corresponding to the *next state*, and with that, could update the Q-value to the *new q value*.

5.4 DQN solution formulation for FPSO main deck maintenance

The novelty of this work is that a deep Q-reinforcement learning has been employed in this work for the problem formulation of FPSO main deck maintenance.

The DQN problem statement has been defined as to carry out activities that have minimal site constraints, so as to get higher weighted sum of the completion times at short time as possible, which leads to higher resource utilisation. The goal is to achieve the best trade-off between the turnaround time for the activities and liquidating the risks to the asset's performance, based on completion of activities in the FPSO work management system (WMS).

5.4.1 Constraints

Similar to most literature, this work considers that the site constraints on main deck involves shadow areas and locations with accessibility issues, restricted access spaces that require additional risk assessment prior accessing, overside sections of the deck that need boat cover and additional risk assessment prior accessing, locations having presence of continuous water and need special equipment for carrying out maintenance, locations with accessibility issues during normal operations and need to be dealt during a pre-specified period such as plant shut down as an opportunistic work. However, differing from the existing literature, this work considers the new important factor, the impact of time required to carry out offshore maintenance activities, to achieve the optimal personnel resource utilisations.

5.4.2 Decision variables

The decision variables considered in this work are the design features, operating conditions, deteriorations experienced and the consequences of not doing the maintenance activities, as detailed in Section 3.3.5 of Chapter 3.

5.4.3 Objective functions

The main objective of this work to carry out activities that have minimal site constraints, so as to get higher weighted sum of the completion times at short time as possible, which leads to higher resource utilisation. The goal is to achieve the best trade-off between the turnaround time for the activities and liquidating the risks to the asset's performance, based on completion of activities in the FPSO work management system (WMS).

5.4.4 Implementation of multi-objective problem formulation and optimisation model

The Figure 5.1 provides an overview of formulation of multi-objective optimisation with Deep Q-Reinforcement Learning (DQN), for FPSO main deck maintenance.

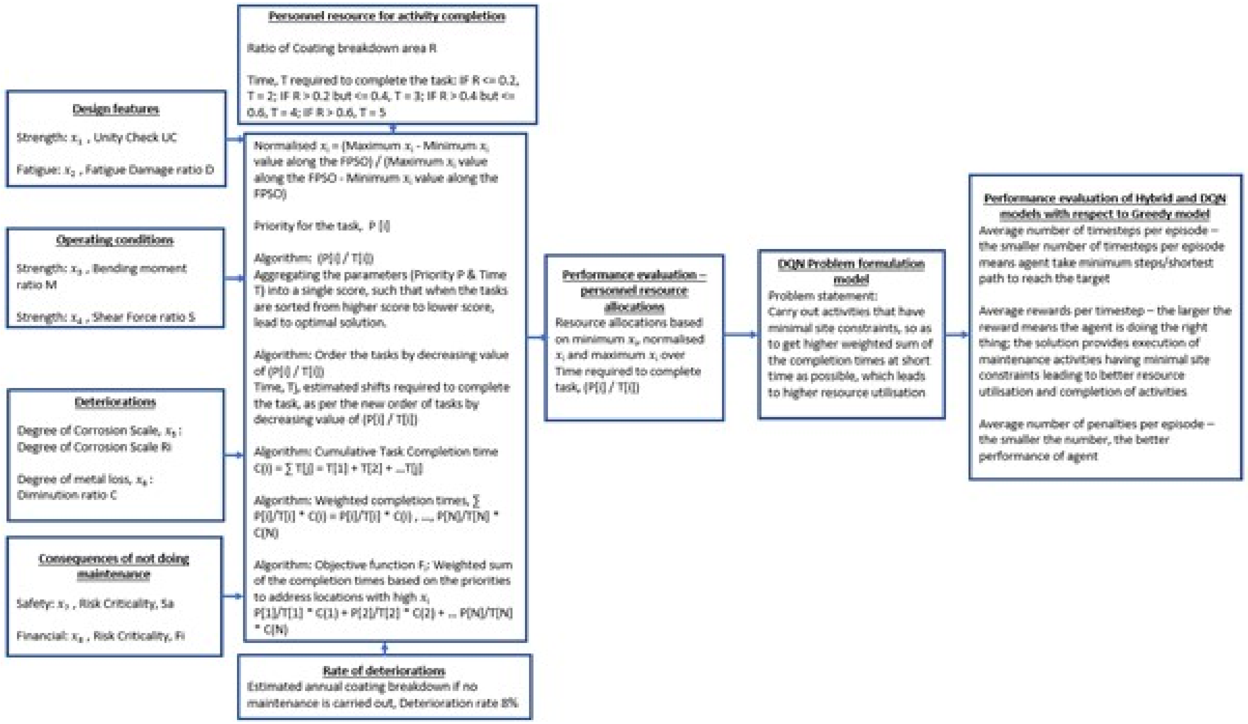

Figure 5.1: Multi-objective Optimisation with Deep Q-Reinforcement Learning (DQN), for FPSO main deck maintenance

The DQN problem formulation model for FPSO main deck maintenance has been indicated in Figure 5.2 below.

The DQN Solution Formulation for Maintenance Activities involves:

5.4.4.1 State Space

FPSO Main Deck has been split into a 5 X 5 grid, which will give 25 possible locations on the Main Deck. For these grid locations the priority of the objective function over the time required to complete task ($P[i] / T[i]$) has been assigned from 0.1 with increments of 0.1 up to the maximum value of 2.5 (that was found for the Safety and Financial Risks, from the Greedy Algorithm). Four locations were assigned on the FPSO Main Deck, Aft Port, Fwd Port, Aft Stbd and Fwd Stbd, where the resources for carrying out the maintenance

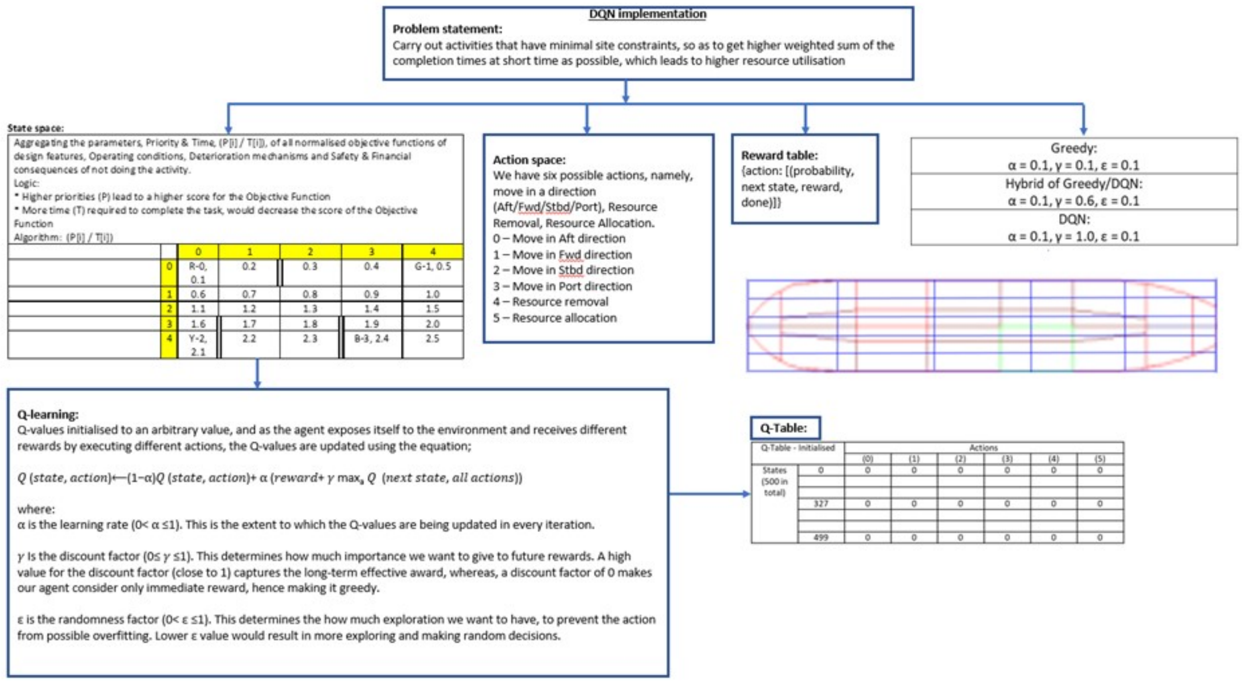

Figure 5.2: DQN Problem formulation model for FPSO main deck maintenance

activity could be allocated and removed. This forms the (row, column) co-ordinates of (0,0), (0,4), (4,0), (4,3). Also, a state of the resource has been accounted for carrying out the maintenance activity while moving along the grids, between resource removal and resource allocation periods. Thus, while considering all combinations of resource locations and the locations where resources could be allocated and removed, the total number of states for our Work Management System (WMS) Environment will be 4 destination locations of co-ordinates (0,0), (0,4), (4,0), (4,3), and Five (4 + 1) resource locations. Therefore, our WMS has a total possible States of 5 x 5 x 5 x 4 =500 states. WMS cannot perform certain actions in certain states due to site constraints (denoted by double bold lines).

5.4.4.2 Action Space

The agent comes across one of the 500 states and takes an action. The Action is to move in a direction along the FPSO, or to decide to remove resource and allocate resource at a location. The agent has six possible actions, namely, move in a direction (Aft/Fwd/Stbd/Port), Resource Removal and Resource Allocation.

0 – Move in Aft direction

1 – Move in Fwd direction

2 – Move in Stbd direction

3 – Move in Port direction

4 – Resource removal

5 – Resource allocation

5.4.4.3 Rewards

Points considered while deciding the rewards and penalties were that the agent should receive a high positive reward for a successful resource allocation, as this action was highly desired. By trial and error, a +20 points reward was assigned for a successful resource allocation. Agent should be penalised if it tries to allocate or allocate resources at wrong locations. By trial and error, a −10 points penalty was assigned for an illegal resource allocation or removal. Agent should receive a slight negative reward for every site constraint hit and for not moving anywhere, and for not making it to the assigned location for resource removal/ allocation after every time-step. By trial and error, a -1-point penalty was assigned for these actions.

The Reward table has been considered to be a matrix that has the number of states as rows and number of actions as columns, which would be a States X Actions matrix. Since every state is in this matrix, we could see the default reward values assigned to our WMS's state, as

$\{action\ :\ [\,(probability,\ next\ state,\ reward,\ done)\,]\}$

The game environments available in Open AI Gym library have been used for providing the resource allocation environment, to plug in the Python Code algorithm and to test the agent.

Table 5.2: Hyperparameters for the Greedy, Hybrid of Greedy/DQN and DQN models

Greedy: $\alpha = 0.1, \gamma = 0.1, \varepsilon = 0.1$
Hybrid of Greedy/DQN: $\alpha = 0.1, \gamma = 0.6, \varepsilon = 0.1$
DQN: $\alpha = 0.1, \gamma = 1.0, \varepsilon = 0.1$

5.4.5 Benchmarking and performance evaluation

After enough random exploration of actions, the Q-values tend to converge serving our agent as an action-value function, which it could exploit to pick the most optimal action from a given state.

The Hyperparameters for the DQN model includes,α, γ ϵ, whereby, α is the learning rate ($0 < \alpha \leq 1$). This is the extent to which the Q-values are being updated in every iteration.

γ is the discount factor ($0 \leq \gamma \leq 1$). This determines how much importance we want to give to future rewards. A high value for the discount factor, nearer to 1, captures the long-term effective award, whereas a discount factor nearer to zero makes the agent consider only immediate reward, hence making it greedy.

ϵ the randomness factor ($0 < \epsilon \leq 1$) determines how much exploration we want to have, to prevent the action from possible overfitting. Lower ϵ value would result in more exploring and making random decisions.

Considering the afore-mentioned points, the hyperparameters α, γ ϵ have been varied between $0.1,\ 0.6\ and\ 1$ as indicated in Table 5.2, to generate the Greedy, Hybrid of Greedy/DQN and DQN models.

The agent for Greedy, Hybrid of Greedy/DQN and DQN models were evaluated on the following features:

Average number of timesteps per episode – the smaller number of timesteps per episode means agent take minimum steps/shortest path to reach the target.

Average rewards per timestep – the larger the reward means the agent is doing the right thing. In this work, as both timesteps and penalties are negatively rewarded, a higher average reward would mean that the agent reaches the target as fast as possible with the least penalties. i.e. the solution provides execution of maintenance activities having minimal site constraints leading to better resource utilisation, and completion of activities.

Average number of penalties per episode – the smaller the number ideally be zero or very close to zero, the better performance of agent.

The evaluation of Greedy, Hybrid of Greedy & DQN and DQN models for up to $25,000$ training episodes have been carried out for the following 3 states:

• State 1, where current location state addressed by WMS is illustrated to be at a state of highest P/T value of 2.5, and the maintenance activities are ongoing at location 3 (B), which has the next highest P/T value of 2.4, and the intent is to carry out activities at location 2 (Y), which has the next highest P/T value of 2.1, from our defined objective functions.

• State 2, where current location state addressed by WMS is illustrated to be at a state of P/T value of 2.1, and the maintenance activities are ongoing at location 2 (Y), and the intent is to carry out activities at location 1 (G), which has the P/T value of 0.5, from our defined objective functions.

• State 3, where current location state addressed by WMS is illustrated to be at a state of P/T value of 0.5, and the maintenance activities are ongoing at location 1 (G), and the intent is to carry out activities at location 0 (R), which has the lowest P/T value of 0.1, from our defined objective functions.

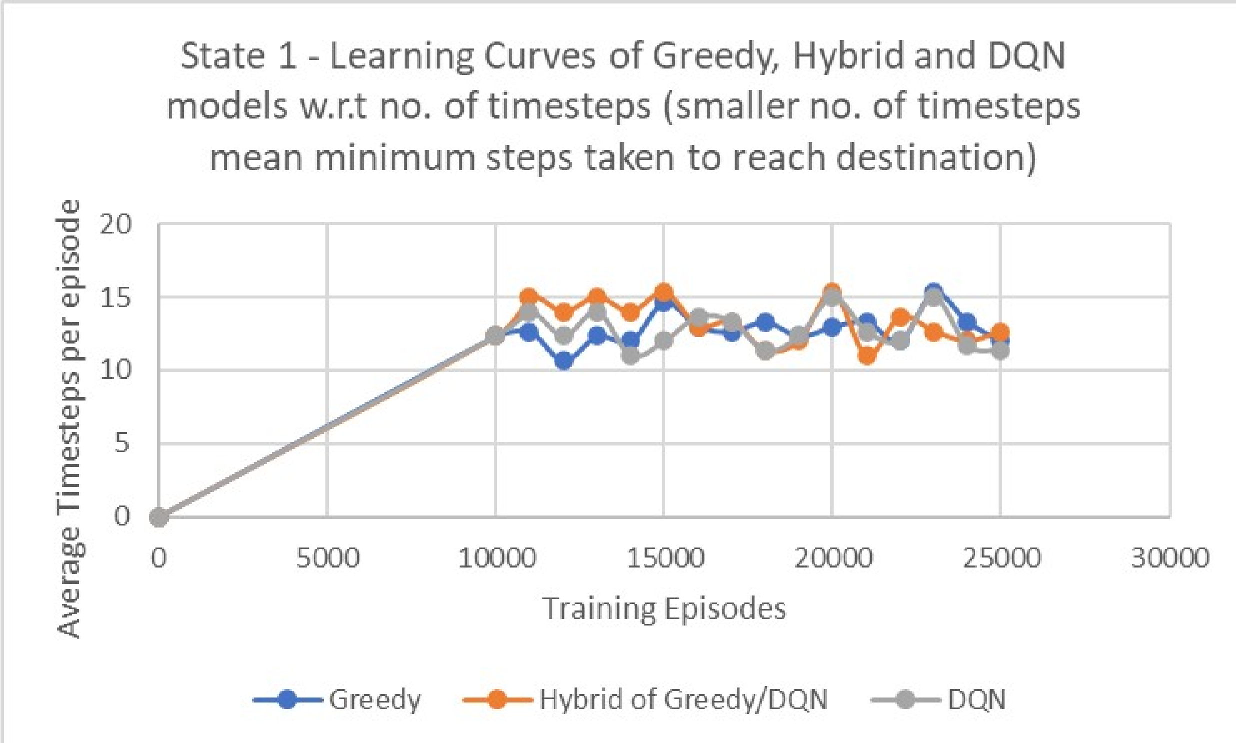

Figure 5.3: Learning curves of Greedy, Hybrid and DQN models with respect to the number of timesteps, for the state 1

5.4.6 Benchmarking and evaluation of agent's performance in State 1

In this simulation in Figure 5.3, the learning curves of Greedy, Hybrid and DQN models with respect to the number of timesteps taken to reach destination have been shown for the state 1, where current location state addressed by WMS is illustrated to be at a state of highest P/T value of 2.5, and the maintenance activities are ongoing at location 3 (B), which has the next highest P/T value of 2.4, and the intent is to carry out activities at location 2 (Y), which has the next highest P/T value of 2.1, from our defined objective functions.

Figure 5.3 presents the learning curves of Greedy, Hybrid and DQN models with respect to the number of timesteps for the state 1. The smaller number of timesteps per episode indicates minimum time steps taken to reach the destination. It has been noted that the

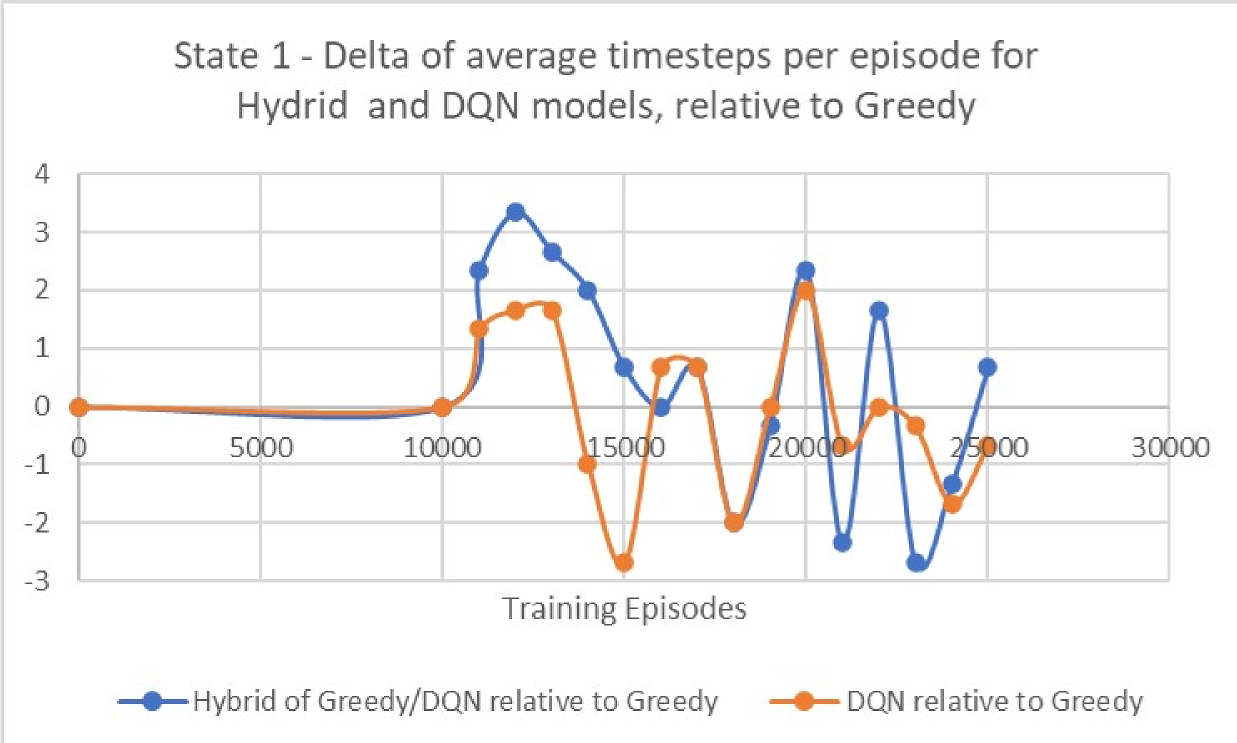

Figure 5.4: Variation of average timesteps per episode for the Hybrid and DQN models relative to Greedy model, for the state 1

Hybrid model with hyperparameters of $\alpha = 0.1,\ \gamma = 0.6,\ \epsilon = 0.1$ and the DQN model with hyperparameters of $\alpha = 0.1,\ \gamma = 1.0,\ \epsilon = 0.1$ achieve better results when compared with the Greedy model with hyperparameters of $\alpha = 0.1,\ \gamma = 0.1,\ \epsilon = 0.1$, as the training episode increases.

In the simulation in Figure 5.4, the variation of average timesteps per episode for the Hybrid and DQN models with respect to Greedy model has been shown for the state 1.

Figure 5.4 presents the variation of average timesteps per episode for the Hybrid and DQN models relative to Greedy model, for the state 1. It has been noted that the DQN model with hyperparameters of $\alpha = 0.1,\ \gamma = 1.0,\ \epsilon = 0.1$ achieve better results when compared with the Hybrid model with hyperparameters of $\alpha = 0.1,\ \gamma = 0.6,\ \epsilon = 0.1$ and the Greedy model with hyperparameters of $\alpha = 0.1,\ \gamma = 0.1,\ \epsilon = 0.1$, as the training episode

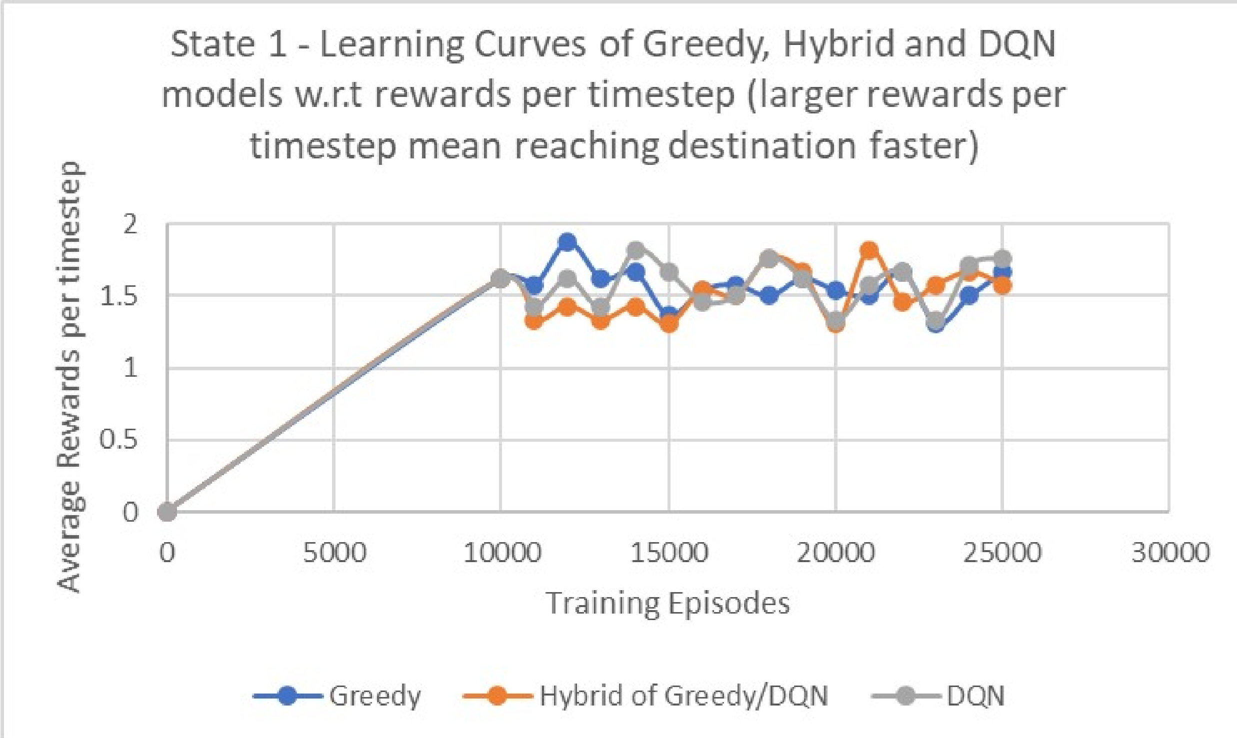

Figure 5.5: Learning curves of Greedy, Hybrid and DQN models with respect to the rewards per timestep, for the state 1

increases.

In the simulation in Figure 5.5, the learning curves of Greedy, Hybrid and DQN models with respect to the rewards per timestep have been shown for the state 1.

Figure 5.5 presents the learning curves of Greedy, Hybrid and DQN models with respect to the rewards per timestep, for the state 1. The larger rewards per timestep indicates reaching destination faster. It has been noted that the Hybrid model with hyperparameters of$\alpha = 0.1,\ \gamma = 0.6,\ \epsilon = 0.1$ and the DQN model with hyperparameters of $\alpha = 0.1,\ \gamma = 1.0,\ \epsilon = 0.1$ achieve better results when compared with the Greedy model with hyperparameters of $\alpha = 0.1,\ \gamma = 0.1,\ \epsilon = 0.1$, as the training episode increases.

In the simulation in Figure 5.6, the variation of average rewards per timestep for the

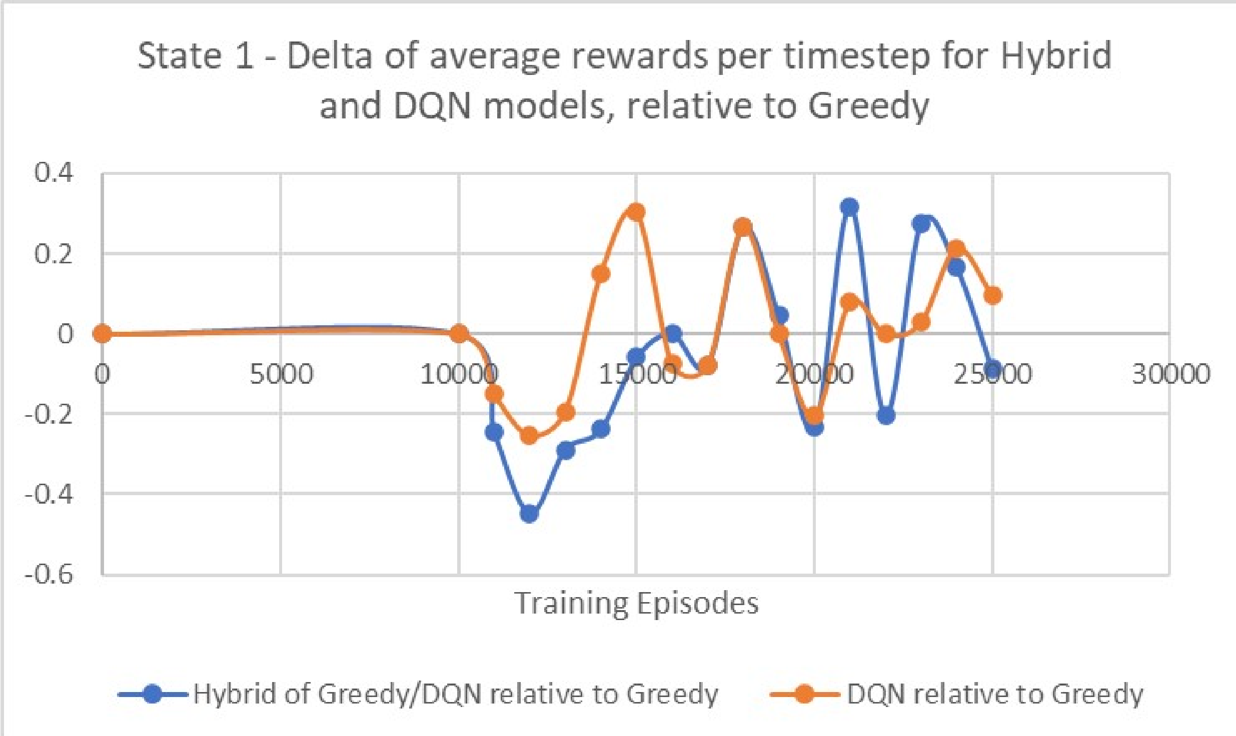

Figure 5.6: Variation of average rewards per timestep for the Hybrid and DQN models relative to Greedy model, for the state 1

Hybrid and DQN models with respect to Greedy model has been shown for the state 1.

Figure 5.6 presents the variation of average rewards per timestep for the Hybrid and DQN models relative to Greedy model, for the state 1. It has been noted that the DQN model with hyperparameters of $\alpha = 0.1,\ \gamma = 1.0,\ \epsilon = 0.1$ achieve better results when compared with the Hybrid model with hyperparameters of $\alpha = 0.1,\ \gamma = 0.6,\ \epsilon = 0.1$ and the Greedy model with hyperparameters of $\alpha = 0.1,\ \gamma = 0.1,\ \epsilon = 0.1$, as the training episode increases.

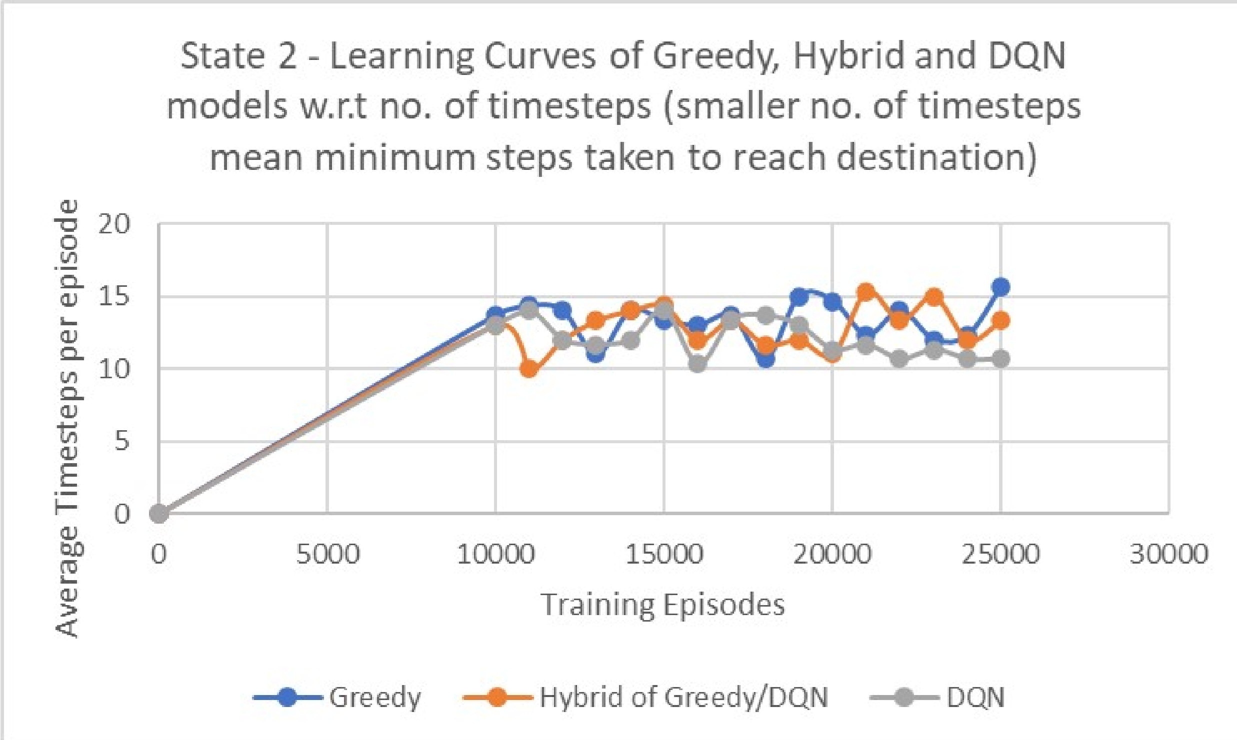

Figure 5.7: Learning curves of Greedy, Hybrid and DQN models with respect to the number of timesteps, for the state 2

5.4.7 Benchmarking and evaluation of agent's performance in State 2

In this simulation in Figure 5.7, the learning curves of Greedy, Hybrid and DQN models with respect to the number of timesteps taken to reach destination have been shown for the state 2, where current location state addressed by WMS is illustrated to be at a state of P/T value of 2.1, and the maintenance activities are ongoing at location 2 (Y), and the intent is to carry out activities at location 1 (G), which has the P/T value of 0.5, from our defined objective functions.

Figure 5.7 presents the learning curves of Greedy, Hybrid and DQN models with respect to the number of timesteps for the state 2. The smaller number of timesteps per episode indicates minimum time steps taken to reach the destination. It has been noted that the

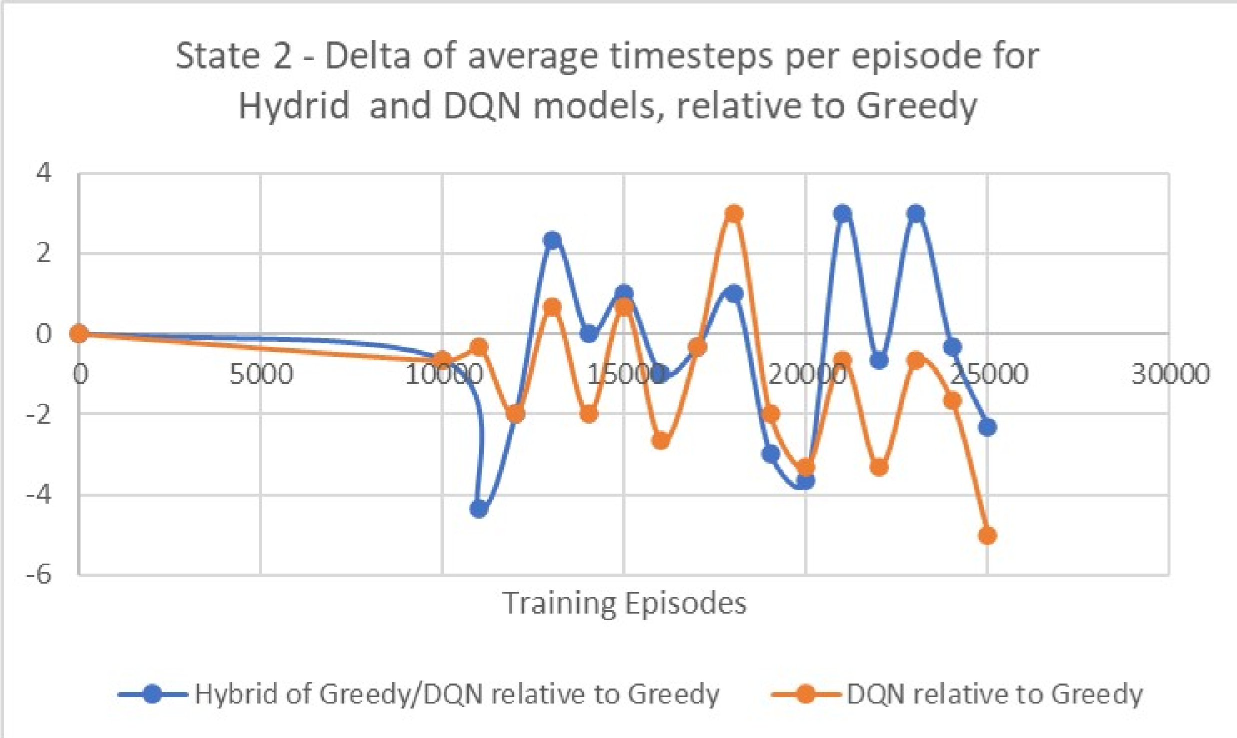

Figure 5.8: Variation of average timesteps per episode for the Hybrid and DQN models relative to Greedy model, for the state 2

Hybrid model with hyperparameters of $\alpha = 0.1,\ \gamma = 0.6,\ \epsilon = 0.1$ and the DQN model with hyperparameters of $\alpha = 0.1,\ \gamma = 1.0,\ \epsilon = 0.1$ achieve better results when compared with the Greedy model with hyperparameters of $\alpha = 0.1,\ \gamma = 0.1,\ \epsilon = 0.1$, as the training episode increases.

In the simulation in Figure 5.8, the variation of average timesteps per episode for the Hybrid and DQN models with respect to Greedy model has been shown for the state 2.

Figure 5.8 presents the variation of average timesteps per episode for the Hybrid and DQN models relative to Greedy model, for the state 2. It has been noted that the DQN model with hyperparameters of $\alpha = 0.1,\ \gamma = 1.0,\ \epsilon = 0.1$ achieve better results when compared with the Hybrid model with hyperparameters of $\alpha = 0.1,\ \gamma = 0.6,\ \epsilon = 0.1$ and the Greedy model with hyperparameters of $\alpha = 0.1,\ \gamma = 0.1,\ \epsilon = 0.1$, as the training episode

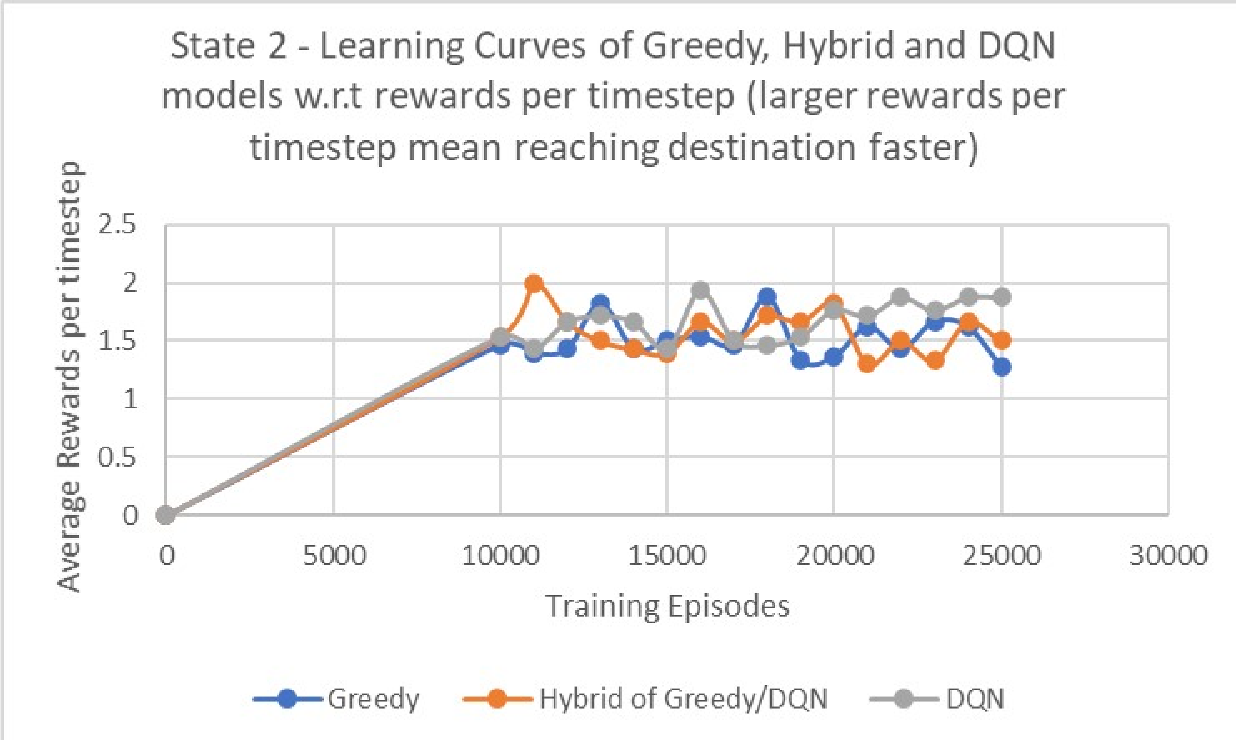

Figure 5.9: Learning curves of Greedy, Hybrid and DQN models with respect to the rewards per timestep, for the state 2

increases.

In the simulation in Figure 5.9, the learning curves of Greedy, Hybrid and DQN models with respect to the rewards per timestep have been shown for the state 2.

Figure 5.9 presents the learning curves of Greedy, Hybrid and DQN models with respect to the rewards per timestep, for the state 2. The larger rewards per timestep indicates reaching destination faster. It has been noted that the Hybrid model with hyperparameters of $\alpha = 0.1,\ \gamma = 0.6,\ \epsilon = 0.1$ and the DQN model with hyperparameters of $\alpha = 0.1,\ \gamma = 1.0,\ \epsilon = 0.1$ achieve better results when compared with the Greedy model with hyperparameters of $\alpha = 0.1,\ \gamma = 0.1,\ \epsilon = 0.1$, as the training episode increases.

In the simulation in Figure 5.10, the variation of average rewards per timestep for the

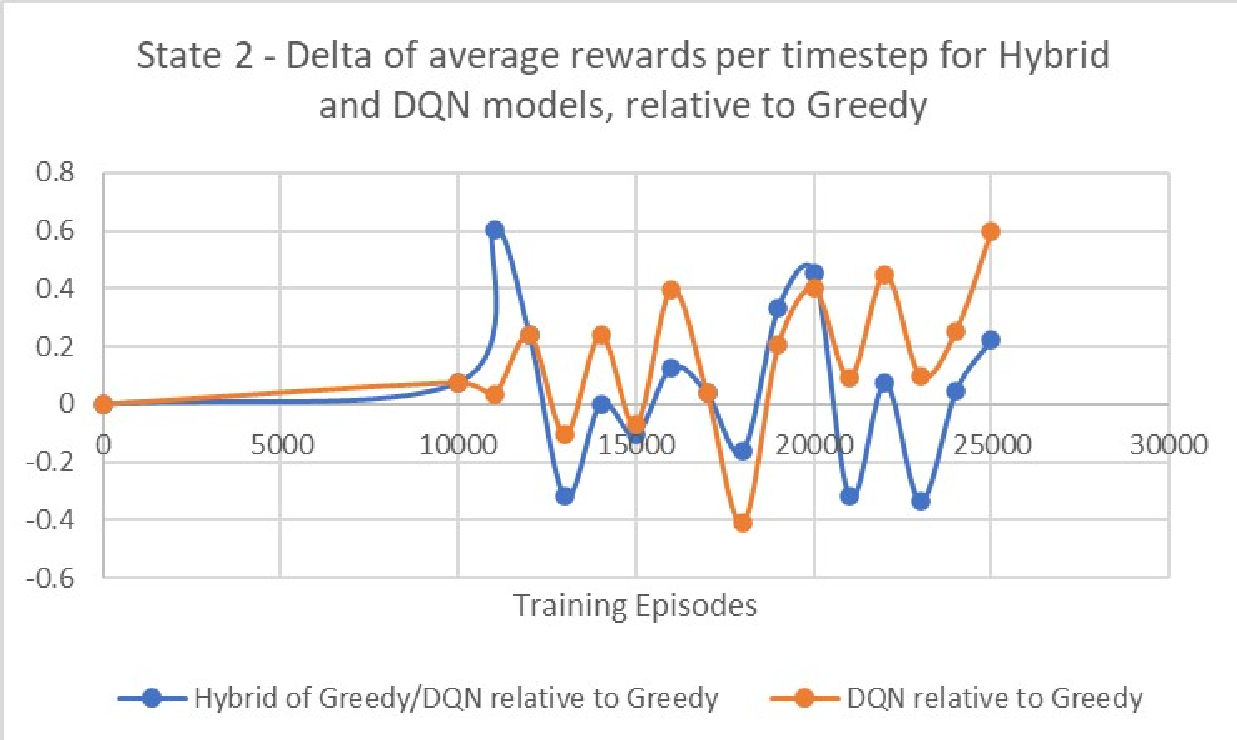

Figure 5.10: Variation of average rewards per timestep for the Hybrid and DQN models relative to Greedy model, for the state 2

Hybrid and DQN models with respect to Greedy model has been shown for the state 2.

Figure 5.10 presents the variation of average rewards per timestep for the Hybrid and DQN models relative to Greedy model, for the state 2. It has been noted that the DQN model with hyperparameters of $\alpha = 0.1,\ \gamma = 1.0,\ \epsilon = 0.1$ achieve better results when compared with the Hybrid model with hyperparameters of $\alpha = 0.1,\ \gamma = 0.6,\ \epsilon = 0.1$ and the Greedy model with hyperparameters of $\alpha = 0.1,\ \gamma = 0.1,\ \epsilon = 0.1$, as the training episode increases.

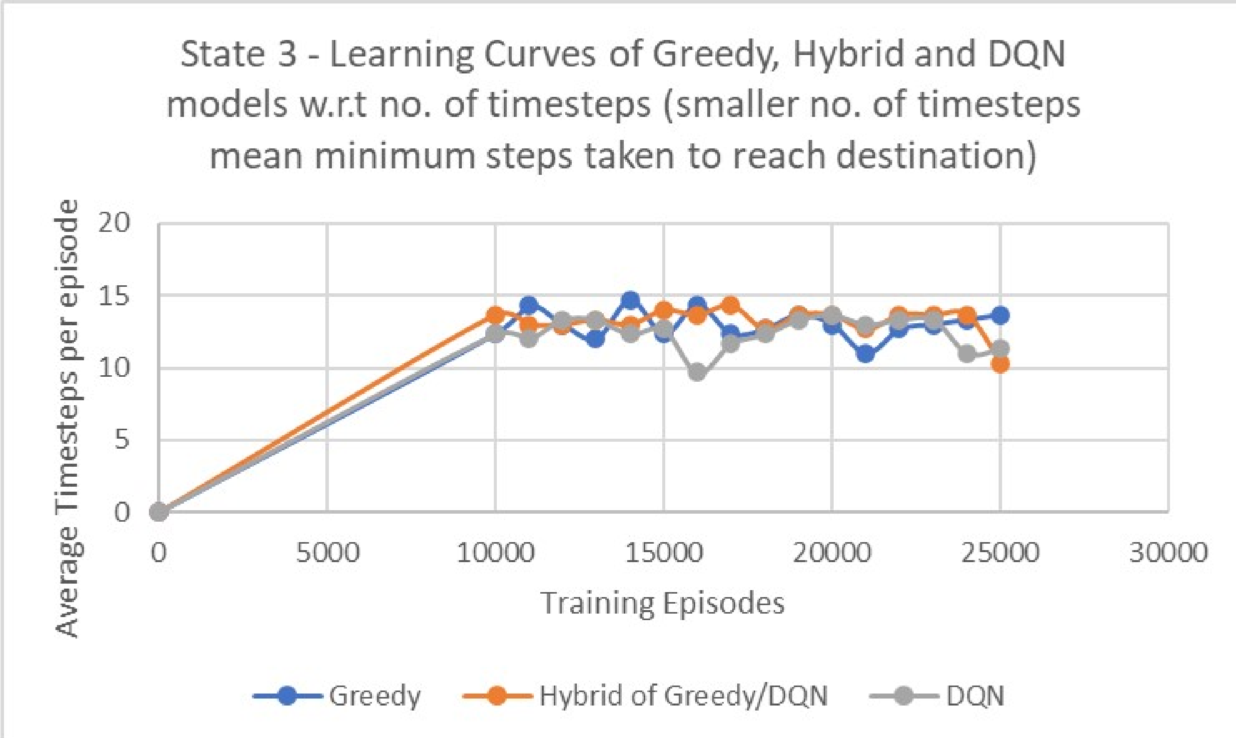

Figure 5.11: Learning curves of Greedy, Hybrid and DQN models with respect to the number of timesteps, for the state 3

5.4.8 Benchmarking and evaluation of agent's performance in State 3

In this simulation in Figure 5.11, the learning curves of Greedy, Hybrid and DQN models with respect to the number of timesteps taken to reach destination have been shown for the state 3, where current location state addressed by WMS is illustrated to be at a state of P/T value of 0.5, and the maintenance activities are ongoing at location 1 (G), and the intent is to carry out activities at location 0 (R), which has the lowest P/T value of 0.1, from our defined objective functions.

Figure 5.11 presents the learning curves of Greedy, Hybrid and DQN models with respect to the number of timesteps for the state 3. The smaller number of timesteps per episode indicates minimum time steps taken to reach the destination. It has been noted that the

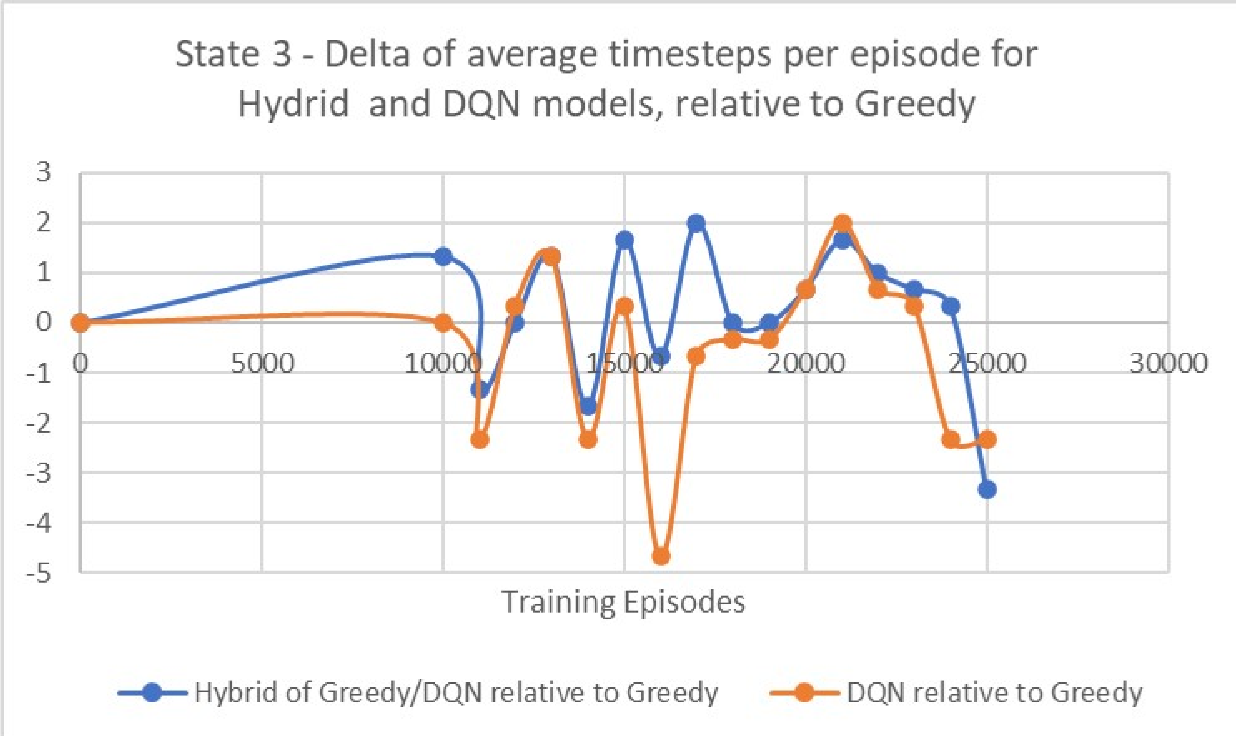

Figure 5.12: Variation of average timesteps per episode for the Hybrid and DQN models relative to Greedy model, for the state 3

Hybrid model with hyperparameters of $\alpha = 0.1,\ \gamma = 0.6,\ \epsilon = 0.1$ and the DQN model with hyperparameters of $\alpha = 0.1,\ \gamma = 1.0,\ \epsilon = 0.1$ achieve better results when compared with the Greedy model with hyperparameters of $\alpha = 0.1,\ \gamma = 0.1,\ \epsilon = 0.1$, as the training episode increases.

In the simulation in Figure 5.12, the variation of average timesteps per episode for the Hybrid and DQN models with respect to Greedy model has been shown for the state 3.

Figure 5.12 presents the variation of average timesteps per episode for the Hybrid and DQN models relative to Greedy model, for the state 3. It has been noted that the DQN model with hyperparameters of $\alpha = 0.1,\ \gamma = 1.0,\ \epsilon = 0.1$ achieve better results when compared with the Hybrid model with hyperparameters of $\alpha = 0.1,\ \gamma = 0.6,\ \epsilon = 0.1$ and the Greedy model with hyperparameters of $\alpha = 0.1,\ \gamma = 0.1,\ \epsilon = 0.1$, as the training episode

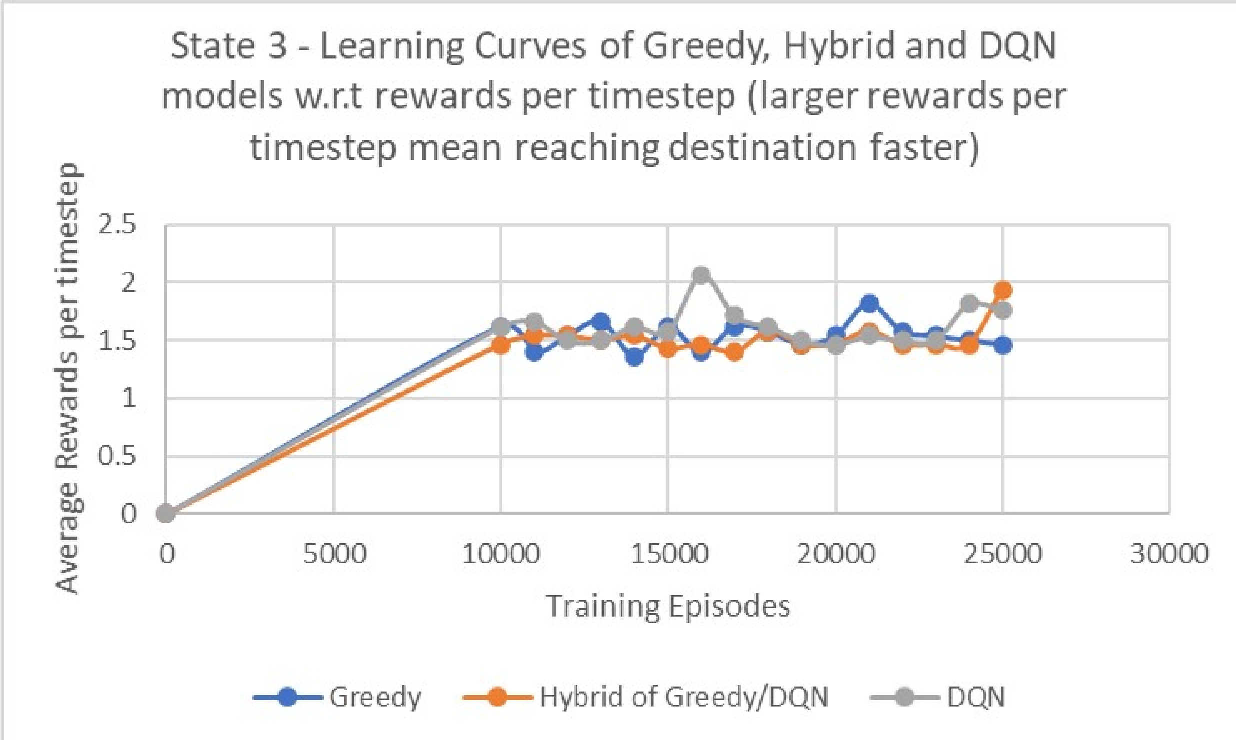

Figure 5.13: Learning curves of Greedy, Hybrid and DQN models with respect to the rewards per timestep, for the state 3

increases.

In the simulation in Figure 5.13, the learning curves of Greedy, Hybrid and DQN models with respect to the rewards per timestep have been shown for the state 3.

Figure 5.13 presents the learning curves of Greedy, Hybrid and DQN models with respect to the rewards per timestep, for the state 3. The larger rewards per timestep indicates reaching destination faster. It has been noted that the Hybrid model with hyperparameters of $\alpha = 0.1$, $\gamma = 0.6$, $\epsilon = 0.1$ and the DQN model with hyperparameters of $\alpha = 0.1$, $\gamma = 1.0$, $\epsilon = 0.1$ achieve better results when compared with the Greedy model with hyperparameters of $\alpha = 0.1$, $\gamma = 0.1$, $\epsilon = 0.1$, as the training episode increases.

In the simulation in Figure 5.14, the variation of average rewards per timestep for the

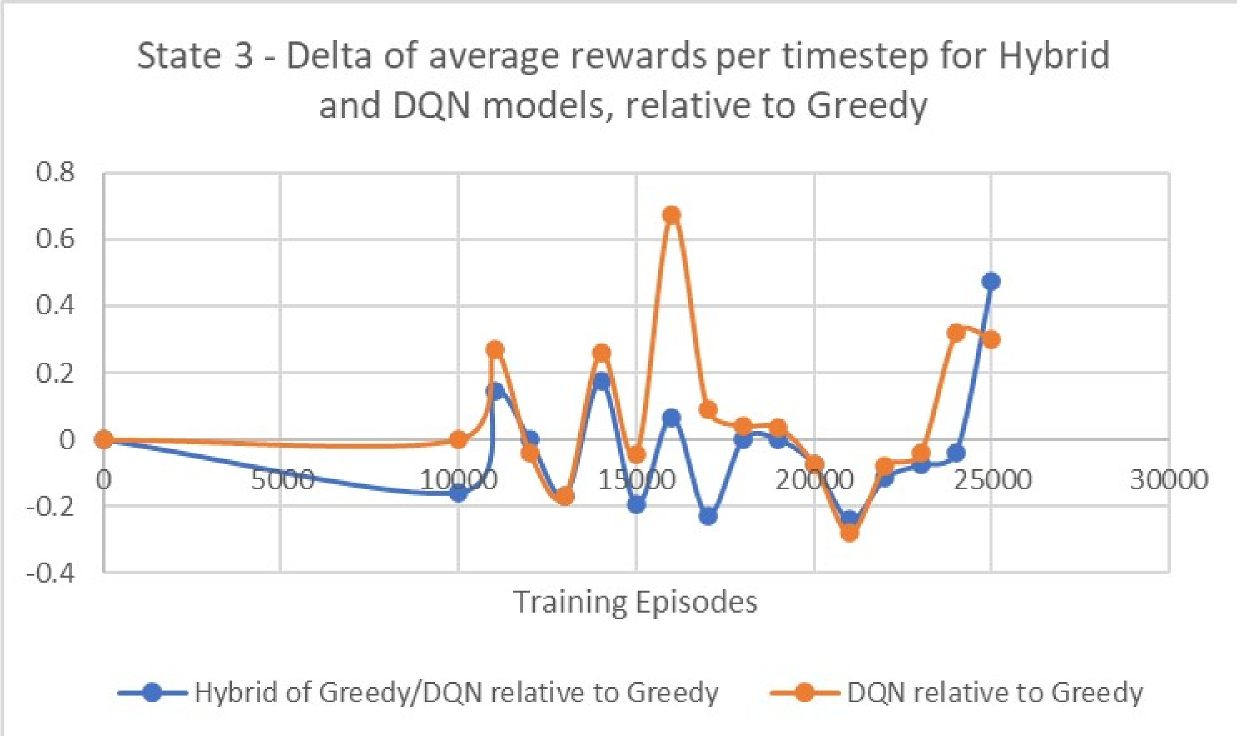

Figure 5.14: Variation of average rewards per timestep for the Hybrid and DQN models relative to Greedy model, for the state 3

Hybrid and DQN models with respect to Greedy model has been shown for the state 3.

Figure 5.14 presents the variation of average rewards per timestep for the Hybrid and DQN models relative to Greedy model, for the state 3. It has been noted that the DQN model with hyperparameters of $\alpha = 0.1,\ \gamma = 1.0,\ \epsilon = 0.1$ achieve better results when compared with the Hybrid model with hyperparameters of $\alpha = 0.1,\ \gamma = 0.6,\ \epsilon = 0.1$ and the Greedy model with hyperparameters of $\alpha = 0.1,\ \gamma = 0.1,\ \epsilon = 0.1$, as the training episode increases.

5.5 Conclusion

A novel work management framework has been proposed in this Chapter that comprises of Deep Q-Reinforcement Learning (DQN) algorithm implementation, to enable carrying out activities that have minimal site constraints, considering the design features, operating conditions, deteriorations, consequences of not doing the activities and time required to complete the activities, to get higher weighted sum of the completion times at short time as possible, whereby achieving higher resource utilisations. Also, by using the optimal path liquidates the risks to the asset's performance and reach the next state.

The goal was to achieve the best trade-off between the turnaround time for the activities and liquidating the risks to the asset's performance, based on completion of activities in the FPSO work management system.

The greedy algorithm benchmarks the performances of DQN model and a hybrid model comprising of greedy and DQN parameters.

It has been noted that overall, the Hybrid model with hyperparameters of $\alpha = 0.1,\ \gamma = 0.6,\ \epsilon = 0.1$ and the DQN model with hyperparameters of $\alpha = 0.1,\ \gamma = 1.0,\ \epsilon = 0.1$ achieve better results when compared with the Greedy model with hyperparameters of$\alpha = 0.1,\ \gamma = 0.1,\ \epsilon = 0.1$, as the training episode increases, towards task completion time and liquidating the risks to the asset's performance.

Chapter6

Conclusions and Recommendations for further work

6.1 Introduction

The overall aim of this chapter is to summarise the conclusions of this work and propose a further research direction incorporating DQN algorithm to position the succeeding research that could in turn lead to the development of a comprehensive maintenance management tool, which would be consistent, unaffected by human factors and incorporates the integration of the risks and site constraints on the overall offshore operations.

The aim of this research work was to develop an effective maintenance management approach for offshore floating systems, governed by overall risks and site constraints and thereby enhancing the effectiveness and confidence of the framework. Within the frame of the overall aim, the main objectives of this thesis have been specified to:

Research Objective 1: Investigate the maintenance frameworks and offshore operational conditions, addressing the significance of overall risks and site constraints in better decision making for maintenance planning, so as to develop an algorithm for multi-objective decision making for maintenance planning.

Research Objective 2: Investigate how the logic behind qualitative risk assessment on prioritisation of activities on the asset and managing the risks could be incorporated into multi-objective decision making for maintenance planning.

Research Objective 3: Investigate how to employ artificial intelligence to enhance the effectiveness of maintenance frameworks for offshore floating systems, by incorporating overall risks, operational priorities, and site constraints.

The above-mentioned objectives 1, 2 and 3 have been satisfied through the work presented in Chapters 2 to 5 of this thesis and the following main conclusions were obtained.

6.2 Conclusions

• From the investigation work carried out in Chapter 2, it could be concluded as follows:

It has been noted that the maintenance performance indicators widely considered relates to the asset availability, reliability, and safety compliance, whereas the site constraints and impact of time required to carry out activities are not regarded as a performance indicator in the existing literature, which is a major limitation of the existing frameworks, as the availability of bed space offshore for any activity is the prime performance indicator for any maintenance execution. It has been noted that probabilistic assessment models, Bayesian Networks and Multi-objective optimisation techniques have been widely used in the literature for optimisation of maintenance activities. There exists scope for further research work that would incorporate site constraints and impact of time required to carry out activities including the Offshore resource availability into the maintenance plan and its impact on asset condition due to the maintenance execution, in order to achieve the optimal maintenance strategy.

The constraints of offshore personnel availability for the maintenance activity due to maximum allowable bed space is a factor not considered in any of the frameworks identified in the literature review. This is a major limitation of the existing state-of-the art maintenance frameworks. There are still research gaps in frameworks, towards incorporating the overall risks, practical site constraints encountered mainly with regards to the availability of bed space onboard for the personnel, impact of time required to carry out activities and its impact on other activities due to this maintenance.

Also, no dynamic and autonomous resource allocations for maintenance activities take place in the offshore maintenance planning systems that allows each maintenance item to independently adjust its resource allocation based on the time required to complete the activity, to improve the resource utilisation. In that respect, the maintenance models have to incorporate the site operational constraints related to personnel resources, environmental factors, and its impact on the overall activities in the maintenance planning system.

It could be concluded that there exists scope for further research work that addresses the above-mentioned gaps by examining machine learning and deep Q- reinforcement learning network based artificial intelligence approach, considering the design features, actual condition of the component, site constraints, deterioration factors, consequences of not doing the activities, time required to complete the activities and investigating the impact on key maintenance performance indicators regarding resource allocations and resource utilisations.

- From investigation work carried out in Chapter 3, it could be concluded as follows:

The main objective of this Chapter was to formulate a maintenance plan optimisation problem that maximise the maintenance personnel resource utilisation and enable FPSO condition enhancement, considering the priorities with respect to design features, operating conditions, deteriorations, and the consequences of not doing the maintenance, taking into consideration the personnel resource time required for activity completion. This has been achieved by developing a FPSO main deck maintenance system model incorporating design features, operating conditions, deteriorations, consequences of not doing the maintenance and the personnel resource estimated to complete the activity. To enable the problem formulation, a novel approach has been utilised such that the decision variables for each location on the FPSO have been normalised between the maximum and minimum values along the length of FPSO in order to bring the variables related to the functionality in proportion with that at other locations along the FPSO, and also to enable scaling all of the decision variables and whereby their respective objective functions to the same magnitude.

Also, a novel approach has been employed for the multi-objective optimisation of FPSO main deck maintenance activities, such that to find the Pareto-optimal solution, an overall objective function has been developed as a linear combination of the multiple objective functions corresponding to maintenance priorities with respect to normalised Stress Unity Check, Fatigue Damage Ratio, Bending Moment Ratio, Shear Force Ratio, Degree of Corrosion Scale, Degree of Metal Loss, Safety Risks in the event of not doing maintenance and Financial Risks in the event of not doing maintenance respectively, taking into consideration the personnel resource time required for activity completion. Depending on the priority of the objective function when compared to other objective functions, a relative weight has been associated to the prioritised objective function, using the weighted sum approach. Also, the formulation enables maximisation and minimisation of the objective functions and provides flexibility to direct the focus of the overall objective function towards any one or more of the objective functions by adjusting their respective weight according to the maintenance strategy followed.

- From investigation work carried out in Chapter 4, it could be concluded as follows:

A novel greedy algorithm has been proposed in this Chapter that incorporate the impact of time required to complete the activities on the optimisation objectives of FPSO design features, operating conditions, deteriorations, consequences of not doing the maintenance and the personnel resource availability for activity completion. Also, the benchmarking of the algorithm has been carried out by comparing the parameters, with and without considering the time required to complete the task, which reflects influence of the time required to carry out the activity, on the prioritisation of activities.

The evaluation of the model has been carried out by comparing the priorities for each scenario based on 3 different loading conditions of the FPSO – Light load condition, Medium load condition and Full Load condition. The performance of the greedy algorithm has been evaluated in terms of the personnel resource allocation and resource utilisation. To evaluate the satisfaction of resource allocation, the weighted sum of the task completion times based on the priorities have been considered. To evaluate the satisfaction of resource utilisation, it has been considered that the higher weighted sum of the completion times at as short time as possible, leads to higher resource utilisations.

The changes in priorities and productivity, if no maintenance is carried out in 1 years' time and 2 years' time has been simulated and compared with the present planned resource allocations and resource utilisations, taking into account the ($P[i] \,/\, T[i]$) change based on change in T only, as a function of coating break down, and ignoring the effect of coating breakdown on other decision variables.

- From investigation work carried out in Chapter 5, it could be concluded as follows:

A novel work management framework has been proposed in this Chapter that comprises of Deep Q-Reinforcement Learning (DQN) algorithm implementation, to enable carrying out activities that have minimal site constraints, considering the design features, operating conditions, deteriorations, consequences of not doing the activities and time required to complete the activities, to get higher weighted sum of the completion times at short time as possible, whereby achieving higher resource utilisations. Also, by using the optimal path liquidates the risks to the asset's performance and reach the next state.

The goal was to achieve the best trade-off between the turnaround time for the activities and liquidating the risks to the asset's performance, based on completion of activities in the FPSO work management system.

The greedy algorithm benchmarks the performances of DQN model and a hybrid model comprising of greedy and DQN parameters.

It has been noted that overall, the Hybrid model with hyperparameters of $\alpha = 0.1,\ \gamma = 0.6,\ \epsilon = 0.1$ and the DQN model with hyperparameters of $\alpha = 0.1,\ \gamma = 1.0,\ \epsilon = 0.1$ achieve better results when compared with the Greedy model with hyperparameters of$\alpha = 0.1,\ \gamma = 0.1,\ \epsilon = 0.1$, as the training episode increases, towards task completion time and liquidating the risks to the asset's performance.

6.3 Recommendations for further work

Based on the insights developed from this research work, the following further work is being proposed.

The offshore maintenance planning systems are expected to provide the capability of resource allocations to access the resources on demand, confirm quality service on demand, and provide maintenance activities on demand as well as to provide maintenance with lower costs. It would be challenging to have different systems served independently with a proper resource allocation made according to their own requirements. A dynamic resource management and deep reinforcement learning based autonomous resource allocation for the deteriorating offshore systems could be investigated as a further work.

The work could investigate the capability of maintenance planning systems to periodically reserve the unused resources from the maintenance activities based on their ratio of minimum resource requirements, and thereafter, the maintenance activity autonomously control their resource amount using deep reinforcement learning based on the average quality of service utility and resource utilisation of maintenance items. With the proposed framework, the offshore systems could customise their own utility function and objective function based on their own requirements.

A two-level framework for maintenance resource allocation could be developed in the proposed work. In the top level, the work management system could dynamically reserve the available unused resource to the appropriate maintenance systems. In the bottom level, the maintenance systems could autonomously adjust their resource allocated to their maintenance items.

In the investigation of dynamic resource management, the work management system could collect the unused resources from the maintenance items and reserves them back to the maintenance items that might need extra resource. The unused resources from the maintenance items would be reserved back to them to prevent one maintenance activity from affecting the performance of the other maintenance activity.

In the investigation of autonomous resource management for multiple maintenance items, a deep reinforcement learning algorithm that autonomously adjusts resource allocated to maintenance items based on the feedback of average quality of service utility and average resource utilisation of their maintenance activities, could be employed.

This would in turn lead to the development of a comprehensive maintenance management tool that would be consistent, unaffected by human factors and incorporates the integration of the risks and site constraints on the overall Offshore operations. Also, the tool could be adapted to predict the asset condition in future and could be used to estimate repair costs, schedule repairs, evaluate consequences of repair strategy.

AppendixA

List of Publications

Published Manuscript:

1. George, B., Loo, J., Jie, W. (2021). "Recent Advances and Future Trends on Maintenance Strategies and Optimisation Solution techniques for Offshore sector".
In: *Ocean Engineering* 250, 110986 (2022).

The list of journal manuscripts submitted for publication are:

1. George, B., Loo, J., Jie, W. (2021). Novel Multi-objective Optimisation for Maintenance Activities of Floating Production Storage and Offloading Facilities.
Elsevier Journal – Applied Ocean Research; *Manuscript no. APOR – D – 21 – 00884*, *Submitted Oct* 2021.

2. George, B., Loo, J., Jie, W. (2022). Novel Multi-objective Optimisation with Deep Q-Reinforcement Learning for Maintenance Activities of Floating Production Storage and Offloading Facilities.
Taylor & Francis Journal – Ships and Offshore Structures; *Manuscript no.* 220812080, *Submitted Feb* 2022.

AppendixB

List of Abbreviations

The abbreviations used in this thesis are:

α *Learning rate*

γ *Discount factor*

ϵ *Randomness factor*

$8Q$ *8 Quarter*

BN *Bayesian Network*

C *Diminution ratio*

$C(i)$ *Total task completion time*

D *Fatigue Damage ratio*

DQN *Deep Q reinforcement learning Network*

Fi *Financial Risks*

F_i *Objective Function*

$FPSO$ *Floating Production Storage and Offloading Facility*

M *Bending Moment ratio*

$P[i]$ *Priority*

R *Ratio of Coating Breakdown area*

Ri *Degree of Corrosion Scale*

S *Shear Force ratio*

Sa *Safety Risks*

$T[i]$ *Time required to complete the task*

UC *Stress Unity Check*

WMS *Work Management System*

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