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EVALUATING MILLIONS OF DECOMMISSIONING ALTERNATIVES: A MCDA-BASED FRAMEWORK APPLIED TO THE MARLIM FIELD (BRAZIL)

Jean-David Caprace[1,*], Carlos E. Durange De Carvalho Infante[2], Fernanda Rodrigues Lago[1], Marcelo I. Lourenço De Souza[1]

[1]Federal University of Rio de Janeiro (UFRJ), Rio de Janeiro, Brazil
[2]Federal University of São João del-Rei (UFSJ), São João del-Rei, Brazil

ABSTRACT

The decommissioning of mature offshore oil fields poses growing technical, environmental, and regulatory challenges, particularly in Brazil, where large subsea systems coexist with environmentally sensitive deep-sea ecosystems and a regulatory framework that generally favors full removal. The Marlim Field, located in the Campos Basin, represents one of the largest subsea decommissioning projects planned in the country.

Existing decommissioning decision-support approaches are often limited to a small number of predefined scenarios or qualitative trade-off analyses, lacking the scalability and transparency required to explore complex combinatorial decision spaces. This study addresses this gap by proposing a scalable multicriteria decision analysis (MCDA) framework capable of systematically evaluating a very large number of decommissioning configurations.

The framework combines exhaustive combinatorial modeling, MCDA, Pareto dominance analysis, and criterion-level contribution decomposition. Two baseline strategies—stay-in-situ (TSIS) and total removal by reverse reel-lay (TRRL)—are combined across multiple equipment groups and environmental sensitivity zones, generating more than 10^6 *field-scale decommissioning configurations evaluated without heuristic pre-filtering.*

Results demonstrate that neither full removal nor full permanence constitutes an optimal strategy. Hybrid configurations consistently dominate both zone-level and field-scale analyses, achieving net preference flow values exceeding 57% *while limiting subsea weight removal to approximately* 17–29%. *Although the P-33 subsea system analyzed in this study had already been decommissioned at the time of the analysis and the Marlim Field application is therefore conducted* ex post *as a validation exercise, the proposed MCDA framework has been developed for and is applied in* ex ante *decision-support contexts for ongoing and future offshore decommissioning projects in Brazil. These findings provide quantitative evidence that sustainability-optimal offshore decommissioning solutions emerge from balanced, partial-intervention strategies.*

Keywords: Offshore decommissioning, Multi-criteria decision analysis, PROMETHEE, Subsea pipelines

1. INTRODUCTION

1.1. Offshore Decommissioning as a Large-Scale Decision Problem

Offshore oil and gas decommissioning has emerged as a critical phase in the life cycle of energy assets as mature offshore regions worldwide approach the end of production [1, 2]. Regions such as the North Sea, the Gulf of Mexico, Southeast Asia, and offshore Australia are currently facing an unprecedented volume of decommissioning activities involving complex offshore and subsea infrastructures installed over several decades [3]. These activities require decisions that simultaneously address technical feasibility, environmental protection, operational safety, economic efficiency, and social acceptance [2, 4, 5].

In response to this multidimensionality, multi-criteria decision analysis (MCDA) has increasingly been adopted as a formal decision-support framework in offshore decommissioning [2, 6]. MCDA methods provide a structured means to integrate heterogeneous criteria, incorporate stakeholder preferences, and ensure transparency and traceability in comparative assessments under uncertainty [7]. However, despite their growing adoption, most MCDA applications in offshore decommissioning remain limited to the evaluation of a small number of predefined scenarios, typically selected *a priori* by analysts or decision-makers [8].

This scenario-based paradigm implicitly assumes that a limited set of alternatives is sufficient to represent the decision space. In practice, however, offshore decommissioning—particularly for large subsea systems—is inherently combinatorial, as decisions made at the component or equipment-group level interact across the field. As a result, restricting MCDA to a handful of scenarios risks masking dominant trade-offs, overlooking efficient hybrid

*Corresponding author: jdcaprace@oceanica.ufrj.br

strategies, and biasing conclusions toward analyst-selected options rather than system-level behavior.

1.2. Limitations of Scenario-Based MCDA in Offshore Decommissioning

The limitations of scenario-based MCDA become especially pronounced in large-scale subsea decommissioning problems. Subsea fields typically comprise dozens of pipelines, flowlines, umbilicals, and ancillary components, each of which may be subject to different technical constraints, environmental sensitivities, and regulatory expectations. When decommissioning strategies such as full removal, partial removal, or in-situ abandonment are combined across multiple assets, the number of feasible configurations grows exponentially.

Despite this intrinsic combinatorial nature, most published MCDA studies in offshore decommissioning evaluate only a small number of alternatives, often corresponding to extreme or stylized strategies such as full removal or full abandonment [8]. While such analyses are useful for illustrating trade-offs, they do not allow for systematic exploration of the full decision space, nor do they support statistically meaningful interpretation of performance trends across thousands or millions of feasible configurations.

Moreover, in regulatory contexts where approvals are granted at the field or campaign level rather than at the level of individual components, decision-makers require evidence that selected strategies are not only locally optimal but also globally efficient within the broader space of feasible solutions. Addressing this gap requires moving beyond MCDA as a ranking tool for a few scenarios and toward MCDA as an analytical instrument for large-scale decision-space exploration.

1.3. Brazilian Regulatory Context and Motivation for Field-Scale Analysis

In Brazil, offshore decommissioning has become a strategic issue over the last decade as major deepwater developments initiated in the 1990s and early 2000s approach the end of their productive lives [8, 9]. The Brazilian regulatory framework, enforced primarily by the National Agency of Petroleum, Natural Gas and Biofuels (ANP) and the Brazilian Institute of Environment and Renewable Natural Resources (IBAMA), establishes strict requirements for offshore decommissioning, with a general presumption in favor of full removal [6, 8].

Although alternative strategies such as partial removal or in-situ abandonment are permitted under specific conditions, these options require robust technical, environmental, and safety justification supported by transparent and auditable analyses [2, 7, 10–12]. In practice, this places a high burden on operators to demonstrate that proposed solutions represent a defensible balance between environmental protection, operational risk, and economic proportionality.

1.4. The Marlim Field: A Representative Large-Scale Decommissioning Case

The Marlim Field, located in the Campos Basin approximately 105 km offshore the coast of Rio de Janeiro, represents one of the most emblematic deepwater developments in Brazil. The decommissioning case examined in this study focuses on the subsea production system connected to the P-33 FPSO, operating at water depths between approximately 650 and 1,050 m [2, 13].

The P-33 subsea system comprises an extensive and heterogeneous network of flexible pipelines and electro-hydraulic umbilicals connecting multiple wet-completion wells and interfacing with neighboring production units. The system includes approximately 65 km of subsea lines encompassing oil and gas production, water injection, gas-lift, and control functions. This heterogeneity, combined with variations in installation history, functional role, and seabed interaction, results in a highly complex decommissioning problem [2].

A further challenge arises from the presence of environmentally sensitive deepwater habitats. Autonomous underwater vehicle (AUV) surveys and remotely operated vehicle (ROV) inspections have identified multiple deep-sea coral banks in close proximity to, and in some cases directly beneath, subsea pipelines and umbilicals [14]. Physical disturbance associated with removal operations may pose risks to these benthic ecosystems [15], while in-situ strategies raise concerns related to long-term integrity, interference, and regulatory acceptance.

At the time this research was conducted, the P-33 FPSO and its associated subsea infrastructure had already undergone decommissioning activities. Consequently, the present study does not seek to reconstruct or assess the historical decision-making process that led to the executed decommissioning strategy. Instead, the P-33 system is used as a representative, data-rich case to retrospectively apply and validate the proposed large-scale MCDA framework under realistic technical, environmental, and regulatory conditions.

1.5. Contribution and Scope of the Present Study

Motivated by the limitations of scenario-based MCDA and by the regulatory and environmental challenges associated with large subsea systems, this paper proposes a large-scale MCDA framework combined with Pareto dominance analysis to support offshore decommissioning decisions at the field level. Unlike conventional approaches that rely on a small number of predefined scenarios, the proposed methodology systematically generates and evaluates more than one million feasible decommissioning configurations, thereby enabling explicit exploration of the full combinatorial decision space.

This study builds directly upon previous MCDA-based investigations of offshore subsea decommissioning [16, 17], including the application presented in [12], where machine learning–augmented MCDA was employed to assess representative decommissioning scenarios. While these earlier contributions demonstrated the relevance of multicriteria approaches for structuring and supporting decommissioning decisions, they remained inherently limited to scenario-based comparisons. The present work extends this line of research by explicitly addressing the combinatorial nature of large subsea systems and by shifting the analytical focus from scenario ranking to field-scale exploration of feasible strategy spaces.

Within this framework, the PROMETHEE outranking method is used to evaluate technical, economic, environmental, socio-economic, health and safety, and waste management criteria within a unified decision-support architecture [18–20]. Pareto front analysis is subsequently employed to relate global multicriteria performance to the extent of subsea mass removed, allowing the identification of non-dominated strategies and the explicit characterization of trade-offs between intervention intensity and overall sustainability performance.

Applied to the Marlim Field subsea system, the proposed approach demonstrates that hybrid partial-removal strategies systematically outperform both full-removal and full in-situ alternatives. This result, which cannot be inferred from limited scenario-based analyses, emerges only through large-scale combinatorial evaluation and dominance analysis. By transforming MCDA from a ranking exercise into a large-scale exploratory and analytical tool, this study provides quantitative, regulator-relevant evidence to support defensible decommissioning strategies in complex deepwater environments.

2. THEORETICAL BACKGROUND AND METHODOLOGICAL FOUNDATIONS

2.1. Offshore Decommissioning as a Multidimensional Decision Problem

Offshore decommissioning decisions are intrinsically multidimensional, requiring the simultaneous consideration of technical feasibility, environmental protection, economic performance, operational safety, and social acceptance [2, 5]. These dimensions are often conflicting: for example, strategies that minimize environmental disturbance may increase operational complexity or cost, while economically attractive solutions may raise concerns regarding long-term environmental or safety risks [9].

The growing scale and complexity of offshore subsea developments have amplified these trade-offs. Modern subsea fields typically comprise extensive networks of pipelines, flowlines, umbilicals, and associated infrastructure deployed across heterogeneous seabed environments [12, 21–23]. Decisions taken at the level of individual components may interact nonlinearly at the field scale, giving rise to cumulative impacts that cannot be adequately assessed through single-criterion or sequential decision-making approaches [4]. Consequently, offshore decommissioning problems cannot be meaningfully reduced to purely technical or economic optimization exercises, but instead require structured frameworks capable of explicitly addressing multiple, often competing objectives.

2.2. Regulatory and International Drivers for Structured Decision Support

International regulatory practices further reinforce the need for transparent and auditable decision-support methodologies in offshore decommissioning. In the United Kingdom, comparative assessment procedures explicitly require operators to demonstrate, through structured analysis, that proposed decommissioning strategies represent the best practicable environmental option. In contrast, regulatory frameworks in the Gulf of Mexico allow alternative end-of-life strategies such as rigs-to-reefs programs, reflecting a different balance between environmental, economic, and social considerations [15, 24].

In Brazil, offshore decommissioning has emerged as a strategic issue over the last decade as mature deepwater developments approach the end of production. The Brazilian regulatory framework, enforced primarily by the National Agency of Petroleum, Natural Gas and Biofuels (ANP) and the Brazilian Institute of Environment and Renewable Natural Resources (IBAMA), establishes strict requirements for asset decommissioning, with a general presumption in favor of full removal. Although partial removal or in-situ abandonment may be permitted under specific conditions, such alternatives require robust technical, environmental, and safety justification supported by transparent and reproducible analyses [25].

This regulatory context highlights the importance of decision-support tools that not only compare predefined alternatives, but also provide a defensible rationale for selecting hybrid or non-standard solutions. In particular, regulators increasingly require evidence that proposed strategies are efficient not only locally, but also at the scale of entire fields or decommissioning campaigns [12].

2.3. Multi-Criteria Decision Analysis in Offshore Decommissioning

Multi-criteria decision analysis (MCDA) has been widely adopted as a methodological framework for supporting complex engineering decisions involving multiple conflicting objectives and stakeholder perspectives [26]. In the offshore decommissioning context, MCDA enables the systematic integration of technical, economic, environmental, and social criteria within a unified decision-support structure, while preserving transparency and traceability throughout the decision-making process [2].

Several MCDA applications have been reported in the offshore decommissioning literature, demonstrating the usefulness of multicriteria approaches for structuring discussions, comparing alternatives, and supporting regulatory dialogue [8]. However, most existing studies remain inherently scenario-based, evaluating a limited number of predefined alternatives selected *a priori*. While such approaches are effective for illustrative comparisons, they are not designed to explore the full decision space associated with large-scale subsea systems, where the number of feasible decommissioning configurations may be extremely large [21].

As a result, conventional MCDA applications risk overlooking efficient hybrid strategies and masking structural trade-offs that emerge only when decisions are analyzed at the system level. Addressing this limitation requires extending MCDA beyond comparative ranking toward large-scale analytical exploration of feasible decision spaces.

2.4. PROMETHEE and Outranking Methods for Non-Compensatory Decisions

Among the various MCDA families, outranking methods are particularly well suited to offshore decommissioning problems, where strong compensation between criteria is often undesirable [19]. In such contexts, poor performance with respect to critical environmental or safety criteria should not be fully offset by favorable economic outcomes.

The PROMETHEE (Preference Ranking Organization Method for Enrichment Evaluations) method provides a flexible outranking framework that enables pairwise comparison of alternatives based on preference functions and criterion-specific thresholds [18]. PROMETHEE has been successfully applied in a wide range of engineering and environmental decision problems, including offshore decommissioning, due to its transparency, interpretability, and ability to accommodate both quantitative and qualitative criteria [2, 20].

In the present study, PROMETHEE is adopted as the core multicriteria evaluation engine. For completeness and reproducibility, the formal mathematical formulation of the PROMETHEE method is provided in Appendix A. The main body of the paper focuses on how PROMETHEE is integrated within a large-scale combinatorial framework rather than on its standard mathematical derivation.

2.5. Relevance of PROMETHEE for Large-Scale, Combinatorial Decommissioning Problems

While PROMETHEE is well suited for comparing individual alternatives, its true analytical potential emerges when embedded within a framework capable of handling large numbers of feasible solutions. Large subsea decommissioning problems are inherently combinatorial, as different strategies may be applied to different equipment groups, environmental sensitivity zones, or operational contexts, leading to an exponential growth in the number of possible configurations [12].

To address this challenge, the present study combines PROMETHEE outranking with Pareto dominance analysis, enabling systematic exploration of the relationship between global multicriteria performance and key physical indicators such as the extent of subsea mass removed. This integration allows the identification of non-dominated strategies and the explicit characterization of trade-offs between intervention intensity and sustainability performance at the field scale.

By shifting the analytical focus from scenario ranking to decision-space exploration, the proposed framework extends the role of MCDA from a comparative decision aid to a large-scale analytical instrument. This capability is essential for supporting regulator-relevant insights and for identifying defensible decommissioning strategies in complex deepwater environments.

3. METHODOLOGY

This section presents the methodological framework adopted to support large-scale offshore decommissioning decision-making. The proposed approach follows a structured, step-by-step workflow that integrates system definition, combinatorial generation of feasible decommissioning configurations, multicriteria evaluation, and dominance-based synthesis. The overall methodology is illustrated in Fig. 1.

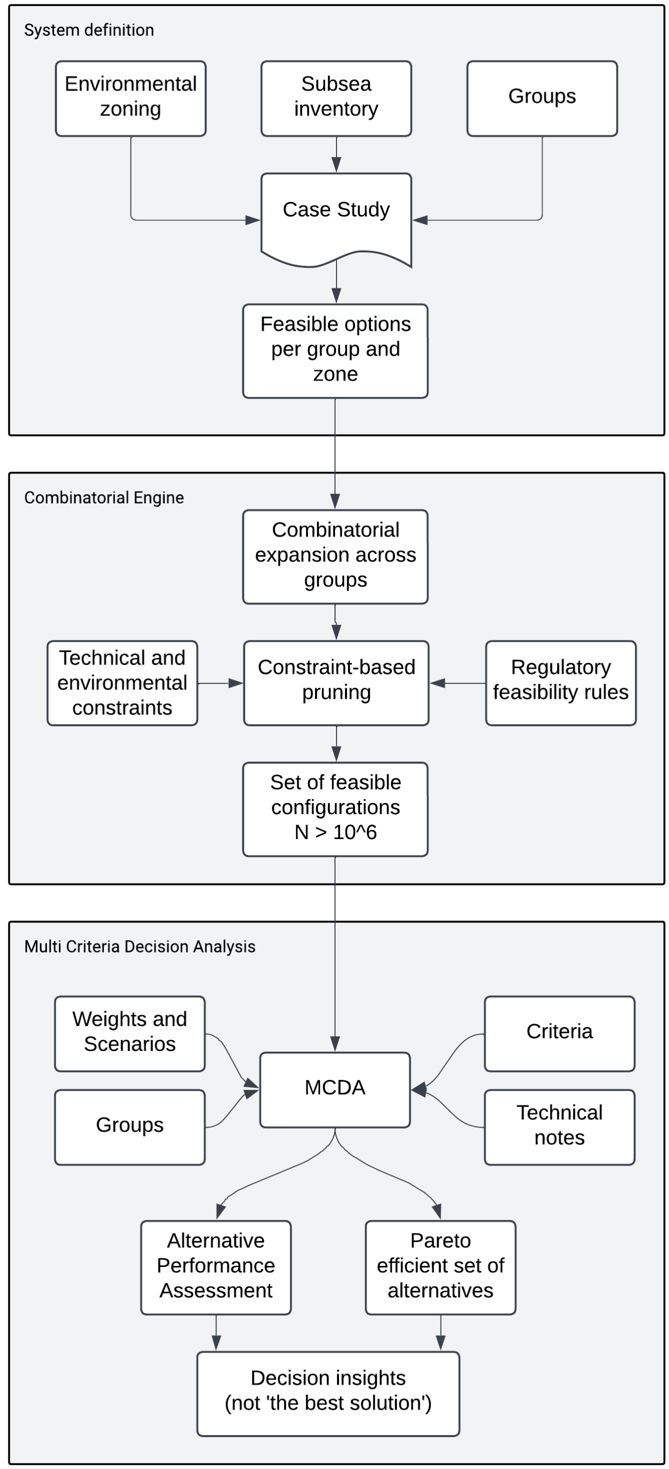

FIGURE 1: Workflow of the proposed large-scale MCDA methodology for offshore decommissioning. The process starts with system definition, integrating subsea inventory, equipment grouping, and environmental zoning. Feasible decommissioning options are defined for each group and zone and combined through a combinatorial engine with constraint-based pruning enforcing technical, environmental, and regulatory feasibility. The resulting set of more than 10^6 feasible field-scale configurations is evaluated using a PROMETHEE-based MCDA framework and synthesized through Pareto dominance analysis to explore trade-offs between multicriteria performance and intervention intensity, leading to the identification of dominant strategy families and decision insights rather than a single optimal solution.

3.1. System Definition and Case Study Modeling

The first step of the methodology consists in defining the decommissioning system at the field level. This involves three complementary elements: (i) the subsea inventory, (ii) the definition of equipment groups, and (iii) environmental zoning.

The subsea inventory includes all pipelines, flowlines, and umbilicals within the scope of the case study, together with their main physical, functional, and operational characteristics. To enable tractable system-level analysis, individual assets are aggregated into equipment groups sharing similar technical functions, installation characteristics, and decommissioning constraints. This grouping strategy reduces dimensionality while preserving the structural heterogeneity of the subsea system.

Environmental zoning is defined based on seabed characteristics and environmental sensitivity, notably the presence of deep-sea coral banks identified through AUV and ROV surveys. Each equipment group is associated with one or more environmental zones, which directly influence the feasibility and impacts of decommissioning actions. The combination of subsea inventory, grouping strategy, and environmental zoning defines the case study model used in subsequent steps.

3.2. Definition of Feasible Decommissioning Options

For each equipment group and associated environmental zone, a discrete set of feasible decommissioning options is defined. These options may include, for example, full removal, partial removal, or in-situ abandonment, subject to technical, environmental, and regulatory constraints.

Technical and environmental constraints reflect physical feasibility, installation characteristics, seabed interaction, and potential environmental disturbance. Regulatory feasibility rules encode compliance with applicable decommissioning regulations and guidelines, including restrictions on allowable strategies in environmentally sensitive areas. The outcome of this step is a set of feasible options defined independently for each group-zone combination, forming the basic building blocks of the decision space.

3.3. Combinatorial Generation of Decommissioning Configurations

The feasible options defined at the group level are combined through a combinatorial expansion process to generate field-scale decommissioning configurations. Each configuration represents a unique combination of decommissioning options applied across all equipment groups.

Given the exponential growth of possible combinations, constraint-based pruning is applied during the generation process to eliminate infeasible or non-compliant configurations. Pruning rules incorporate technical incompatibilities, environmental exclusions, and regulatory constraints, ensuring that only admissible configurations are retained.

This combinatorial engine produces a large set of feasible decommissioning configurations, with cardinality exceeding 10^6 in the present case study. Each configuration represents a distinct, internally consistent decommissioning strategy at the field scale.

3.4. Multi-Criteria Performance Evaluation

Each feasible decommissioning configuration is evaluated using a multi-criteria decision analysis (MCDA) framework. The evaluation model adopted in this study is derived from our previous work [16], to which the reader is referred for a detailed methodological description.

Briefly, the MCDA framework is designed to capture the multidimensional nature of offshore decommissioning decisions through a hierarchical set of criteria. A total of 25 subcriteria are considered, aggregated into six main criteria: Technical [**TE**], Environmental [**EN**], Social [**SO**], Health and Safety [**HS**], Socio-Economic [**EC**], and Waste Management [**WA**], the latter explicitly including air emissions. The full list of criteria and subcriteria, together with their definitions, is provided in Table 1.

TABLE 1: List of criteria and subcriteria used in the MCDA

Criteria	Sub-criteria	ID	Goal	Unit
Technical [TE]	*Complexity of operations*	COMP	Min	Score
	Technological risk	RISC	Min	
Environment [EN]	*Benthos of consolidated substrate*	BC	Min	Score
	Benthos of unconsolidated substrate	BN	Min	
	Demersal nekton	ND	Min	
	Pelagic nekton	NP	Min	
	Plankton	PL	Min	
Social [SO]	*External context*	IDE	Min	Score
	Restriction of fishing activities	PESC	Min	
	Restriction on tourist activities	TURI	Min	
	Offshore direct and indirect jobs	LE	Max	
	Logistics and infrastructure	LOGEM	Min	
	Onshore direct and indirect jobs	LOGNB	Max	
Health & Safety [HS]	*Exposure to toxic materials*	TOX	Min	Score
	Exposure to TNORM	NORM	Min	
	Exposure to hyperbaric conditions	HIPE	Min	
	Impacts on other users of the sea	UMAR	Min	
	Fatal accidents	FATA	Min	LOL
Economic [EC]	*Project cost*	COST	Min	MM USD
LCA of waste [WA]	*Climate change*	CLIM	Min	t CO2eq
	Marine eutrophication	MEUT	Min	t N-eq
	Particulate matter formation	PMF	Min	t PM2.5-eq
	Photochemical oxidant formation	POF	Min	t NOx-eq
	Terrestrial acidification	TACI	Min	t SO2-eq
	Water depletion	WDEP	Min	mil m^3

Criteria values are computed consistently across all configurations based on the characteristics of the selected decommissioning options and the underlying system model. Criteria definitions, normalization procedures, and technical assumptions are documented to ensure transparency and reproducibility.

Criteria weights and preference parameters are defined to reflect relative importance and decision-maker priorities. The preference functions and associated parameter values adopted in the PROMETHEE evaluation are identical to those reported in [16], ensuring methodological consistency with previous applications. In contrast, the criteria weights are specific to the present case study and reflect the characteristics and regulatory context of the Marlim P-33 subsea system. These weights are detailed in the Case Study section. Multiple weighting scenarios may be considered to explore the sensitivity of results to preference assumptions, without restricting the analysis to a single subjective weighting scheme.

3.5. MCDA Evaluation Using PROMETHEE

The PROMETHEE outranking method is employed as the core MCDA evaluation engine. For each configuration, PROMETHEE preference flows are computed based on the evaluated criteria, weights, and preference functions. This process results in a global multicriteria performance assessment for each feasible configuration.

PROMETHEE is used here as an evaluation and structuring tool rather than as a prescriptive decision rule. The method enables consistent comparison across a very large number of alternatives while limiting excessive compensation between criteria, which is particularly important in environmental and safety-critical contexts. The formal mathematical formulation of the PROMETHEE method is provided in Appendix A.

3.6. Pareto Dominance and Decision-Space Exploration

To synthesize the large volume of MCDA results, Pareto dominance analysis is applied. Multicriteria performance indicators obtained from PROMETHEE are analyzed jointly with a physical indicator of intervention intensity, such as the total subsea mass removed.

This dominance-based analysis enables identification of Pareto-efficient configurations, defined as those for which no other feasible configuration performs better across all considered dimensions simultaneously. Rather than identifying a single optimal solution, the analysis reveals families of non-dominated strategies and characterizes trade-offs between sustainability performance and intervention extent.

3.7. Interpretation and Decision Insights

The final step of the methodology focuses on interpretation of the Pareto-efficient set and extraction of decision-relevant insights. Configurations are analyzed to identify dominant patterns, such as the systematic performance of hybrid partial-removal strategies relative to full-removal or full in-situ alternatives.

The objective of this step is not to recommend a unique "best" solution, but to provide structured, quantitative insights that support informed decision-making and regulatory dialogue. By revealing trade-offs and dominant strategy families at the field scale, the proposed methodology supports transparent and defensible offshore decommissioning decisions in complex deepwater environments.

4. CASE STUDY: FIELD-SCALE DECOMMISSIONING MODEL OF THE MARLIM P-33 SUBSEA SYSTEM

This section presents the Marlim Field P-33 subsea system as a structured case study used to instantiate the proposed large-scale MCDA framework. It should be interpreted as a retrospective analytical exercise aimed at validating the behavior, scalability, and interpretability of the proposed MCDA framework, rather than as a real-time decision-support process for the decommissioning campaign. The case study is formulated as a field-scale decision model, explicitly defining the system boundary, subsea inventory, equipment grouping, environmental zoning, and decommissioning option space. These elements constitute the inputs to the combinatorial generation and evaluation of feasible decommissioning configurations described in the previous section.

4.1. Field Location, System Boundary, and Interconnections

The Marlim Field is located in the Campos Basin, approximately 105 km offshore the coast of Rio de Janeiro, and represents one of the most significant deepwater oil developments in Brazil. Figure 2 shows the location of the field within offshore Brazil [12, 13].

As illustrated in Fig. 3, the P-33 FPSO is embedded within a broader field-scale network, with subsea connections linking

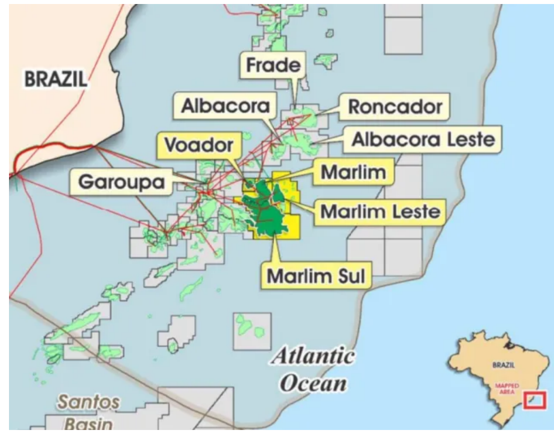

FIGURE 2: Location of the Marlim Field within the Campos Basin, offshore Brazil.

neighboring platforms and production systems. This configuration highlights that decommissioning decisions associated with the P-33 subsea system cannot be addressed in isolation, as they may interact with shared infrastructure and adjacent developments. Based on this layout, the system boundary adopted in the present study encompasses all subsea assets functionally connected to the P-33 unit and relevant to field-scale decommissioning analysis.

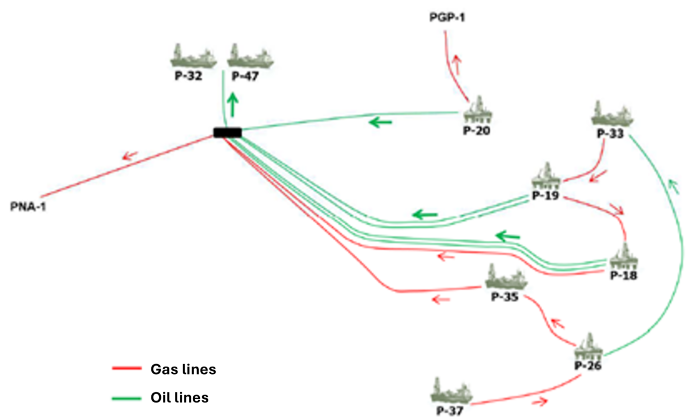

FIGURE 3: Diagram highlighting the main production units of the Marlim Field and the interconnecting subsea infrastructure relevant to the P-33 system.

4.2. Subsea Inventory and Technical Heterogeneity

The subsea system within the defined boundary comprises flexible pipelines and electro-hydraulic umbilicals supporting oil and gas production, water injection, gas lift, and control functions. The total length of subsea lines considered in the analysis is approximately 65 km, deployed in water depths ranging from about 650 to 1,050 m [2, 13].

Figure 4 provides a detailed overview of the subsea layout associated with the P-33 unit, illustrating the spatial distribution, routing, and functional diversity of pipelines and umbilicals [13]. The figure highlights the technical heterogeneity of the system, including differences in line function, routing complexity, and seabed interaction. This heterogeneity plays a central role in decommissioning decision-making, as it leads to differentiated technical feasibility, environmental impact, and operational risk across the system.

4.3. Environmental Zoning and Sensitivity Constraints

A major challenge in the decommissioning of the Marlim P-33 subsea system arises from its location within an environmentally sensitive deepwater region. Environmental zoning is therefore introduced to explicitly account for spatial variability in ecological sensitivity across the field. Figure 5 presents the zoning adopted in this study, derived from seabed characteristics and the presence of deep-sea coral banks identified through AUV and ROV surveys [14].

For the purposes of the decision model, the subsea system is partitioned into two environmental zones reflecting both ecological sensitivity and operational context. Zone 1 comprises equipment located in areas of moderate seabed sensitivity and lower coral density, where selective removal operations may be feasible with reduced environmental penalties. Zone 2 encompasses assets located in highly sensitive ecological regions, characterized by dense coral presence and increased vulnerability to physical disturbance. This zoning scheme enables differentiated evaluation of decommissioning strategies under context-specific environmental constraints.

As illustrated in Fig. 5, several pipelines and umbilicals are located in close proximity to, or directly above, coral formations, represented by the thick dark line segments. This spatial configuration introduces significant constraints on feasible decommissioning actions, as physical disturbance associated with removal operations—such as pipeline lifting, seabed contact, anchoring, and subsea intervention—may result in elevated ecological impacts [15]. Environmental zoning is therefore used to directly influence both the feasibility and impact assessment of candidate decommissioning options.

Deep-sea coral ecosystems are widely recognized for their ecological importance and vulnerability to mechanical disturbance. While in-situ abandonment strategies may reduce immediate physical impacts in sensitive zones, they may also raise concerns related to long-term seabed interaction, asset integrity, and potential future interference. Conversely, removal-based strategies may offer long-term risk reduction at the cost of increased short-term environmental disturbance. These opposing considerations reinforce the need for a structured decision-support framework capable of explicitly evaluating trade-offs between environmental protection, operational feasibility, and long-term system behavior.

4.4. Equipment Grouping Strategy

To enable tractable field-scale analysis while preserving the essential technical characteristics of the subsea system, individual assets are aggregated into equipment groups. Grouping is performed based on functional role, physical characteristics (e.g., flexible pipeline or umbilical), and decommissioning-relevant attributes such as installation method, diameter, weight, and interaction with the seabed.

The grouping strategy is directly informed by the technical characteristics of the subsea inventory and by the environmental zoning defined in the previous subsection. Assets exhibiting similar functions, physical properties, and decommissioning constraints are assumed to be treated uniformly within the decision model. This approach substantially reduces the dimensionality of the decision space while maintaining the ability to represent heterogeneous technical, environmental, and operational impacts across the subsea system. Each equipment group therefore constitutes a fundamental decision unit in the subsequent combinatorial generation of decommissioning configurations.

Table 2 summarizes the resulting equipment groups by environmental zone, functional role, admissible decommissioning alternatives, and key physical attributes, including total length, weight, and representative diameters.

The equipment groups encompass oil production flowlines, gas-lift and water-injection lines, and electro-hydraulic umbilicals distributed across two environmental zones. Production flowline groups (e.g., G111–G113) account for a substantial share of the total subsea length and mass and play a critical role in hydrocarbon transport, resulting in moderate to high technical and environmental decommissioning considerations depending on seabed interaction and location [12].

Gas-lift and water-injection groups are generally shorter but introduce specific operational and safety considerations related to residual hydrocarbons, internal pressure, and fluid handling, leading to differentiated impacts across environmental zones. Umbilical groups, while typically lighter and associated with lower contamination risk, are frequently routed through environmentally sensitive seabed areas, including coral-rich zones, making their decommissioning particularly relevant from an ecological and regulatory perspective.

Assets located in Zone 2 are explicitly represented as separate decision units due to their distinct spatial distribution and environmental context, even when their individual physical characteristics are comparatively limited. This grouping approach enables a balanced representation of functional importance, physical scale, and environmental exposure within the field-scale decommissioning model.

Overall, the equipment grouping strategy presented in Table 2 enables differentiated evaluation of decommissioning alternatives according to functional importance, physical characteristics, environmental exposure, and operational risk, while ensuring computational tractability of the large-scale combinatorial analysis.

4.5. Definition of Decommissioning Options and Constraints

For each equipment group and associated environmental zone, a discrete set of decommissioning options is defined. These options include, where admissible, full removal, partial removal, and in-situ abandonment. The admissibility of each option is governed by technical feasibility, environmental sensitivity, and regulatory requirements enforced by Brazilian authorities [6, 10].

Technical constraints reflect physical limitations related to installation characteristics, accessibility, and operational safety. Environmental constraints are derived from the zoning shown

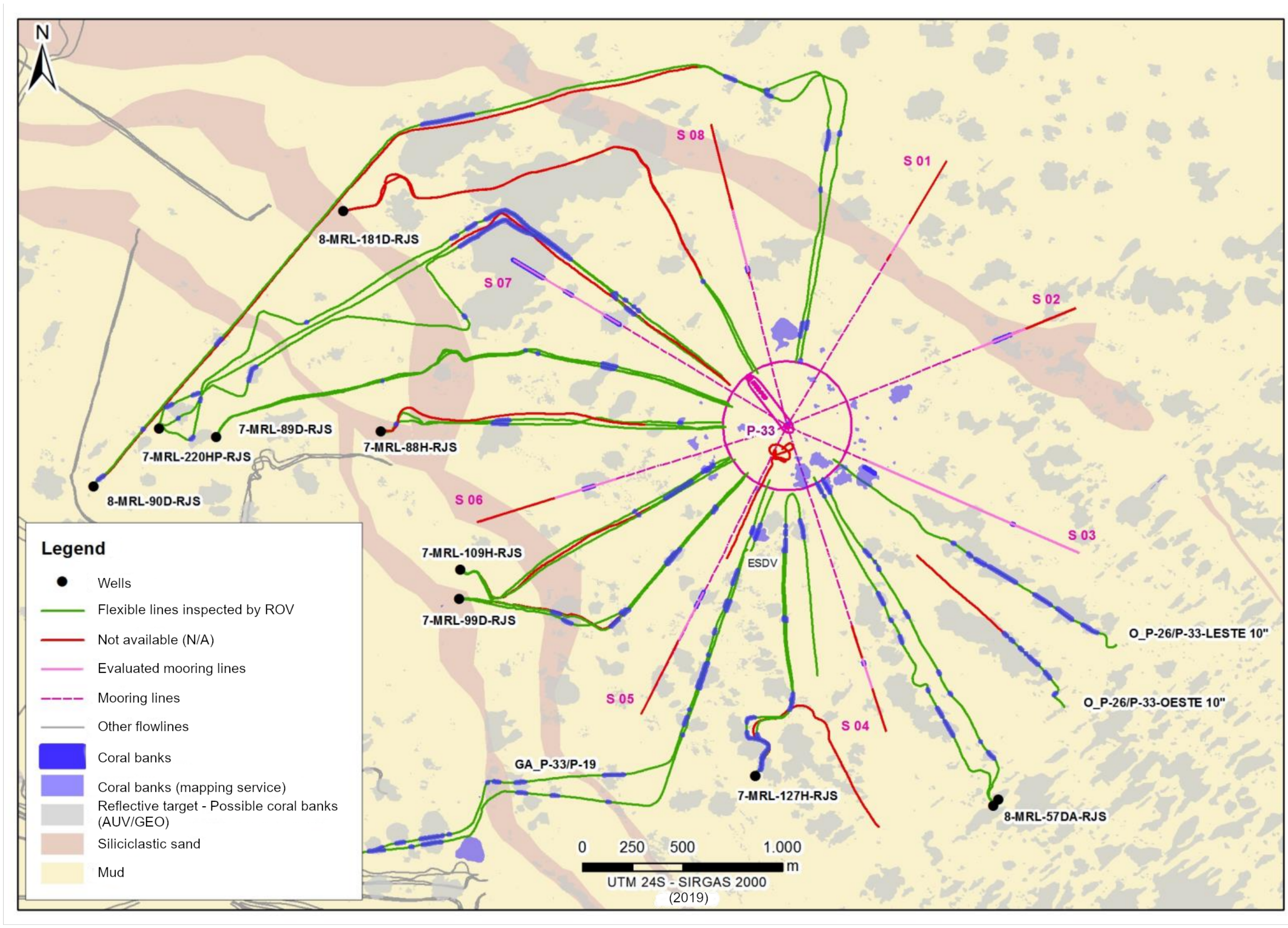

FIGURE 4: Overview of the Marlim Field subsea layout.

in Fig. 5, restricting or penalizing options that may result in unacceptable disturbance in sensitive areas. Regulatory feasibility rules encode compliance with applicable decommissioning guidelines, with a general presumption in favor of full removal unless robust justification is provided for alternative strategies.

In order to structure the decision space, two baseline decommissioning strategies are defined as reference configurations. The first strategy corresponds to stay-in-situ without intervention (**TSIS**), in which flexible pipelines and umbilicals remain permanently on the seabed following disconnection, sealing, and preparatory abandonment activities supported by ROV operations. The second strategy corresponds to total removal by reverse reel-lay (**TRRL**), involving the complete retrieval of flexible pipelines and umbilicals using pipe-laying support vessels, with subsea interventions performed by ROVs to disconnect, prepare, and recover the assets [12, 13].

From the definition of equipment groups, environmental zones, and admissible decommissioning options, a root decision matrix is constructed to support the MCDA evaluation. Table 3 illustrates the structure of this matrix. At this stage, each row represents a basic decommissioning alternative defined at the level of a given equipment group and environmental zone, prior to the combinatorial generation of field-scale configurations. Each column corresponds to one evaluation subcriterion, as listed in Table 1.

Matrix entries contain the quantified performance values of each group–zone–option combination with respect to the 25 subcriteria considered in this study, aggregated into the six main criteria: Technical (TE), Environmental (EN), Social (SO), Health and Safety (HS), Economic (EC), and Waste Management (WA). This base decision matrix constitutes the fundamental input to the subsequent combinatorial assembly of field-scale decommissioning configurations and to the PROMETHEE-based MCDA evaluation, enabling consistent, systematic, and scalable assessment of a very large number of feasible strategies.

In the present study, a single weighting vector is adopted for the six main criteria in order to clearly illustrate the behavior and scalability of the proposed framework without introducing additional layers of complexity. The selected weights were derived from a structured consultation with a diverse set of stakeholders involved in offshore decommissioning, including oil and gas operators, the national oil and gas regulatory agency, the environ-

TABLE 2: Equipment grouping by environmental zone for the Marlim P-33 subsea system and associated technical characteristics.

Zone	Group	Function	Alternatives	Length km	Weight tons	Diameter	Lines
1	G111	Oil production	TSIS | TRRL	4.863	321.35	4" and 6"	7-MRL-99D/P-33; 7-MRL-109/P-33; 7-MRL-220HP-RJS/P-33 7-MRL-89D/P-33; 7-MRL-89D/P-33
1	G112	Oil production	TSIS | TRRL	4.7	324.23	6"	7-MRL-220HP-RJS/P-33; 7-MRL-88H/P-33; 7-MRL-99D/P-33
1	G113	Oil production	TSIS | TRRL	0.302	18.1	4"	7-MRL-88H/P-33; 7-MRL-89D/P-33; 7-MRL-99D/P-33
1	G131	Gas lift	TSIS | TRRL	5.143	139.38	2.5"	P-33/7-MRL-109; P-33/7-MRL-88H; P-33/7-MRL-89D
1	G141	Water injection	TSIS | TRRL	1.96	117.53	4" and 6"	P-33/8-MRL-090D; P-33/8-MRL-090D
1	G142	Gas lift & Water injection	TSIS | TRRL	11.163	616.12	btw 6" and 30"	P-33 /7-MRL-220HP-RJS; P-33 /7-MRL-220HP-RJS; P-33/7-MRL-99D P-33/8-MRL-090D; P-33/8-MRL-090D; P-33/8-MRL-181D; P-33/8-MRL-181D
1	G152	Gas production	TSIS | TRRL	2.441	288.99	8"	P-33/P-19; P-33/P-19; P-33/P-19 (TRACK)
1	G161	Umbilical	TSIS | TRRL	6.798	185.42	138mm	P-33 /7-MRL-220HP-RJS; P-33/7-MRL-88H; P-33/7-MRL-89D; P-33/8-MRL-090D
1	G162	Umbilical	TSIS | TRRL	9.55	220.1	138mm	P-33 /7-MRL-220HP-RJS; P-33/7-MRL-99D; P-33/8-MRL-090D; P-33/8-MRL-181D
1	G163	Umbilical	TSIS | TRRL	1.62	48.89	138mm	P-33/7-MRL-109; P-33/7-MRL-109
2	G211	Oil production	TSIS | TRRL	1.35	104.16	6"	7-MRL-127H/P-33
2	G212	Oil production	TSIS | TRRL	0.078	5.22	4"	7-MRL-127H/P-33
2	G222	Oil production	TSIS | TRRL	2.33	255.11	9.5"	P-26/P-33-LESTE 10"; P-26/P-33-LESTE 10"
2	G232	Gas lift	TSIS | TRRL	1.34	35.59	2.5"	P-33/7-MRL-127H
2	G241	Water injection	TSIS | TRRL	1.52	103.22	6"	P-33/8-MRL-57DA
2	G242	Water injection	TSIS | TRRL	0.09	5.11	6"	P-33/8-MRL-57DA
2	G243	Water injection	TSIS | TRRL	0.150	8.71	6"	P-33/8-MRL-57DA; P-33/8-MRL-090D
2	G251	Gas production	TSIS | TRRL	3.44	465.09	btw 6" and 9"	P-33/P-19; P-33/P-19 (TRACK 1); P-33/P-19 (TRACK)
2	G252	Gas production	TSIS | TRRL	1.84	229.45	btw 8" and 9"	P-33/P-19; P-33/P-19 (TRACK)
2	G262	Umbilical	TSIS | TRRL	4.43	124.09	btw 86 and 128mm	P-33/7-MRL-127H; P-33/8-MRL-57DA

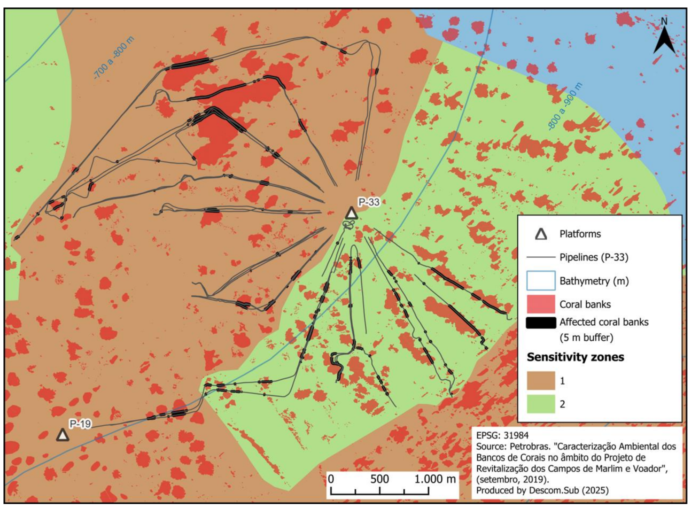

FIGURE 5: Environmental zoning of the Marlim P-33 subsea system, showing the distribution of flexible pipelines and umbilicals relative to bathymetry and mapped deep-sea coral banks. Zone 1 (brown) denotes areas of higher environmental sensitivity, while Zone 2 (green) corresponds to areas of lower sensitivity. Coral banks are shown in red, with pipeline segments within a 5 m buffer highlighted in black.

mental licensing authority, offshore service companies, representatives of the fishing sector, and academic experts. This process reflects a multi-actor governance perspective rather than a purely operator-centric business viewpoint.

As a result, the elicited preference structure emphasizes sustainability, environmental protection, and risk mitigation over short-term economic optimization. Environmental factors were assigned the highest weight (25.4%), followed by Health and Safety (20.6%), Technical (14.0%), Social (13.7%), Waste Management (13.2%), and Economic (13.1%). In this context, economic performance is not disregarded but is considered alongside regulatory compliance, environmental stewardship, and long-term liability reduction, which are dominant concerns for non-commercial stakeholders and for decommissioning decisions governed by strict public regulation.

These weights are held constant across all zones and configurations, ensuring that differences in multicriteria performance arise solely from variations in decommissioning decisions rather than from changes in preference assumptions. While the proposed MCDA framework is fully capable of accommodating alternative weighting schemes and stakeholder-specific scenarios, the use of a single stakeholder-informed weighting vector facilitates transparent interpretation of results and provides a consistent basis for demonstrating the methodological contribution of large-scale combinatorial evaluation.

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TABLE 3: Decision matrix used in the MCDA evaluation. Each row corresponds to a feasible field-scale decommissioning configuration defined by environmental zone, equipment group, and selected decommissioning alternative. Columns report the quantified performance of each configuration with respect to the 25 evaluation subcriteria aggregated into the six main criteria: Technical (TE), Environmental (EN), Social (SO), Health and Safety (HS), Economic (EC), and Waste Management (WA), as defined in Table 1. The criteria IDE, LOGNB, NORM, and HIPE take constant values across all configurations in this case study and are therefore omitted from the decision matrix.

Zone	Group	Alts	COMP	RISC	BC	BN	ND	NP	PL	PESC	TURI	LE	LOGEM	TOX	UMAR	FATA	COST	CLIM	MEUT	PMF	POF	TACI	WDEP
1	G111	TSIS	1.24	5.0	13.2	3.3	6.6	12.2	1.0	5.6	3.2	3.9	0.0	12880	3	29.9	0.3	0.8	1.0	0.5	0.3	0.3	1.0
1	G111	TRRL	2.95	6.5	4.1	0.0	2.1	26.1	2.8	7.8	5.1	1.3	6.6	14952	18	311.0	4.1	1.0	0.4	1.0	1.0	1.0	0.3
1	G112	TSIS	1.24	5.0	13.2	3.3	6.6	12.2	1.0	5.6	3.2	3.9	0.0	1344	3	30.1	0.3	0.8	1.0	0.6	0.3	0.4	1.0
1	G112	TRRL	2.94	6.5	16.0	0.0	8.0	25.7	2.8	7.6	4.7	1.5	6.6	11356	18	237.3	3.0	1.0	0.4	1.0	1.0	1.0	0.3
1	G113	TSIS	1.24	5.0	0.0	3.3	6.6	12.2	1.0	5.6	3.0	3.0	0.0	264	3	7.0	0.1	0.2	1.0	0.1	0.1	0.1	1.0
1	G113	TRRL	2.66	6.5	0.0	1.0	2.0	25.1	2.7	7.4	4.1	2.0	5.1	7424	18	160.9	1.9	1.0	0.4	1.0	1.0	1.0	0.3
1	G131	TSIS	1.07	5.0	13.1	3.3	6.6	12.2	1.0	5.6	3.2	3.9	0.0	1292	3	30.2	0.4	0.6	1.0	0.4	0.2	0.2	1.0
1	G131	TRRL	2.73	6.5	4.2	0.0	2.1	25.8	2.8	7.6	4.7	1.5	5.7	12012	18	245.3	3.3	1.0	0.4	1.0	1.0	1.0	0.3
1	G141	TSIS	1.07	5.0	13.1	3.3	6.6	12.2	1.0	5.6	3.0	3.0	0.0	252	3	6.7	0.1	0.7	1.0	0.5	0.2	0.3	1.0
1	G141	TRRL	2.71	6.5	4.2	0.0	2.1	25.0	2.7	7.3	3.9	2.1	5.6	4776	18	105.6	1.7	1.0	0.4	1.0	1.0	1.0	0.3
1	G142	TSIS	1.07	5.0	13.4	3.3	6.7	12.2	1.0	5.7	3.3	3.8	0.0	1676	3	40.5	0.5	0.2	1.0	0.1	0.1	0.1	1.0
1	G142	TRRL	2.85	6.5	16.0	0.0	8.0	27.3	2.9	8.2	6.0	1.0	8.0	19356	18	379.4	5.6	1.0	0.4	1.0	1.0	1.0	0.3
1	G152	TSIS	1.07	5.0	13.2	3.3	6.6	12.2	1.0	5.6	3.1	3.9	0.0	1188	3	26.0	0.3	0.8	1.0	0.6	0.3	0.4	1.0
1	G152	TRRL	2.81	6.5	8.8	0.0	4.4	25.6	2.7	7.5	4.5	1.6	6.4	10544	18	220.5	3.0	1.0	0.4	1.0	1.0	1.0	0.3
1	G161	TSIS	1.07	5.0	13.1	3.3	6.6	12.2	1.0	5.7	3.2	3.8	0.0	1400	3	33.1	0.4	0.5	0.3	0.4	0.2	0.3	0.6
1	G161	TRRL	2.81	6.5	4.7	0.0	2.3	26.1	2.8	7.8	5.1	1.4	5.9	14252	18	296.9	3.9	1.0	1.0	1.0	1.0	1.0	1.0
1	G162	TSIS	1.07	5.0	13.2	3.3	6.6	12.2	1.0	5.7	3.2	3.8	0.0	1568	3	37.6	0.4	0.5	0.3	0.4	0.2	0.3	0.6
1	G162	TRRL	2.81	6.5	16.0	0.0	8.0	26.3	2.8	7.9	5.3	1.3	6.1	15524	18	320.1	4.2	1.0	1.0	1.0	1.0	1.0	1.0
1	G163	TSIS	1.07	5.0	13.1	3.3	6.6	12.2	1.0	5.6	3.1	3.9	0.0	1244	3	29.0	0.3	0.3	0.3	0.3	0.2	0.2	0.6
1	G163	TRRL	2.69	6.5	4.0	0.0	2.0	25.5	2.7	7.4	4.2	1.8	5.3	8132	18	174.5	2.4	1.0	1.0	1.0	1.0	1.0	1.0
2	G211	TSIS	1.24	5.0	11.5	3.3	6.6	12.2	1.0	5.7	3.2	3.8	0.0	1052	3	23.9	0.3	0.7	1.0	0.5	0.3	0.3	1.0
2	G211	TRRL	2.79	6.5	8.4	0.0	4.8	25.4	2.7	7.6	4.8	1.5	5.7	6584	18	142.6	2.0	1.0	0.4	1.0	1.0	1.0	0.3
2	G212	TSIS	1.24	5.0	11.5	3.3	6.6	12.1	1.0	5.6	3.0	3.0	0.0	560	3	10.8	0.0	0.3	1.0	0.2	0.1	0.1	1.0
2	G212	TRRL	2.65	6.5	3.5	0.0	2.0	24.9	2.7	7.0	3.4	2.4	5.1	1956	18	40.1	0.5	1.0	0.4	1.0	1.0	1.0	0.3
2	G222	TSIS	1.24	5.0	11.5	3.3	6.6	12.2	1.0	5.7	3.3	3.8	0.0	1112	3	25.5	0.3	0.8	1.0	0.6	0.3	0.4	1.0
2	G222	TRRL	2.92	6.5	14.0	0.0	8.0	25.5	2.7	7.8	5.3	1.3	6.6	8736	18	185.1	2.5	1.0	0.4	1.0	1.0	1.0	0.3
2	G232	TSIS	1.07	5.0	11.5	3.3	6.6	12.2	1.0	5.7	3.2	3.8	0.0	1052	3	23.9	0.3	0.4	1.0	0.3	0.2	0.2	1.0
2	G232	TRRL	2.56	6.5	6.9	0.0	4.0	25.4	2.7	7.6	4.8	1.5	5.3	6536	18	141.8	2.0	1.0	0.4	1.0	1.0	1.0	0.3
2	G241	TSIS	1.07	5.0	11.5	3.3	6.6	12.2	1.0	5.7	3.2	3.8	0.0	1064	3	24.2	0.3	0.7	1.0	0.5	0.3	0.3	1.0
2	G241	TRRL	2.69	6.5	9.6	0.0	5.5	25.4	2.7	7.7	4.9	1.4	5.7	6844	18	147.9	2.0	1.0	0.4	1.0	1.0	1.0	0.3
2	G242	TSIS	1.07	5.0	11.5	3.3	6.6	12.1	1.0	5.6	3.0	3.0	0.0	120	3	3.2	0.0	0.3	1.0	0.2	0.1	0.1	1.0
2	G242	TRRL	2.54	6.5	3.5	0.0	2.0	24.9	2.7	7.0	3.4	2.4	5.1	2232	18	45.0	0.5	1.0	0.4	1.0	1.0	1.0	0.3
2	G243	TSIS	1.07	5.0	0.0	3.3	6.6	12.2	1.0	5.6	3.1	3.8	0.0	1100	3	25.1	0.3	0.2	1.0	0.2	0.1	0.1	1.0
2	G243	TRRL	2.63	6.5	0.0	1.0	2.0	25.5	2.7	7.6	4.8	1.4	5.1	8460	18	181.8	2.3	1.0	0.4	1.0	1.0	1.0	0.3
2	G251	TSIS	1.07	5.0	11.6	3.3	6.6	12.2	1.0	5.7	3.3	3.8	0.0	1184	3	27.4	0.3	0.9	1.0	0.6	0.3	0.4	1.0
2	G251	TRRL	2.86	6.5	8.0	0.0	4.6	25.7	2.8	8.2	6.0	1.0	8.0	11936	18	247.1	3.4	1.0	0.4	1.0	1.0	1.0	0.3
2	G252	TSIS	1.07	5.0	11.5	3.3	6.6	12.2	1.0	5.7	3.2	3.8	0.0	980	3	21.9	0.3	0.8	1.0	0.5	0.3	0.4	1.0
2	G252	TRRL	2.78	6.5	14.0	0.0	8.0	25.5	2.7	7.8	5.3	1.3	6.5	8536	18	181.4	2.5	1.0	0.4	1.0	1.0	1.0	0.3
2	G262	TSIS	1.07	5.0	11.5	3.3	6.6	12.2	1.0	5.7	3.3	3.8	0.0	1244	3	29.0	0.4	0.6	1.0	0.4	0.2	0.3	1.0
2	G262	TRRL	2.78	6.5	14.0	0.0	8.0	25.6	2.7	8.0	5.6	1.2	5.8	9512	18	200.2	2.7	1.0	0.3	1.0	1.0	1.0	0.6

4.6. Configuration Space and Model Outputs

A field-scale decommissioning configuration is defined as a unique combination of admissible decommissioning options selected across all equipment groups. The joint consideration of equipment grouping, environmental zoning, and option definition results in a discrete and inherently combinatorial decision space.

As summarized in Table 2, each environmental zone comprises ten equipment groups, and for each group two admissible decommissioning alternatives are considered (**TSIS** and **TRRL**). When analyzed independently, the configuration space associated with each zone therefore contains $2^{10} = 1{,}024$ feasible group-level combinations. These zone-specific configuration spaces already illustrate the rapid growth in the number of possible strategies, even before considering field-scale interactions.

At the field scale, the full problem consists of twenty equipment groups distributed across the two environmental zones, each with two admissible alternatives. Neglecting feasibility constraints, this results in a total of $2^{20} = 1{,}048{,}576$ possible decommissioning configurations.

In the present case study, this process yields a set of admissible configurations exceeding 10^6 distinct field-scale decommissioning strategies. Each configuration represents a self-consistent decommissioning plan that can subsequently be evaluated using the MCDA and Pareto dominance framework presented in the following sections.

5. APPLICATION AND RESULTS

5.1. Structure of the Evaluated Decision Space

The results presented in this section are derived from the configuration space defined in Section 4.6, which encompasses all feasible combinations of decommissioning alternatives across equipment groups and environmental zones. Rather than reiterating the combinatorial formulation, this subsection clarifies how the resulting solution space is explored and interpreted in the analysis that follows.

The evaluation of decommissioning strategies is conducted using two complementary analytical perspectives. First, zone-level results are examined independently in order to isolate the influence of environmental sensitivity on multicriteria performance. This decomposition enables a clear interpretation of criterion behavior, ranking patterns, and trade-offs within relatively homogeneous environmental contexts, and serves as a validation step for the MCDA formulation and weighting structure.

Second, the complete field-scale configuration space—comprising more than 10^6 distinct decommissioning alternatives—is analyzed in an integrated manner. This global analysis does not aim to interpret individual configurations exhaustively, but rather to characterize the overall structure of the solution space. In particular, it is used to identify dominance relationships, performance distributions, and Pareto-efficient regions that emerge only when the full combinatorial set of alternatives is considered.

This two-level reading of the results supports both interpretability and robustness. Zone-level analyses provide insight into the mechanisms driving multicriteria performance under different environmental conditions, while the global analysis demonstrates the scalability of the proposed framework and the statistical consistency of the observed trends. Accordingly, the following subsections first present criteria-level performance, rankings, and Pareto frontiers for each zone, before moving to an aggregate assessment of the full configuration space.

5.2. PROMETHEE Ranking Results

The PROMETHEE method was applied to rank the feasible decommissioning configurations defined in Section 4.6, using the net preference flow ϕ as the global multicriteria performance indicator. Tables 4(a) and 4(b) summarize the highest-ranked, intermediate, and lowest-ranked alternatives for Zones 1 and 2, respectively, together with their associated removal indicators and composite performance metrics.

It is important to emphasize that the PROMETHEE net preference flow (ϕ) is a relative performance indicator rather than an absolute measure of acceptability or compliance. Values such as ϕ exceeding approximately 50%–60% do not represent predefined approval thresholds, but instead express the degree to which a given configuration outranks other feasible alternatives within the evaluated decision space. Consequently, the interpretation of ϕ values is inherently comparative and context-dependent, and their significance arises from relative ranking, dominance relationships, and robustness across the solution set, rather than from their absolute magnitude. More details on the theoretical meaning of the outranking flows are provided in Section A.

In Zone 1 (Table 4(a)), the PROMETHEE ranking reveals a clear stratification of decommissioning strategies. Hybrid configurations (HYB), combining selective total removal by reverse reel-lay (TRRL) with stay-in-situ (TSIS) decisions across equipment groups, consistently occupy the top-ranked positions. The highest-performing alternatives (id:25 and id:26) achieve ϕ values around 50%, while limiting length and weight removal to intermediate levels (LR% and WR% between approximately 15% and 25%). These configurations outperform both extreme strategies (id:1 and id:1024) by balancing technical robustness and safety gains against economic, environmental, and waste-related penalties.

Pure TSIS configurations (id:1), characterized by zero removal (LR% = WR% = 0), exhibit moderate ϕ value (approximately 43%). Although this alternative benefits from low operational impact and minimal waste generation, its ranking is constrained by weaker performance in technical feasibility, long-term integrity, and regulatory alignment. As a result, TSIS solutions are systematically dominated by hybrid configurations that introduce targeted removal where it yields significant multicriteria gains.

Full TRRL configurations occupy the lower end of the ranking in Zone 1, with strongly negative ϕ values for high removal rates. Despite achieving maximum LR% and WR%, these alternatives incur substantial penalties associated with cost, waste generation, and environmental disturbance, which outweigh the benefits obtained in technical and safety-related criteria. This pattern confirms the presence of diminishing returns when extensive removal is applied in areas of moderate environmental sensitivity.

The ranking results for Zone 2 (Table 4(b)) exhibit similar structural behavior, but with more pronounced contrasts. The best-performing hybrid alternative reaches a ϕ value exceeding 53%, surpassing the maximum achieved in Zone 1. This indicates that, under high environmental sensitivity, carefully targeted removal can deliver proportionally greater improvements in overall multicriteria performance.

Pure TSIS alternatives in Zone 2 (id:1) again show intermediate performance, with ϕ values close to 42%. While these configurations minimize immediate environmental disturbance, their limited contribution to risk reduction and regulatory robustness constrains their ranking relative to hybrid strategies. As in Zone 1, hybrid alternatives dominate the upper portion of the ranking by concentrating TRRL decisions on selected equipment groups while preserving TSIS where removal impacts would be disproportionate.

The composite indicator OPT%, reported in Tables 4(a) and 4(b), further highlights the superiority of hybrid solutions. By combining normalized multicriteria performance (ϕ) with the extent of weight removal, OPT% identifies configurations that are simultaneously close to optimal in terms of sustainability performance and intervention minimization. The highest OPT% values are consistently associated with hybrid alternatives in both zones, whereas pure TSIS and full TRRL solutions exhibit lower composite performance.

Overall, the PROMETHEE ranking results demonstrate that neither full removal nor full permanence constitutes an optimal decommissioning strategy for the Marlim Field. Instead, the most effective solutions emerge from hybrid configurations that selectively allocate removal efforts in response to environmental sensitivity and asset-specific characteristics. These ranked outcomes provide the empirical basis for the criteria-level interpretation and Pareto-based trade-off analysis presented in the following subsections.

5.3. Criteria-Level Performance Assessment

Following the PROMETHEE ranking analysis presented in Section 5.2, this subsection examines the criteria-level behavior of representative decommissioning configurations in order to explain the observed ranking patterns. Radar charts are used here as diagnostic tools to visualize how individual criteria contribute to the global multicriteria performance index ϕ for selected alternatives. The configurations shown correspond to those reported in Tables 4(a) and 4(b), including top-ranked, intermediate, and dominated solutions.

Figure 6(a) presents the criteria-level performance of selected alternatives in Zone 1. The highest-ranked hybrid configurations (id:25 and id:26), which achieve the maximum ϕ values in this zone (maximum radar area), exhibit balanced radar profiles with strong performance in Technical Feasibility (TE) and Health and Safety (HS), while maintaining moderate penalties in Economic Cost (EC), Environmental Impact (EN), and Waste Management (WA). This balance explains their superior position in the PROMETHEE ranking relative to both pure TSIS (id:1) and high-removal alternatives.

The pure TSIS configuration (id:1), although achieving favorable outcomes in EC and WA due to the absence of offshore removal operations, shows reduced performance in TE and HS. These weaknesses, already reflected in its intermediate ϕ value,

TABLE 4: PROMETHEE-ranked decommissioning alternatives and associated performance indicators for (a) Zone 1 and (b) Zone 2. Each row corresponds to a representative decommissioning configuration, with columns indicating the selected option for each equipment group. A filled circle (●) denotes a stay-in-situ (TSIS) decision, while an empty circle (○) denotes total removal by reverse reel-lay (TRRL). HYB indicates hybrid configurations combining TSIS and TRRL decisions across different equipment groups. The PROMETHEE net preference flow ϕ represents the global multicriteria performance index, with higher values indicating better-ranked alternatives. LR% and WR% denote, respectively, the percentage of total line length and total subsea weight removed. OPT% is a composite indicator defined as the average of normalized ϕ and weight removal percentage, and provides a synthetic measure of proximity to solutions that simultaneously maximize multicriteria performance while minimizing removal extent.

Id	**Alt.**	G111	G112	G113	G131	G141	G142	G152	G161	G162	G163	ϕ	LR%	WR%	OPT%
1	TSIS	●	●	●	●	●	●	●	●	●	●	42.8%	0%	0%	21%
5	HYB	●	●	○	●	●	●	●	●	●	●	44.5%	1%	1%	23%
18	HYB	○	●	●	●	○	●	●	●	●	●	49.9%	14%	19%	35%
21	HYB	●	●	○	●	○	●	●	●	●	●	47.8%	5%	6%	27%
25	HYB	●	●	●	○	○	●	●	●	●	●	**50.1%**	15%	11%	31%
26	HYB	○	●	●	○	○	●	●	●	●	●	**50.1%**	25%	25%	38%
34	HYB	○	●	●	●	●	○	●	●	●	●	39.7%	33%	41%	40%
50	HYB	○	●	●	●	○	○	●	●	●	●	36.5%	37%	46%	41%
82	HYB	○	●	●	●	○	●	○	●	●	●	47.7%	19%	32%	40%
98	HYB	○	●	●	●	●	○	○	●	●	●	31.1%	38%	54%	**42%**
488	HYB	○	○	○	●	●	○	○	○	○	●	-47.1%	82%	87%	20%
1024	TRRL	○	○	○	○	○	○	○	○	○	○	-29.9%	100%	**100%**	35%

(a) Zone 1

Id	**Alt.**	G211	G212	G222	G232	G241	G242	G243	G251	G252	G262	ϕ	LR%	WR%	OPT%
1	TSIS	●	●	●	●	●	●	●	●	●	●	42.1%	0%	0%	21%
35	HYB	●	○	●	●	●	○	●	●	●	●	**53.1%**	1%	1%	27%
36	HYB	○	○	●	●	●	○	●	●	●	●	51.5%	9%	9%	30%
132	HYB	○	○	●	●	●	●	●	○	●	●	42.2%	29%	43%	43%
134	HYB	○	●	○	●	●	●	●	○	●	●	25.1%	43%	62%	43%
135	HYB	●	○	○	●	●	●	●	○	●	●	34.8%	35%	54%	45%
163	HYB	●	○	●	●	●	○	●	○	●	●	49.5%	22%	36%	43%
389	HYB	●	●	○	●	●	●	●	○	○	●	19.9%	46%	71%	**45%**
990	HYB	○	●	○	○	○	●	○	○	○	○	-44.6%	99%	99%	27%
1024	TRRL	○	○	○	○	○	○	○	○	○	○	-36.1%	100%	**100%**	32%

(b) Zone 2

are clearly visible in the radar representation and explain why TSIS solutions are consistently dominated by hybrid configurations that introduce selective removal.

Conversely, high-removal configurations in Zone 1 (e.g., id:488 and id:1024) display pronounced penalties in almost all criteria. Although these alternatives quite well in EN and WA, the magnitude of the negative contributions in cost-, technical-, and safety-related criteria outweighs the associated benefits, leading to strongly negative or low ϕ values in the ranking.

Figure 6(b) illustrates the corresponding criteria-level behavior for Zone 2. The best-performing hybrid alternatives (id:35 and id:36), which attain the highest ϕ values in this zone, again present well-balanced radar profiles. Compared to Zone 1, however, the penalties associated with extensive removal are more pronounced in EN and EC, reflecting the higher environmental sensitivity of this zone. As a result, selective TRRL decisions yield proportionally greater gains in multicriteria performance when carefully targeted, while extensive intervention rapidly degrades overall performance.

Pure TSIS solutions in Zone 2 (id:1) show similar patterns to those observed in Zone 1, with low penalties in EC and WA but reduced performance in EN. Meanwhile, near-full and full TRRL configurations (id:990 and id:1024) exhibit severe penalties across all criteria which dominate the radar profiles and explain their highly negative ϕ values despite strong technical performance.

Across both zones, the radar charts confirm that the PROMETHEE ranking is driven by the ability of hybrid configurations to distribute gains across multiple criteria while avoiding extreme penalties in any single dimension. Full TSIS and full TRRL strategies concentrate benefits in a limited subset of criteria but incur disproportionate losses elsewhere, leading to inferior global performance. These criteria-level patterns provide a clear explanatory basis for the dominance of hybrid solutions observed in the ranking results and prepare the ground for the Pareto frontier and rainbow chart analyses presented in the following subsections.

5.4. Pareto Frontier Analysis

To further investigate the trade-off between multicriteria performance and intervention effort, a Pareto frontier analysis was conducted using the PROMETHEE net preference flow ϕ and the percentage of subsea weight removed (WR%) as competing objectives. In this formulation, higher values of ϕ indicate better overall sustainability performance, while lower values of WR% correspond to reduced removal effort. Figure 7 presents the resulting Pareto distributions for Zones 1 and 2.

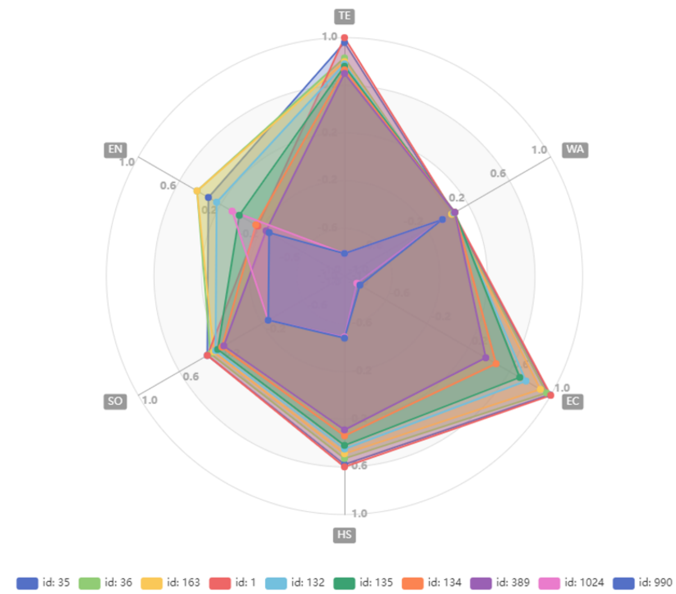
In both zones, the full set of feasible configurations exhibits a clear inverse relationship between ϕ and WR%, confirming that improvements in global multicriteria performance generally require increased removal effort. However, this relationship is highly nonlinear. A large fraction of configurations cluster in regions characterized by either low removal and moderate ϕ values, or high removal associated with strongly negative ϕ, indicating inefficient use of intervention effort.

In Zone 1 (Fig. 7a), the Pareto-efficient solutions form a relatively narrow frontier concentrated at intermediate WR% levels. These solutions achieve ϕ values close to the maximum observed in the zone while avoiding the steep performance degradation associated with extensive removal. Beyond this region, further increases in WR% lead to rapidly diminishing returns, with ϕ decreasing despite higher intervention levels. This behavior is consistent with the PROMETHEE ranking results, where full TRRL configurations occupy the lower end of the ranking despite maximizing removal.

The Pareto distribution for Zone 2 (Fig. 7b) exhibits a similar structure, but with more pronounced gradients. The Pareto-efficient frontier spans a broader range of ϕ values and shows a steeper decline in performance as WR% increases. This reflects the higher environmental sensitivity of Zone 2, where intrusive operations incur stronger penalties in environmental and safety-related criteria. As a result, the marginal benefit of additional removal decreases more rapidly than in Zone 1, reinforcing the importance of selective intervention.

The highlighted Pareto-efficient solutions were selected to illustrate key regions of the frontier, including: (i) high-performing hybrid configurations located near the upper envelope of the Pareto front, (ii) intermediate trade-off solutions characterized by

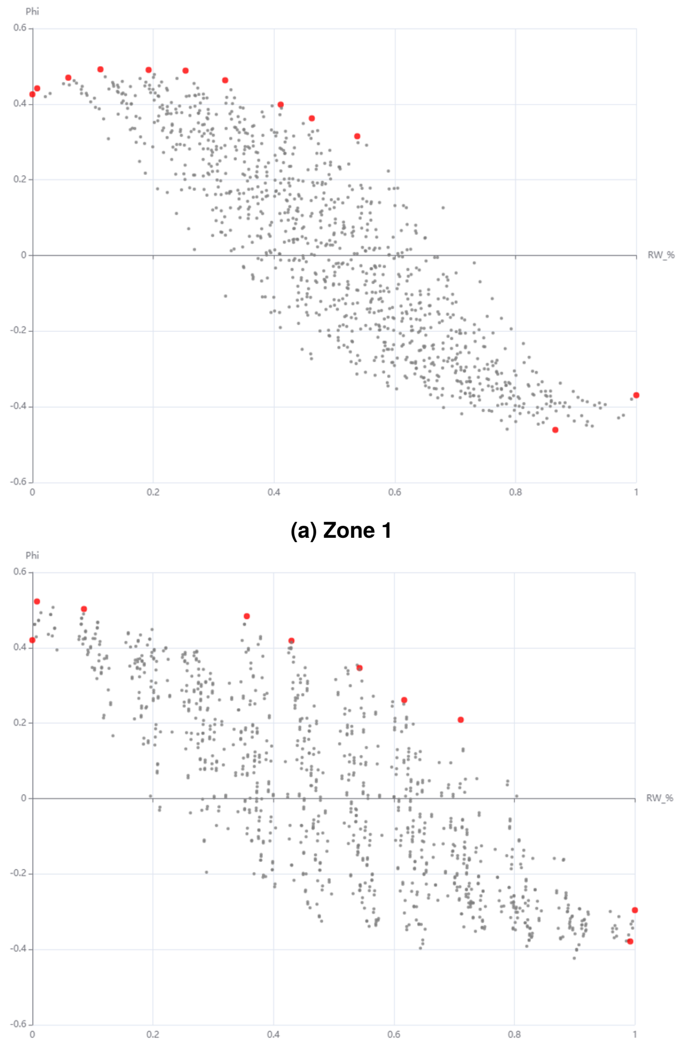
(a) Zone 1 — Moderate environmental sensitivity



(b) Zone 2 — High environmental sensitivity

FIGURE 6: Radar charts illustrating the criteria-level performance of representative decommissioning configurations in the Marlim Field. The charts compare normalized scores across Technical Feasibility (TE), Environmental Impact (EN), Socio-economic Effects (SO), Health and Safety (HS), Economic Cost (EC), and Waste Management (WA). Baseline solutions (TSIS and full TRRL) and representative hybrid alternatives are shown to highlight performance trade-offs under different environmental sensitivities.

moderate removal percentages and balanced performance, and (iii) extreme configurations corresponding to full TRRL and full TSIS strategies. This selection enables a structured interpretation of the frontier and provides a direct link between dominance-based optimization and criteria-level performance analysis.



(a) Zone 1

(b) Zone 2

FIGURE 7: Pareto analysis of decommissioning configurations for (a) Zone 1 and (b) Zone 2, showing the relationship between the PROMETHEE net preference flow ϕ and the percentage of subsea weight removed (WR%). Each gray point represents a feasible decommissioning configuration in the evaluated decision space. Red points identify Pareto-efficient solutions, for which no other configuration simultaneously achieves a higher multicriteria performance (ϕ) and a lower removal effort. The Pareto fronts highlight the trade-off between sustainability performance and intervention extent, and reveal the region where hybrid configurations provide the most efficient compromise between competing objectives.

Across both zones, Pareto-efficient solutions are predominantly associated with hybrid configurations that combine TRRL and TSIS decisions across different equipment groups. These alternatives occupy the region of the Pareto front where high multicriteria performance is achieved with limited removal effort, providing an efficient compromise between competing objectives. In contrast, pure TSIS solutions lie away from the frontier due to insufficient performance gains, while full TRRL strategies are Pareto-dominated by hybrid alternatives that achieve comparable or superior ϕ values at substantially lower WR%.

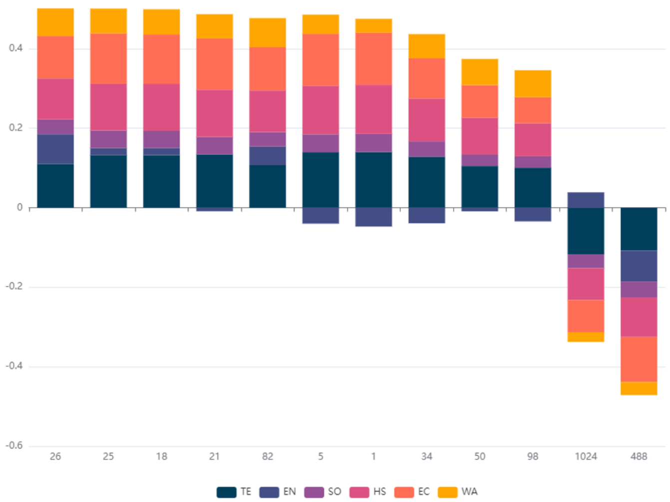
Overall, the Pareto frontier analysis demonstrates that maximum removal does not equate to maximum sustainability. Instead, strategic partial removal yields the most favorable balance between regulatory compliance, environmental preservation, operational feasibility, and cost. By linking large-scale combinatorial modeling (2^n configurations) with dominance-based frontier construction, the proposed framework provides quantitative evidence in support of hybrid decommissioning strategies for the Marlim Field. These findings are consistent with Brazilian regulatory provisions, which allow exceptions to full removal when justified on technical, environmental, and safety grounds, and provide a transparent basis for informed decision-making.

5.5. Rainbow Chart Decomposition of Multicriteria Performance

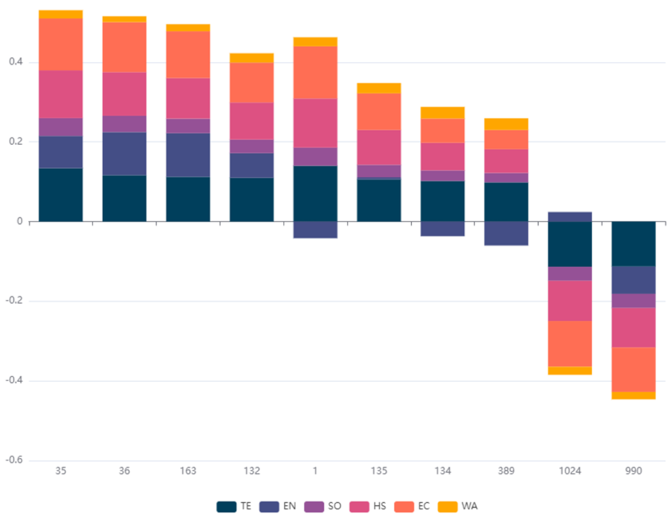
To provide a criterion-level explanation of the PROMETHEE ranking and Pareto frontier results, the net preference flow ϕ was decomposed into its individual criterion contributions using rainbow (stacked-contribution) charts. Figure 8 presents this decomposition for representative configurations in Zones 1 and 2, selected from key regions of the Pareto frontier, including high-performing hybrid solutions, intermediate trade-off alternatives, and extreme strategies corresponding to full TSIS and near- or full TRRL configurations.

In both zones, the rainbow charts confirm that high-ranked hybrid configurations achieve positive ϕ values through a balanced aggregation of contributions across multiple criteria. These alternatives typically combine strong positive contributions from Technical Feasibility and Health and Safety with moderate or limited penalties in Economic Cost , Environmental Impact , and Waste Management . The absence of dominant negative contributions explains why these configurations occupy the upper envelope of the Pareto frontier and achieve the highest PROMETHEE rankings.

Pure TSIS configurations exhibit a distinct contribution structure. As illustrated by id:1 in both zones, the only substantial negative contribution to the net preference flow originates from the Environmental Impact criterion (EN), whereas the remaining criteria provide predominantly positive but relatively modest contributions. In particular, Waste Management (WA) and Socio-economic Effects (SO) contribute only weakly, and the cumulative positive contributions are not sufficient to compensate



(a) Zone 1



(b) Zone 2

FIGURE 8: Rainbow (stacked-contribution) charts for representative decommissioning configurations in (a) Zone 1 and (b) Zone 2. Each vertical bar corresponds to one configuration (identified by its ID on the horizontal axis). Colored segments represent the signed contributions of each criterion to the PROMETHEE net preference flow ϕ (TE: Technical Feasibility, EN: Environmental Impact, SO: Socio-economic Effects, HS: Health and Safety, EC: Economic Cost, WA: Waste Management). Segments above the zero line indicate criteria that contribute positively to the overall ranking, whereas segments below zero indicate penalizing contributions. The total height of each bar (sum of all segments) equals the net multicriteria performance ϕ for that configuration. This decomposition enables interpretation of why certain hybrid solutions achieve high ϕ values (balanced positive contributions) and why extreme strategies (full TSIS or near/full TRRL) may become dominated.

for the EN penalty and to reach the highest ϕ levels attained by the best hybrid solutions. This contribution pattern is consistent with the intermediate PROMETHEE ranking of TSIS alternatives and explains why targeted hybrid configurations, which improve the balance across criteria, populate the upper region of the Pareto frontier.

Configurations characterized by extensive or near-complete removal display a markedly different pattern. Although they may show a positive contributions in EN (id:1024) this gain is offset by large negative contributions in all other criteria.

Comparing Zones 1 and 2 reveals that the relative magnitude of criterion contributions is zone-dependent. In Zone 2, penalties associated with most of the criteria increase more rapidly with removal effort, reflecting the higher environmental sensitivity of the area. Consequently, the range of hybrid configurations that maintain positive ϕ values is narrower than in Zone 1, reinforcing the importance of targeted intervention strategies in sensitive environments.

Overall, the rainbow chart decomposition demonstrates that superior multicriteria performance does not arise from maximizing a single criterion, but from managing trade-offs across all evaluation dimensions. By explicitly linking PROMETHEE rankings and Pareto-efficient solutions to their underlying criterion contributions, this analysis moves beyond abstract optimization and provides transparent, criterion-level justification for the dominance of hybrid decommissioning strategies. Together with the large-scale combinatorial evaluation and dominance-based frontier analysis, these results provide robust quantitative support for selective removal approaches in the decommissioning of the Marlim Field.

5.6. Rainbow Chart Analysis

The rainbow charts for Zones 1 and 2 provide additional insight into the relative contribution of each criterion to the overall PROMETHEE net flow (ϕ). By decomposing the global score into stacked bars for the six evaluation dimensions , it is possible to understand not only which alternatives perform better but also why they do so.

The comparison between zones reinforces that the criteria driving performance differ in weight and intensity according to environmental sensitivity. Zone 1 admits a broader range of TRRL configurations before negative impacts dominate, whereas Zone 2 penalizes intrusive operations more strongly. In both cases, however, the consistent dominance of hybrid bars over full and minimal removal solutions confirms that multicriteria-optimal decommissioning strategies emerge from selective intervention, rather than extreme choices at either end of the spectrum. Figure 8a illustrates the stacked contributions of each criterion for the best and worst alternatives in Zone 1 and Figure 8b illustrates the stacked contributions of each criterion for the best and worst alternatives in Zone 2.

In Zone 1, the highest ranked hybrid alternatives (Ids 25, 26, and 18) exhibit balanced contributions across TE, HS, and EN, while maintaining moderate penalties in EC and WA. These solutions deliver positive cumulative bar heights due to the absence of major negative contributions in any single criterion. In contrast, the full TRRL configurations display large negative bars in EC and WA, which outweigh the technical and safety advantages of complete removal. This confirms that economic and waste penalties dominate when intervention intensity increases in moderately sensitive environments.

The Zone 2 rainbow chart shows a similar qualitative pattern, but with more pronounced negative contributions in EN and HS for extensive TRRL strategies. Sensitive seabed conditions amplify penalties for large-scale disturbance, which is reflected in deeper negative bars for environmental and safety criteria in Ids 1024 and 990. Hybrid alternatives (Ids 35 and 36) achieve the best ϕ values by targeting TRRL where it yields significant EN and HS gains, while relying on TSIS to avoid excessive EC and WA penalties. As a result, their stacked bars are more uniformly positive, illustrating a more favorable trade-off between risk reduction and operational impact.

5.7. Global Analysis of the Full Field-Scale Configuration Space

To demonstrate the scalability and robustness of the proposed framework, the PROMETHEE-based evaluation was extended to the full field-scale configuration space, jointly considering all equipment groups across Zones 1 and 2. This global analysis encompasses more than 10^6 distinct decommissioning configurations, corresponding to all possible combinations of TRRL and TSIS decisions at the field level, as defined in Section 4.6. The objective is to assess whether the dominance patterns identified in the zone-based analyses persist when the entire decision space is evaluated simultaneously.

Figure 9 presents the global Pareto distribution in the space defined by the PROMETHEE net preference flow ϕ and the percentage of subsea weight removed (WR%). Each gray point represents a feasible field-scale configuration, while red points identify Pareto-efficient solutions. Despite the size and density of the configuration space, a well-defined efficiency boundary clearly emerges, indicating that the multicriteria evaluation remains structurally coherent at large scale.

The global Pareto front confirms and generalizes the trends observed in the zone-level analyses. Pareto-efficient configurations are concentrated in a continuous region characterized by partial removal and positive ϕ values, whereas extreme strategies corresponding to either near-zero or near-complete removal are consistently dominated. In particular, configurations involving extensive removal exhibit strongly negative ϕ values despite high intervention effort.

To enable a quantitative interpretation of this global structure, a subset of seven representative Pareto-efficient configurations was selected from the frontier and is reported in Table 5. These configurations span the full range of efficient trade-offs between multicriteria performance and intervention effort, from zero removal to full removal. The best-performing hybrid solutions (id:43034 and 165914) achieve ϕ values exceeding 57% while limiting WR% to 17–29%, quantitatively confirming that high multicriteria performance can be attained without extensive removal at the field scale.

Intermediate Pareto-efficient configurations illustrate diminishing returns with increasing removal effort. For example, id:135268 reaches a WR% of 63% with a ϕ of 32.3%, while

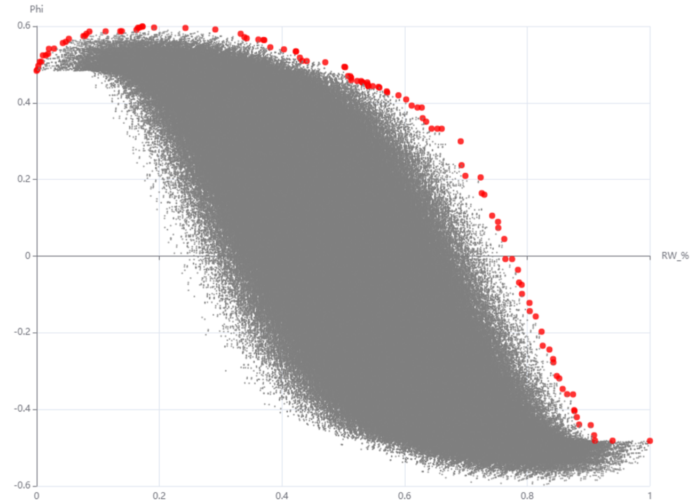


FIGURE 9: Global Pareto analysis of the full field-scale decommissioning problem, considering all equipment groups across Zones 1 and 2 simultaneously. Each gray point represents one feasible decommissioning configuration among more than 10^6 evaluated alternatives, plotted as a function of the PROMETHEE net preference flow ϕ and the percentage of subsea weight removed (WR%). Red points identify Pareto-efficient solutions, for which no other configuration achieves both a higher multicriteria performance (ϕ) and a lower removal effort. The resulting Pareto front reveals a continuous efficiency boundary spanning hybrid configurations with partial removal, while confirming that extreme strategies characterized by either minimal or near-total removal are dominated at the field scale.

id:165946 achieves ϕ = 48.2% at WR%= 46%. These results confirm that beyond moderate intervention levels, additional removal yields progressively smaller gains—or even losses—in multicriteria performance.

Pure TSIS configurations appear at both ends of the efficient set. At low intervention levels (id:1), TSIS achieves a moderate ϕ of 41.2% with zero removal, remaining competitive but clearly suboptimal compared to the best hybrid solutions. At the opposite extreme, full removal (id:1048576) results in a strongly negative ϕ of −41.1% despite WR%= 100%, confirming the dominance of penalty effects at excessive intervention levels.

Overall, the global analysis confirms that the dominance of hybrid decommissioning strategies is not an artifact of zone-level decomposition. The convergence of global Pareto structure and quantitative performance indicators demonstrates that selective, partial removal strategies occupy the most efficient region of the full field-scale decision space, thereby validating both the scalability of the proposed MCDA framework and the robustness of the conclusions derived from zone-based analyses.

From a regulatory perspective, the identification of Pareto-efficient hybrid decommissioning strategies provides structured technical evidence to support comparative assessment and regulatory dialogue. Rather than prescribing a single optimal solution, the framework enables the transparent exploration of non-dominated alternatives that balance environmental, safety, and operational considerations, while excluding clearly inefficient options. Large-scale dominance analysis thus supports the technical justification of partial-removal strategies without replacing regulatory judgment or approval processes.

5.8. Limitations and Practical Implications

The contribution of this study is primarily methodological, demonstrating the feasibility, scalability, and interpretability of large-scale MCDA combined with Pareto dominance analysis for offshore decommissioning problems. The Marlim Field application is used as an *ex post* validation case and did not directly inform or implement an operational decommissioning decision. Consequently, the results should be interpreted as decision-support evidence rather than prescriptive outcomes.

6. CONCLUSIONS AND FUTURE WORK

This study presented a comprehensive multicriteria decision analysis framework for the evaluation of offshore decommissioning strategies, applied to the Marlim Field as a large-scale, real-world case study. By explicitly modeling all possible combinations of stay-in-situ (TSIS) and total removal by reverse reel-lay (TRRL) decisions across multiple equipment groups and environmental zones, the framework enabled the systematic assessment of more than 10^6 field-scale decommissioning configurations.

While the Marlim Field application is conducted *ex post*, the MCDA framework has been designed for prospective use and is currently employed in decision-support activities for other offshore decommissioning projects in Brazil. The retrospective nature of the P-33 case study provides a robust validation environment, allowing the methodology to be tested against a fully characterized system without influencing operational outcomes.

At the case-study level, the results consistently demonstrate that neither full removal nor full permanence constitutes an optimal decommissioning strategy. Across zone-based analyses, global Pareto frontiers, and criterion-level contribution decompositions, hybrid configurations combining selective removal with stay-in-situ decisions systematically dominate extreme strategies. The best-performing alternatives achieve high multicriteria performance while limiting removal effort to moderate levels, thereby avoiding the strong penalties associated with excessive intervention. These findings remain robust when extending the analysis from individual environmental zones to the full field-scale configuration space, confirming that the observed dominance patterns are not artifacts of spatial decomposition or local weighting effects.

From a methodological perspective, the proposed framework addresses a key gap in the decommissioning literature, where decision-making approaches are often limited to a small number of preselected scenarios, simplified criteria aggregation, or qualitative trade-off arguments. By combining exhaustive combinatorial modeling, PROMETHEE-based multicriteria ranking, Pareto dominance analysis, and contribution-level interpretation tools, the framework provides a transparent and scalable decision-support methodology capable of handling highly complex decommissioning problems. Importantly, the absence of heuristic pre-filtering ensures that efficient solutions emerge directly from the multicriteria formulation, rather than from modeling assumptions.

Beyond the specific case of the Marlim Field, the results contribute to the broader scientific understanding of offshore decommissioning by demonstrating that sustainability-optimal solutions emerge from balanced, partial intervention strategies rather than from maximal technical action. The proposed approach offers a rigorous quantitative basis for comparing alternative decommissioning pathways and supports evidence-based justification of selective removal strategies, in line with regulatory frameworks that allow technically and environmentally justified deviations from full removal requirements.

Future work will focus on two complementary extensions of the proposed framework. First, uncertainty in criteria weights, performance indicators, and environmental sensitivity classifications will be explicitly incorporated to assess the robustness of the identified efficient regions and dominance relationships. Second, constraint-based pruning strategies reflecting technical feasibility, regulatory requirements, and environmental exclusions will be introduced to systematically reduce the dimensionality of the configuration space, enabling efficient exploration of even larger and more complex decommissioning problems without compromising decision transparency.

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APPENDIX A. PREFERENCE RANKING ORGANIZATION METHOD FOR ENRICHMENT EVALUATIONS (PROMETHEE)

When choosing decomissioning alternatives, options typically exhibit a variety of advantages and disadvantages across multiple criteria. To manage this complexity, Multiple Criteria Decision Analysis (MCDA), also known as Multiple Criteria Decision Making (MCDM), is utilized. This approach helps to structure decision-making problems, highlight trade-offs, and improve transparency in the decision process. MCDA is especially valuable for interpreting comparative analyses and evaluating the importance of different parameters.

To address the complexities inherent in decision-making for GHG policies, we have chosen the PROMETHEE method (Preference Ranking Organization Method for Enrichment Evaluations). Created by Brans et al. [27], PROMETHEE is considered renowned for its effectiveness in handling multi-criteria decision challenges. This method allows for the systematic ranking of alternatives through a process that includes pairwise comparisons, the computation of aggregated preference indices, and the determination of outranking flows. This structured approach ensures a thorough evaluation of all available options, grounding

TABLE 5: Representative Pareto-efficient decommissioning configurations selected from the full field-scale analysis combining Zones 1 and 2. Each row corresponds to one field-scale configuration identified on the global Pareto frontier (Fig. 9), illustrating different trade-off regions between multicriteria performance and intervention effort. Columns G111–G262 indicate the selected decommissioning option for each equipment group, where a filled circle (●) denotes a stay-in-situ (TSIS) decision and an empty circle (○) denotes total removal by reverse reel-lay (TRRL). HYB indicates hybrid configurations combining TSIS and TRRL decisions across equipment groups. The PROMETHEE net preference flow ϕ represents the global multicriteria performance indicator, WR% denotes the percentage of total subsea weight removed, and OPT% is a composite efficiency metric combining normalized ϕ and removal effort.

Id	Alt.	G111	G112	G113	G131	G141	G142	G152	G161	G162	G163	G211	G212	G222	G232	G241	G242	G243	G251	G252	G262	ϕ	WR%	OPT%
1	TSIS	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	●	41.2%	0%	20.6%
43034	HYB	○	●	●	○	○	●	●	●	●	●	●	○	●	○	●	○	●	●	●	●	58.0%	17%	37.6%
135268	HYB	○	○	●	●	●	○	○	●	●	●	●	●	○	●	●	●	●	○	●	●	32.3%	63%	47.5%
165914	HYB	○	●	●	○	○	●	●	●	●	●	●	○	●	●	●	○	●	○	●	●	57.1%	29%	43.1%
165946	HYB	○	●	●	○	○	○	●	●	●	●	●	○	●	●	●	○	●	○	●	●	48.2%	46%	47.2%
397436	HYB	○	○	●	○	○	○	○	●	●	●	●	●	○	●	●	●	●	○	○	●	1.6%	76%	38.9%
1048576	TRRL	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	-41.1%	100%	29.5%

the decision-making process in a rigorous and methodical framework, [28].

The MCDA method prioritizes the alternatives for the model once all parameters and values are specified. This method utilizes pairwise comparisons. Consider the multicriteria problem defined in equation 1, where A represents a finite set of possible alternatives $a_1, a_2, ..., a_i, ..., a_n$, and $g_1(\cdot), g_2(\cdot), ..., g_j(\cdot), ..., g_k(\cdot)$ denotes a set of evaluation criteria. It is permissible to maximize some criteria while minimizing others. The goal of the decision maker is to identify an alternative that optimally balances all criteria.

$$\max\{g_1(a), g_2(a), ..., g_j(a), ..., g_k(a) | a \in A\} \tag{1}$$

Initially, the algorithm computes the *aggregated preference indices*, and subsequently determines the *outranking flows*.

To define the *aggregated preference indices*, consider a and b as two distinct alternatives $\in A$, which is a finite set of potential options. The extent of the deviations between the evaluations of these alternatives for each criterion can be represented by equation 2.

$$d_j(a,b) = g_j(a) - g_j(b) \tag{2}$$

Given that k represents the total number of criteria, w_j is a vector of weights (indicating relative importance – the higher the weight, the more significant the criterion) subject to equation 3, and $P_j(a,b)$ is a preference function, we can express equation 5. For criteria that need to be minimized, the preference function should be inverted as shown in equation 4.

$$\sum_{j=1}^{k} w_j = 1 \tag{3}$$

$$P_j(a,b) = \begin{cases} F_j\{(d_j(a,b)\} & \text{if maximized} \\ F_j\{-d_j(a,b)\} & \text{if minimized} \end{cases} \tag{4}$$

$$\begin{cases} \pi(a,b) = \sum_{j=1}^{k} P_j(a,b) \cdot w_j \\ \pi(b,a) = \sum_{j=1}^{k} P_j(b,a) \cdot w_j \end{cases} \tag{5}$$

Where $\pi(a,b)$, referred to as the *aggregated preference index*, indicates the extent to which a is preferred over b across all criteria, and $\pi(b,a)$ reflects the preference of b over a. Generally, there are some criteria where a outperforms b, and others where b outperforms a, resulting in both $\pi(a,b)$ and $\pi(b,a)$ being positive.

In this study, three types of preference function have been utilized. The first is the usual criterion preference function, as defined by equation 6 and illustrated in Fig. 10a.

$$P_j(a,b) = \begin{cases} 0 & \text{if } d_j(a,b) \le 0 \\ 1 & \text{if } d_j(a,b) > 0 \end{cases} \tag{6}$$

The second is the V-shaped criterion preference function, as defined by equation 7 and illustrated in Fig. 10b.

$$P_j(a,b) = \begin{cases} \frac{d}{p} & \text{if } d_j(a,b) \le p \\ 1 & \text{if } d_j(a,b) > p \end{cases} \tag{7}$$

The third is the linear criterion preference function, as defined by equation 8 and illustrated in Fig.10c

$$P_j(a,b) = \begin{cases} 0 & \text{if } d_j(a,b) \le 0 \\ \frac{d}{p} & \text{if } 0 \le d \le p \\ 1 & \text{if } d_j(a,b) > p \end{cases} \tag{8}$$

The properties described in equation 9 hold for all $(a,b) \in A$. Therefore, it is clear that $\pi(a,b)$ close to 0 implies a weak global preference of a over b and $\pi(a,b)$ close to 1 implies a strong global preference of a over b.

$$\begin{cases} \pi(a,a) = 0 \\ 0 \le \pi(a,b) \le 1 \\ 0 \le \pi(b,a) \le 1 \\ 0 \le \pi(a,b) + \pi(b,a) \le 1 \end{cases} \tag{9}$$

Taking into account that n is the total number of alternatives and each alternative a faces $(n-1)$ other alternatives in A, we can define *outranking flow* by writing the equation 10.

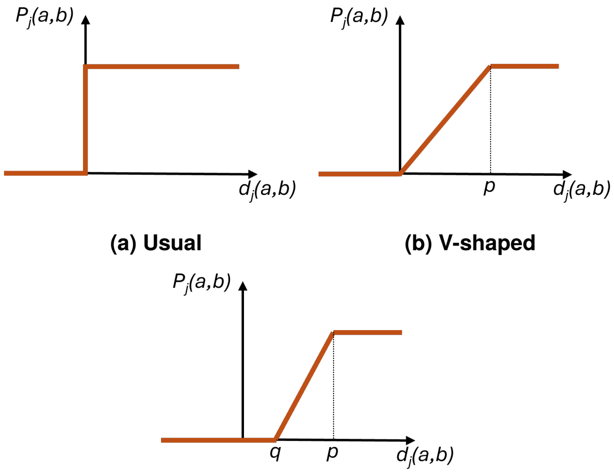

FIGURE 10: Preference functions used in this study.

$$\begin{cases} \phi^+(a) = \frac{1}{n-1} \sum_{x \in A} \pi(a,x) \\ \phi^-(a) = \frac{1}{n-1} \sum_{x \in A} \pi(x,a) \end{cases} \tag{10}$$

The positive outranking flow expresses how an alternative a ranks above all others. It is its **strength**, its outranking character. The higher $\phi^+(a)$, the better the alternative. The negative outranking flow expresses how an alternative a is outranked by all others. It is its **weakness**, its outranked character. The lower $\phi^-(a)$, the better the alternative. It is often the case that the decision-maker requests a complete ranking. The *net outranking flow* can then be considered by equation 11.

$$\phi(a) = \phi^+(a) - \phi^-(a) \tag{11}$$

It is the balance between the positive and negative outranking flows. The higher the net outranking flow ϕ, the better the alternative.

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