Preference-Based Optimisation in Group Decision-Making

Addendum to Chapter 6 of

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Summary

This Addendum extends, broadens, and optimises IMAP/ODESYS 1.0, originally presented in Chapter 6 of Open Design Systems (Wolfert, 2023). It enhances its applicability and repositions ODESYS within the landscape of contemporary research and practice. A concise summary is provided, followed by the introduction of the ODESYS structure-in-FIVES formulation: a novel Open Design & Decision Systems framework.

Pure multi-objective optimisation for group decision-making requires a preference-based approach, as stakeholder preferences constitute the only legitimate foundation for choice. A decision-valid solver must satisfy four key conditions: (1) Preference-Key — all objectives, constraints, and trade-offs are evaluated in the preference domain and aggregated without loss of meaning; (2) Integration — system capability ("can") and acceptable stakeholder preferences ("want") coexist within a single design–decision space; (3) Association — individual interests and their relative importance are represented as integrative, weighted preference functions; and (4) Uniqueness — the solver produces a consistent, single best-fit-for-common-purpose solution.

The IMAP (Integrative Maximisation of Aggregated Preferences) solver was developed to satisfy these requirements in complex open design system (ODESYS) contexts, enabling truly integrative multi-objective design optimisation (MODO). Its latest extension within the ODESYS/FIVES framework operationalises affine preference aggregation explicitly and, through the structure-in-FIVES formulation, broadens and simplifies applicability across complex design–decision system contexts, while preserving previously validated design outcomes. Unlike classical CP-, MOO-, or MIP-based methods, which may return numerically optimal solutions or Pareto fronts that do not directly support decision-making, ODESYS resolves heterogeneity by mapping all system behaviour into a common preference domain, in which only goal-oriented preference behaviour is represented and aggregated directly via preference function modelling (PFM), rather than separate objective functions subject to independent minimisation or maximisation. This enables the framework to confront systemic complexity, accommodate multiple actors with differing priorities, and produce a single, fully decision-valid solution — even for highly constrained combinatorial group decision-making problems.

Two illustrative applications demonstrate the methodology: a simplified marine installation design–decision problem and a highly constrained dynamic vessel allocation problem. The results demonstrate that ODESYS produces a unique, preference-consistent, and decision-theoretically sound solution that fully integrates stakeholder preferences across multiple objectives. By doing so, it transforms complex optimisation problems into genuine decision games, where trade-offs, individual freedom, and common purpose are coherently synthesised, delivering a best-fit-for-and-from-the-whole within socio-physical reach.

Introduction

Across systems engineering, design, and decision science, multi-objective optimisation (MOO) is widely recognised as a core group decision-support activity for confronting complexity. Contemporary multifaceted problems involve heterogeneous objectives—e.g., availability, affordability, sustainability, and beauty value—evaluated by multiple stakeholders operating under uncertainty and dynamic conditions. Optimisation methods must therefore move beyond purely physical engineering performance metrics and explicitly incorporate stakeholder preferences (synonymous with utility or value), as only these provide a valid basis for goal-oriented choice. Any separation between optimisation and preference evaluation undermines the design–decision outcome, since only the subject can set objectives and as the basis for decisions, never the object.

Early foundational work, such as Decision-Based Design (DBD) (Hazelrigg, 1998), Value Engineering (King, 2000), and utility-based design formulations (Thurston, 2011), established the conceptual necessity of preference-aware multi-criteria decision-making (MCDM), highlighting that optimisation without explicit value modelling cannot support rational choice. However, these approaches fail to model preferences as a rigorous basis for group decision-making. Subsequent studies formalised preference measurement, most notably Barzilai's Preference Function Modelling (PFM) theory (Barzilai, 2010, 2022), which demonstrates that preferences reside in a one-dimensional affine space and that admissible transformations are strictly affine. Despite this, many commonly used aggregation practices remain mathematically invalid or decision-ambiguous. Recently, in (Wolfert, 2026), a mathematically valid method has been demonstrated for unique preference aggregation in MCDM using PFM.

Classical engineering optimisation texts (Martins & Ning, 2022) and systems engineering reference (Blanchard & Fabrycky, 2021) present a wide range of numerical optimisation techniques—including multi-objective methods—but focus on algorithmic solutions (scalarisation, ε-constraint methods, or Pareto-based heuristics) rather than mathematically valid, preference-based MCDM. Similarly, management science texts (Hillier & Lieberman, 2021) address multi-objective decision-making using weighted sums, lexicographic ordering, or Pareto dominance. This gap persists in contemporary literature (Pajasmaa et al., 2025), highlighting the need for a framework that fully integrates preference, acceptability, performance, and feasibility while explicitly identifying a design–decision vector that integratively maximises aggregated preference, resolving aggregation inconsistencies as highlighted by (Ferdous et al., 2024).

In practice, multi-objective optimisation for multi-constrained complex problems typically uses linear or mixed-integer programming (LP, MIP), hybrid MOO–MCDM frameworks, and/or constraint programming (CP), realised through weighted additive ranking models, ε-constraint formulations, lexicographic ordering, Pareto sets, and/or hierarchical pruning. While these methods may yield numerical solutions under specific parameter settings, the results are often Pareto sets or single optima lacking preference meaning. They solve optimisation problems but do not constitute pure design–decision solutions: they aggregate performance measures rather than human, goal-oriented preferences. More formally, they may produce a numerical optimum, but not a unique best-fit-for-common-purpose decision.

To support the line of argumentation above, the following sections first provide an overview of contemporary MOO methods for group decision-making, then highlight research and practice gaps, and finally present the development statement, including four conditions for preference-based optimisation that enable pure group decision-making.

Contemporary MOO for group decision-making overview

Persistent separation of preferences and system performance behaviour remains a fundamental limitation of classical optimisation approaches. Preferences are typically treated as evaluative overlays applied after technical feasibility has been established, rather than being embedded within a unified design–decision solution space. This separation persists in preference-aware Bayesian optimisation (Ahmadianshalchi et al., 2023), prompt-driven generative design systems (Chen & Xu, 2025), and early work on dynamic preferences (Arezoomand, 2021; Kim et al., 2014; Regenwetter et al., 2022; Saadi et al., 2024). Likewise, interactive evolutionary algorithms (Branke et al., 2016; Thiele et al., 2009), Choquet integral-based methods (Hou et al., 2020), and ordinal classification or constraint-reformulation approaches (Castellanos-Alvarez et al., 2021) incorporate preferences, yet still prioritise feasibility and performance exploration. When feasible system performance (capability: "what it can") and acceptable stakeholder preferences (desirability: "what is wanted") are not represented within a single integrative design–decision space, changes in feasibility, acceptability, project state, or uncertainty fail to propagate coherently through decision evaluation. This limits applicability in dynamic, real-world contexts and results in fragmented solution spaces in which no convergent best-fit solution may exist.

Stakeholders and actor dynamics have become a central theme in post-2010 research, reflecting growing recognition of the socio-technical nature of design decisions and the importance of stakeholder involvement: e.g., (Arkesteijn et al., 2017; Yang et al., 2022; Zhilyaev et al., 2022). Participative, negotiation-based, and group decision-making frameworks improve descriptive realism (Chou et al., 2021; Du & Jiao, 2022; Lagaros et al., 2023; Pérez et al., 2023; Qiao et al., 2024; Rahimi et al., 2022; Shavazipour, 2025), yet preferences are typically treated as episodic inputs rather than as dynamic variables integrated throughout optimisation. Optimisation and decision-making therefore remain conceptually and mathematically segregated, lacking fully transparent and associative integration (Adekoya & Helbig, 2023; Chen & Xu, 2025). Consequently, while contemporary works (Wang et al., 2025; Zhilyaev et al., 2022) have provided initial steps toward integration, a fully unified incorporation of engineering performance, system feasibility, stakeholder preferences, and system acceptability within a single associative preference-based design–decision space remains largely absent from mainstream MOO practice. This leaves the a priori identification of the best-fit-for-common-purpose solution untapped, stakeholder needs insufficiently integrated, and the notion of a free, best-for-project choice vulnerable to becoming curated and illusory.

The absence of a unified preference domain for heterogeneous objectives remains a core limitation in multi-objective optimisation (MOO). Methods either resort to hierarchical, semi-multi-objective formulations or rely on monetisation as a workaround for commensurability, despite longstanding critiques from decision theory, cost–benefit-focused design, and socio-technical research: e.g., (Du & Jiao, 2022; Hirsch Hadorn, 2022)). Even recent hybrid MOO–MCDM frameworks still layer additional a posteriori MCDM steps to reconcile fundamentally incomparable objectives (Chen & Xu, 2025; Ferdous et al., 2024). Although explicit preference modelling is increasingly recognised as essential, systematic use of continuous, individually weighted preference functions grounded in rigorous measurement theory—and applicable across economic, technical, environmental, and social dimensions—remains rare. Notable recent efforts, such as in (Wang et al., 2025), make progress by avoiding ideal point estimation and integrating surrogate-assisted search with preference cues for expensive MOO problems, yet they remain objective-anchored and set-oriented rather than providing a fully associative, decision-valid preference domain (Arezoomand, 2021; Lee et al., 2011; Messac, 1996; Saadi et al., 2024; Wang et al., 2025). In practice, heterogeneous objectives are treated in isolated spaces, with commensurability enforced via scaling, weighting, or dominance filtering rather than a unified preference domain. This confirms that the lack of a common preference domain is a persistent, cross-methodological challenge rooted in fundamental decision-theoretic limits, not mere algorithmic detail (Gunantara, 2018).

Unique preference aggregation is central to MOO–MCDM, as its mathematical validity determines the meaningfulness of decision outcomes. Most classical and post-2010 MOO–MCDM frameworks nevertheless rely on normalisation, weighted sums, surrogate scores, or composite indices (Adekoya & Helbig, 2023; Dehshiri et al., 2022; Ferdous et al., 2024; Kaddani et al., 2017; Zeng et al., 2025), implicitly assuming ratio- or interval-scale properties that preference data do not possess. Preference, however, is not a physical property but a subjective construct of the mind, expressing an individual's free ordering of available alternatives within a given context and defining a decision space that is inherently relational, individual, and situation-dependent. More expressive methods—such as discrete choice models, network-based decision frameworks, and probabilistic preference embeddings (Sha et al., 2023)—increase representational or situational richness without resolving this foundational measurement inconsistency. Likewise, weighted aggregation with partial preference information, fuzzy–stochastic methods, and Pareto-front transformations continue to rely on normalisation, fuzzy membership functions, or transformed dominance relations—approaches that are operationally convenient yet methodologically fragile.Consequently, mathematically admissible and preference-consistent aggregation remains rare. Recent analyses (Pajasmaa et al., 2025) confirm that none of these approaches simultaneously satisfy the axioms of rigorous preference function modeling (PFM). The PFM theory establishes that only differences between preference values are meaningful, admissible transformations are affine, and aggregation must preserve zero-reference stability and commensurability (Barzilai, 2010, 2022; Wolfert, 2026).

Pareto remains the dominant epistemic anchor in multi-objective optimisation (Marler & Arora, 2004), including contemporary preference-aware variants (Ahmadianshalchi et al., 2023; Pajasmaa et al., 2025; Zhao et al., 2025). Most methods terminate in Pareto sets requiring a posteriori selection, negotiation, or heuristic filtering. As a dominance concept rather than a decision principle, Pareto optimality identifies non-inferior alternatives but cannot yield a unique, actionable solution, whereas real-world design and governance demand a single best-fit-for-common-purpose outcome. Even approaches that enhance Pareto-front quality or define "elite" solutions—such as interactive evolutionary algorithms (Thiele et al., 2009), heuristic Pareto-front management (Kesireddy & Medrano, 2024), and hybrid aggregation-transform techniques (Zeng et al., 2025)—still produce sets or ranked subsets. Reviews like (Gunantara, 2018) show Pareto-dominance-based sets dominate MOO, with preferences applied post hoc via weights, constraints, or surrogate indices. Pareto fronts are often mathematically flawed and yield infinite, supposedly equal alternatives, inconsistent with stakeholder-interpreted, single optimal solutions: e.g., (Bai et al., 2015; Golany et al., 2006; Saad et al., 2018), amongst others. Hybrid methods remain a posteriori, confirming the persistent absence of a unified preference domain (Gunantara, 2018).

Emerging preference-based optimisation research challenges traditional dominance-based constructs, including ideal and nadir points (Zhao et al., 2025), signalling a shift toward more explicitly preference-aware optimisation paradigms. Advanced approaches—such as interactive evolutionary algorithms (Branke et al., 2016), constraint-enhanced preference integration (Hou et al., 2020), and recent expensive preference-guided MOO methods (PMEGO) that avoid ideal points (Wang et al., 2025)—improve the incorporation of stakeholder objectives and enable representation of complex criterion interactions. However, even these state-of-the-art methods do not satisfy the axioms of mathematically valid preference aggregation (Pajasmaa et al., 2025; Wolfert, 2026). They remain fundamentally Pareto-set or interaction-based: preferences steer, restrict, or filter candidate solutions, but are not structurally inseparable from system behaviour, nor do they produce a unique, decision-theoretically grounded outcome. Despite growing recognition of preference awareness, pure preference-based optimisation —mathematically valid, preference-meaningful, non-monetary, non-Pareto-based, and capable of yielding a single best-fit-for-common-purpose solution— remains absent from mainstream design and project management practice.

To date, and to the best of the author's knowledge, the IMAP Open Design Systems–driven method is the only approach that operationalises such integrative and associative preference-based optimisation (van Heukelum et al., 2024; Wolfert, 2023), and this paper further extends IMAP to an even broader range of group design-decision applications, confronting systems complexity.

Research Gap

From the above, foundational and contemporary literature converge into a coherent picture of persistent limitations in multi-objective design optimisation. While preference-based design is conceptually acknowledged as necessary, current methods remain incomplete. Pareto-dominance approaches structure search but cannot produce unique, actionable decisions; preferences often guide exploration without being fully integrated; aggregation methods frequently violate measurement-theoretic principles; and decision-making is deferred to episodic heuristics or facilitation rather than continuously embedded.

Some early and contemporary frameworks, such as ODESYS, have advanced the field by introducing a unique preference-over-performance domain that formally integrates individual stakeholder preferences with feasible objectives. Nevertheless, these approaches remain partially objective-anchored, and their application to highly constrained socio-physical systems is limited. Taken together, this highlights a clear gap: no framework yet exists that fully realises a dynamically adaptive, mathematically rigorous preference-driven design-decision space, capable of integrating system performance, stakeholder desirability, feasibility, and uncertainty into a single best-fit-for-common-purpose solution.

Practice Gap

Besides the scientific research gap, industry and public-sector practice faces a parallel challenge: there is no widely adopted methodology that fully integrates system capability, stakeholder preferences, and feasible design freedom within a single, decision-valid framework. Existing approaches remain fragmented, privileging either technical potential (what the system can do) or stakeholder desire (what actors want) without resolving the tension between them. Object-driven optimisation rigorously models technical performance but cannot generate meaningful decisions, as objects do not choose, value, or prioritise and are therefore purposeless from a decision-making standpoint. Subject-driven methods—such as a posteriori ranking of pre-generated alternatives—simulate choice without guaranteeing identification of the best-fit-for-common-purpose solution. Stakeholders are confined to curated options, limiting decision freedom and potentially compromising outcomes. Participative preference elicitation must therefore be intrinsic to the optimisation formulation itself, enabling stakeholders not merely to select among predefined alternatives but to co-design for the best-fit-for-common-purpose. Practitioners require methods that embed capability and desirability within a shared, associative decision space. This enables substantiated, transparent decision-making, allowing actors to confront complex socio-technical constraints and achieve synthesis rather than forced compromise. Individual design freedom can coexist with collective alignment, comparability, and legitimacy, ensuring that the globally optimal solution is identifiable a priori. Explicit preference functions, traceability, and integrated evaluation are essential for iterative reflection, negotiation, and adaptation across high-dimensional, socio-technical design spaces. In short, the practice gap lies in the absence of frameworks capable of concurrent, associative, and fully integrative decision-making, where stakeholder preferences, system feasibility, and performance converge to yield unique, best-fit-for-common-purpose solutions, while maintaining transparency, substantiation, and the capacity to confront complexity.

Development Statement

The limitations identified in both research and practice directly motivate the further evolution of the IMAP (Integrative Maximisation of Aggregated Preferences) solver and the early ODESYS framework (van Heukelum et al., 2024; Wolfert, 2023), which integrated acceptable stakeholder preferences and feasible system performance within a unified preference domain capable of producing a PFM-consistent best-fit design point. While 'ODESYS/IMAP 1.0' already delivered robust results, these earlier formulations remained partially anchored to conventional multi-objective thinking. The radical potential of a **pure performance–preference approach**, removing the objective layer and enabling fully associative, decision-valid MCDM for highly constrained system contexts, is now realized in an extended ODESYS operator that is both simplified and optimized, preserves previously validated design-decision outcomes, and broadens applicability across complex, socio-physical system contexts. So formally, the development statement here can be expressed as:

"There is a need for an open, integrative design–decision methodology that enables complex systems development across all relevant system levels, grounded in mathematically valid preference-based optimisation over system performance dimensions, and supporting transparent, associative group decision-making."

To realise this rigorously, a MOO method produces a unique, best-fit-for-common-purpose MCDM outcome if and only if it satisfies the following four formal conditions. These conditions define group decision-valid, preference-based optimisation for complex design–decision systems.

Condition 1 — Preference-Key

A multi-objective optimisation method is decision-valid only if all objectives, constraints, and trade-offs are represented and evaluated in the preference domain using a mathematically valid preference function model. Methods that rely on objective-space dominance relations (e.g., Pareto fronts), surrogate metrics, or preference-free scoring are decision-indeterminate.

Condition 2 — Integration
Feasible system performance (capability: "what it can") and acceptable stakeholder preferences (desirability: "what they want") shall reside in a single integrative design–decision solution space. The immediately physical-given—representing the system's degrees of freedom—must be integrated with the human will, expressed through individual preferences of free choice; only then can optimisation culminate in genuine design–decision synthesis.

Condition 3 — Association
Individual interests and their relative importance shall be represented as integrative, weighted preference-over-performance functions, within which each stakeholder is free to specify their own preference representation and acceptable limits over the feasible solution space. This formulation enables coherent cooperation and active participation across multiple actors and performance dimensions, aiming at a best-for-group decision defined as the maximisation of aggregated preference. Only within such an associative framework does the group-optimal decision emerge. Here, aggregated preference increases as individual stakeholders moderate exclusive insistence on their own preferred outcomes.

Condition 4 — Uniqueness
A decision-valid optimisation method shall yield a consistent, unique best-fit-for-common-purpose solution that is invariant under admissible transformations of preferences and remains meaningful. Optimisation methods that return sets of non-equivalent solutions are numerical constructs that fail to support group decision-making.

Taking these as a starting point and building on recent ODESYS/IMAP 1.0 developments, the novel ODESYS structure in FIVES transforms preference-guided optimisation into a fully associative, decision-valid method for complex systems development. It rigorously adheres to the four formal MOO group decision-validity conditions and preserves previously validated ODESYS outcomes. Moreover, it enables solutions to highly constrained, socio-physical design–decision problems, moving beyond the forced compromises inherent in conventional multi-objective, constraint-, or Pareto-based optimisation methods to achieve genuine best-fit-for-common-purpose synthesis.

1. Open design and decision system

Let a complex, multifaceted problem, comprising multiple objects and subjects, be formulated as an open design and decision system (ODESYS) synthesis operator:

$$\mathrm{OD}\Big(P_{k,i}(\mathbf{F}(\mathbf{x},\mathbf{y},t));\ w'_{k,i}\Big), \qquad (\mathbf{x},\mathbf{y}) \in S_{f,a}. \tag{1}$$

Here, $\mathbf{F} = F_i(\mathbf{x},\mathbf{y},t)$, with $i = 1,\ldots,I$ (where I is the total number of performance functions), denotes the system performance functions that describe the socio-physical functional behavior of the system — i.e., the system capabilities. These functions represent what the system *can* perform within the design and decision systems solution space $S_{f,a}$.
The vector $\mathbf{x}$ represents the 'controllable' design-decision vector, comprising both product and process variables that can be deliberately selected and adjusted by the decision maker. The vector $\mathbf{y}$ is the 'uncontrollable' parameter vector, containing contextual variables, including external product and process conditions that influence system behaviour but cannot

be controlled. The variable t represents the system state in time. Depending on the nature of the design problem, time may be explicitly modeled, yielding a time-dependent performance $\mathbf{F}(\mathbf{x}, \mathbf{y}, t)$; it may be fixed to a decision horizon $t = T^*$; or it may be absent, in which case the formulation reduces to $\mathbf{F}(\mathbf{x}, \mathbf{y})$.

In contrast to traditional optimisation approaches, these performance functions over the design-decision vector do not represent objectives by themselves. Goal-oriented decision-making is only enabled by transforming the performance functions into preference functions, given by the actor and allowing stakeholder-specific trade-offs to be evaluated within the ODESYS framework.

The preference function $P_{k,i}(\cdot)$ reflects the preference of a decision-making stakeholder $k = 1, \ldots, K$ ($K =$ max. number of actors) with respect to performance function F_i. A preference expresses the relative desirability, *value*, or *utility* of a design alternative or decision option with respect to a functional performance, given its global participation and its local (weight) importance $w'_{k,i}$ across performance functions, where $\sum_i w'_{k,i} = 1$. When the stakeholder has no interest in a certain performance function, its weight is zero. The preferences function are determined by the individual actors themselves, allowing the preference function to be linear, non-linear, convex, concave, or piecewise.

Preference is not a physical property, but a subjective construct representing an individual's choices, thereby defining the decision space. The preference function $P_{k,i}$ maps an actor-independent performance value $f_i(\mathbf{x}, \mathbf{y}, t)$ to a corresponding preference score, reflecting the goal-oriented evaluation of actor k:

$$P_{k,i}\big(f_i(\mathbf{x}, \mathbf{y}, t)\big) \in [0, 100].$$

The relatively worst performance (minimum, least preferred) and best performance (maximum, most preferred) are assigned scores of 0 and 100, respectively (an arbitrary preference reference choice, since preferences have only relative meaning as part of a one-dimensional affine space (Wolfert, 2026)).

The ODESYS system is constrained by hard constraints, such as domain, activity, sequencing, path, and physical constraints, which define the *feasibility* of system behaviour:

$$g_f(\mathbf{F}) := \mathbf{F}(\mathbf{x}, \mathbf{y}, t) - \overline{\mathbf{F}} \leq 0. \tag{2}$$

These hard constraints are typically non-negotiable, as they cannot be changed by the actor (decision maker).

The decision maker can further define constraints on the *acceptability* of solutions through soft ('negotiable') constraints, which are expressed entirely in terms of stakeholder preference. Any implicit performance limits arise solely from the actor's choice of reference points used to construct the preference functions, rather than from explicit bounds imposed directly on the performance functions.

For each performance function f_i, the actor can define an individual reference interval

$$[\, f_i^{\text{loc}}\, ;\, f_i^{\text{upc}}\,] \subseteq [\, f_i^{\min}\, ;\, f_i^{\max}\,],$$

where $f_i^{\min}$ and $f_i^{\max}$ denote the global minimum and maximum of f_i over the feasible system space $\mathcal{S}_f$. The endpoints of this acceptability interval, $(f_i^{\text{loc}}, f_i^{\text{upc}})$, are associated with preference scores of 100 ("best") and 0 ("worst"), while the mapping of intermediate values is left unconstrained, reflecting the individual actor's preference function over the corresponding performance dimension. The acceptability of a system solution can now be expressed as

$$g_a\big(P_{k,i}(\mathbf{F})\big) := P_{k,i}(\mathbf{F}) - \overline{P}_{k,i} \geq 0, \tag{3}$$

where $\overline{P}_{k,i}$ denotes the minimum acceptable preference (typically 0, though the actor can choose to consider only solutions for which $P_{k,i} > \overline{P}_{k,i}$), and where the resulting preference functions over the performance dimensions for actor k is defined as

$$P_{k,i}\big(f_i(\mathbf{x},\mathbf{y},t)\big) \in [0,100], \quad \text{with } f_i(\mathbf{x},\mathbf{y},t) \in [f_i^{\text{loc}}, f_i^{\text{upc}}] \subseteq [\, f_i^{\min}\, ;\, f_i^{\max}\,].$$

Finally, the complete design–decision system solution space is defined as

$$\mathcal{S}_{f,a} := \{\mathbf{x} \mid g_f(\mathbf{x},\mathbf{y},t) \leq 0 \ \wedge \ g_a(P_{k,i}(\mathbf{F})) \geq 0\}\,. \tag{4}$$

Notes:
(1) By distinguishing *objectively measurable performance functions* (e.g., traffic or noise hindrance, determined by the decision vector $\mathbf{x}$) from *subjectively assessed functions* (e.g., costs or aesthetics, evaluated according to stakeholder perception), system performance can be embedded within a design–decision framework, thereby linking the decision vector $\mathbf{x}$ to both quantifiable outcomes and human-centered evaluations.
(2) In this formulation, objective functions are not treated as independent optimisation targets. Instead, goal orientation is fully captured through stakeholder preference functions $P_{k,i}$, which form the basis for decision-making. The actor's performance functions f_i describe what the system 'can' *capability*, while the preferences express what each actor 'wants' (*desirability*). Decisions therefore arise from the aggregation of preferences rather than from direct optimisation of the minima or maxima of f_i. Unlike classical multi-objective optimisation (MOO), which relies on numerical scaling in objective space, ODESYS handles stakeholder heterogeneity by first mapping all system behaviours into a common preference space prior to aggregation.
(3) Hard constraints define the feasible system behaviour $\mathbf{F}$ and are non-negotiable, arising from physical laws, technical limits, regulations, or environmental conditions. All non-negotiable constraints are captured by $g_f(\mathbf{x},\mathbf{y},t) \leq 0$, encompassing domain (bounds), activity, sequencing, path, and physical constraints, so explicit variable bounds $x_n \in [\text{lb}_n, \text{ub}_n]$ are unnecessary. Soft, negotiable, constraints, in contrast, act on the preference functions $P_{k,i}$ to reflect stakeholder priorities and adaptable acceptability conditions; they do not restrict feasibility but specify acceptable performance levels (lower, upper constraints). By defining an acceptability interval $[\, f_i^{\text{lob}}, f_i^{\text{upb}}\,]$, the decision maker can implicitly cap the acceptable range of system performance while keeping all acceptability reasoning entirely within preference space.

2. IMAP solver & ODESYS structure in fives

In complex socio-technical design problems, multiple stakeholders express their preferences over a set of performance functions $\mathbf{F}(\mathbf{x},\mathbf{y},t)$. Each preference function $P_{k,i}$ captures the desirability of multiple performance capabilities F_i for stakeholder k, potentially weighted by $w'_{k,i}$. To determine an optimal design decision, it is necessary to aggregate all stakeholder preferences into a single aggregated score, while ensuring that all non-negotiable feasibility constraints and negotiable acceptability conditions are respected. Formally, this so-ccalled integrative maximisation of aggregated prefrences (IMAP) constraint optimisaton statement can be expressed as:

$$\max_{\mathbf{x}} Z = \mathbf{A}\Big(P_{k,i}(\mathbf{F}(\mathbf{x}, \mathbf{y}, t));\ w'_{k,i}\Big) \tag{5}$$

where $(\mathbf{x}, \mathbf{y}) \in S_{f,a}$ is the set of design decisions satisfying all hard feasibility g_f and soft acceptability constraints g_a, and where $\mathbf{A}$ is the **a-fine-aggregator** that aggregates multiple actors preference functions integratively with their performances. Here $\mathbf{A}$ is uniquely defined as a linear weighted centroid operator of the z-normalised $P_{k,i}(\mathbf{x})$ scores: $z_{k,i}(\mathbf{x})$ (see (Wolfert, 2026) for more details on a-fine aggregation). Now we can search for a **best-fit-for-common-purpose** solution, which is the unique design and decision point $\mathbf{x}^*$ that has the highest aggregated weighted normalized preference score:

$$\mathbf{x}^* = \arg\max_{\mathbf{x}} Z(\mathbf{x}), \quad Z(\mathbf{x}) = \sum_k w'_{k,i}\, z_{k,i}(\mathbf{x}), \quad \sum_k w'_{k,i} = 1 \tag{6}$$

Solvability is defined as the existence and computability of a design decision vector $\mathbf{x}^*$ that maximises the aggregated desirability Z as an integral function of capability F , subject to hard feasibility constraints and soft acceptability conditions : i.e., Integrative Maximisation of Aggregated Preferences (IMAP). Unlike classical decidability, solvability assumes the availability of a solver and focuses on the resolution of a complex design and decision space. The resulting design-decision engine is the so-called Preferendus, a tool that determines the optimal best-fit design: i.e., that candidate solution with the highest aggregated, integrative, preference point, within the given solution space

To solve the optimisation problem underlying IMAP, the Preferendus employs a fit-for-purpose inter-generational genetic algorithm (GA). This solver is specifically designed to handle normalised preference scores and contextual rank changes inherent to preference aggregation methods such as Tetra. Instead of directly comparing successive generations, the algorithm stores the best-ranked solution of each generation and evaluates these solutions separately in an inter-generational reference set, enabling meaningful comparison of aggregated preferences over time. In addition, the GA allows for user-defined initial solutions and applies a selective re-evaluation step that excludes clearly irrelevant or non-competitive alternatives. Together, these modifications ensure robust convergence toward the design configuration that reflects the integrative maximum aggregated group preference, making the inter-generational GA the core IMAP solver engine of the Preferendus tool. This has been implemented in the open-source Preferendus solver (Teuber et al., 2025; van Heukelum et al., 2024), and is also accessible via the links provided in the Data Availability section.

NOTES:

(1) Unlike classical optimisation tools that explore a Pareto front or multiple non-dominated solutions, ODESYS identifies a *unique design–decision point* $\mathbf{x}^*$, representing the best-fit-for-common-purpose solution within an IMAP structure in FIVES.

(2) ODESYS does not rely on multiple independent min–max objectives that require numerical scaling or monetization, as in classical numerical optimisation. Instead, decision-making is entirely driven by the aggregation of stakeholder preferences, with IMAP solving searching for the integarive solution that maximizes the aggregated preference score.

(3) ODESYS can also be applied to single-objective problems. If a single preference weight $w'_{k,i} = 1$ while all other weights are zero, the IMAP aggregation reduces to a single-objective problem, where the preference directly represents this objective. In this case, the method yields a single optimal solution, analogous to a classical `MINIMIZE` or `MAXIMIZE` operation over a single objective (SOO).

(4) ODESYS' FIVES structure further extends the ODESYS/IMAP 1.0 framework to a broader spectrum of group design-decision applications, explicitly confronting systems complexity and socio-technical interactions. Building on the proven robustness of 'ODESYS/IMAP 1.0', it preserves previously validated outcomes while enabling richer integration of capability, feasibility, desirability, acceptability, and solvability across multi-actor settings.

Summary - ODESYS structure in FIVES
The ODESYS operator, describing a multi-faceted design and decision problem, is defined as

$$OD\Big(P_{k,i}(\mathbf{F}(\mathbf{x},\mathbf{y},t));\ w'_{k,i}\Big), \qquad \mathbf{x},\mathbf{y} \in S_{f,a},$$

and is structured in FIVES (with reference to all Equations in Sections 1-2):

(1) Capability (performances)	$\mathbf{F}(\mathbf{x},\mathbf{y},t)$
(2) Feasibility (constraints	$g_f(\mathbf{x},\mathbf{y},t) \leq \overline{\mathbf{F}}$
(3) Desirability (preferences	$P_{k,i}(\mathbf{F}(\mathbf{x},\mathbf{y},t))$
(4) Acceptability (constraints	$g_a(P_{k,i}(\mathbf{F}(\mathbf{x},\mathbf{y},t))) \geq \overline{P}_{k,i}$
(5) Solvability (IMAP)	$\max\limits_{\mathbf{x}} Z = \mathbf{A}(P_{k,i}(\mathbf{F}(\mathbf{x},\mathbf{y},t)); w'_{k,i})$

3. Demonstrative Examples

In this section, we present two illustrative problems to demonstrate the ODESYS structure in FIVES. The first is an integrative design–decision problem for the installation of a floating wind farm, which has been used as a demonstrator in several previous publications (Teuber et al., 2025; van Heukelum et al., 2023, 2024). The aim here is to showcase the further developed and generalised ODESYS/FIVES problem state, including explicit affine preference aggregation. For specific design–decision results, the reader is referred to the ODESYS textbook example in Chapter 8.5 (Wolfert, 2023) or to the links provided in the Data Availability section. While the results remain identical, the problem formulation presented here is novel and preserves previously validated design–decision outcomes. The second example is an allocation decision problem, developed by the globally operating marine contractor Boskalis within their AlloDyn software. Here, the FIVES structure is also presented, along with a demonstration of the modelling approach. As with the first example, this paper does not discuss specific decision vector results, as these are commercially confidential within the context of AlloDyn. Together, these examples provide a concise illustration of the ODESYS structure-in-FIVES: the first example offers a detailed, textbook-based demonstration, while the second shows its application in a highly constrained industrial vessel allocation context.

(1) Integrative design-decision problem - floating wind farm
This demonstrator addresses a complex, socio-technical installation planning problem for a floating wind farm, in which engineering design choices and operational decisions are tightly coupled with the heterogeneous and potentially conflicting interests, namely project duration, cost, fleet utilisation, and emissions. The floating wind farm installation problem,

comprising multiple vessels and two concurrent actors (an energy service provider and a marine contractor), is formulated as an open design and decision system (ODESYS) synthesis operator:

$$\mathrm{OD}\Big(P_{k,i}\big(\mathbf{F}(\mathbf{x},\mathbf{y},t)\big);\ w'_{k,i}\Big), \qquad (\mathbf{x},\mathbf{y}) \in \mathcal{S}_{f,a}, \quad k = 1..2,\ i = 1..4. \tag{7}$$

This problem is formulated as an *integrative design–decision problem*, as it simultaneously addresses decision variables related to process management (e.g. vessel selection and deployment) and engineering design choices (e.g. anchor dimensions).

Capability The system capability is represented by a four-dimensional multi-system performance vector

$$\mathbf{F}(\mathbf{x},\mathbf{y},t) = \big[f_1(\mathbf{x},\mathbf{y},t), f_2(\mathbf{x},\mathbf{y},t), f_3(\mathbf{x},\mathbf{y}), f_4(\mathbf{x},\mathbf{y},t)\big],$$

where the performance functions respectively capture project duration, installation cost, fleet utilisation, and vessel-related emissions. Time-dependence is included only where relevant, reflecting that fleet utilisation is evaluated independently of project duration, while the remaining performance functions depend on operational time.

The project is evaluated using four performance functions, denoted f_1 through f_4. The project duration performance function $f_1(x_{1..3}, \mathbf{y}, t)$ determines the total installation time in days as a function of the selected vessel types and quantities, with the overall duration emerging from a discrete event simulation (DES) that captures installation rates, deck capacities, and anchor reloading operations. The installation cost performance function $f_2(x_{1..5}, \mathbf{y}, t_{\mathrm{vessel}}(x_{1..3}))$ calculates the total project cost by combining anchor manufacturing costs (Capex) and time-dependent vessel day rates (Opex), where vessel operating times are obtained from the DES. The fleet utilisation performance function $f_3(x_{1..3}, \mathbf{y})$ evaluates the strategic suitability of the selected vessels by quantifying the combined probability that they could have been more effectively deployed on alternative projects, independent of time. Finally, the vessel emissions performance function $f_4(x_{1..3}, \mathbf{y}, t_{\mathrm{vessel}}(x_{1..3}))$ measures the total project-related CO_2 emissions by summing the time-dependent emissions of all selected vessels, with operational durations obtained from the DES.

Here the controllable decision vector and their domain constraints are defined as:

Table 1: Controllable design vector $\mathbf{x} = (x_1, \ldots, x_5)$ and domain constraints.

$\mathbf{x}$	**Description**	$g_f^{(0)}(x_i)$
x_1	Number small vessels	$0 \leq x_1 \leq 3, \;\; x_1 \in \mathbb{Z}_{\geq 0}$
x_2	Number large vessels	$0 \leq x_2 \leq 2, \;\; x_2 \in \mathbb{Z}_{\geq 0}$
x_3	Number crane barges	$0 \leq x_3 \leq 2, \;\; x_3 \in \mathbb{Z}_{\geq 0}$
x_4	Anchor diameter	$1.5 \leq x_4 \leq 4$
x_5	Anchor penetration length	$2 \leq x_5 \leq 8$

The uncontrollable parameter vector $\mathbf{y}$ comprises the working point force on the anchor, platform type, mooring configuration, anchor type, soil conditions, and mooring line properties, all of which are fixed per scenario or assumed *a priori*.

Feasibility The feasible system solution space is therefore defined as

$$\mathcal{S}_f = \left\{ (\mathbf{x}, \mathbf{y}) \;\middle|\; g_f^{(i)}(\mathbf{x}, \mathbf{y}) \leq 0,\ i = 1..2 \right\}.$$

$g_f^{(1)}$: logical constraint

$$g_f^{(1)}(\mathbf{x}) = -(x_1 + x_2 + x_3) + 1 \leq 0.$$

$g_f^{(2)}$: physical constraint

$$g_f^{(2)}(\mathbf{x}, \mathbf{y}) = F_a(\mathbf{y}) - R_a(x_4, x_5, \mathbf{y}) \leq 0.$$

Desirability There are two actors in the system, each assigned an equal global weight of 0.5. The first actor, the energy service provider, is only interested in f_1 and f_4, with equal distribution of their individual preferences such that $w_{11} = w_{14} = 0.25$. The second actor, the marine contractor, is only interested in f_2 and f_3, also with equal distribution, i.e., $w_{22} = w_{23} = 0.25$. See Figure 1 for a schematic illustration of the preference curves for both actors. NOTES: The preference structure adopted in this example is intentionally simple and symmetric with respect to the four performance functions. In general, the ODESYS methodology enables asymmetric preference formulations and heterogeneous stakeholder interests, allowing actors to express conflicting priorities and differentiated weight structures within a fully participative decision-making framework that formally integrates global and local weights (see (Teuber & Wolfert, 2024) for methodological details and conjoint-analysis-based preference elicitation).

Acceptability For acceptability, no explicit lower or upper thresholds are imposed on the performance functions. Consequently, for each performance dimension i, the preference function spans the full range defined by the observed minimum and maximum system performance values:

$$P_{1,i}\big(f_i(\mathbf{x}, \mathbf{y}, t)\big) \in [0, 100], \qquad f_i(\mathbf{x}, \mathbf{y}, t) \in \big[f_i^{\text{loc}} = f_i^{\text{min}};\, f_i^{\text{upc}} = f_i^{\text{max}}\big], \quad i = 1, \ldots, 4.$$

In the absence of explicit acceptability constraints ($g_a \geq 0$), all feasible performance values are admissible, and their associated normalized preferences may vary freely over the full interval $[0, 100]$. When acceptability constraints are introduced—such as a maximum allowable project duration, a budget ceiling, or an upper bound on emissions—the admissible ranges of the corresponding performance functions are reduced accordingly. These constraints do not affect feasibility, but further restrict the admissible decision space.
The resulting design–decision solution space is therefore defined as

$$\mathcal{S}_{f,a} := \{ \mathbf{x} \mid g_f(\mathbf{x}, \mathbf{y}, t) \leq 0 \ \wedge \ g_a(P_{k,i}(\mathbf{F})) \geq 0,\ k = 1,\ i = 1, \ldots, 4 \}.$$

In this case, $\mathcal{S}_{f,a}$ is bounded solely by the system feasibility constraints g_f, while the acceptability function g_a spans the full preference range.

Solvability The ODESYS structure-in-FIVES problem formulation can be schematically illustrated in Fig. 1, which visualizes how system performance, actor preferences, and constraints jointly define the solution space.
The objective is to identify the unique design–decision vector $\mathbf{x} \in \mathcal{S}_{f,a}$ that maximizes the aggregated preference score:

$$\max_{\mathbf{x}} Z(\mathbf{x}) = \mathbf{A}\big(P_{k,i}\big(\mathbf{F}(\mathbf{x},\mathbf{y},t)\big);\ w'_{k,i}\big)\,,$$

where $\mathbf{A}$ denotes the affine aggregation operator defined in Eqs. (5) and (). By applying an appropriate **search algorithm** (e.g. an inter-generational genetic algorithm; see Van Heukelum), the optimal design–decision vector $\mathbf{x}^*$ can be determined.

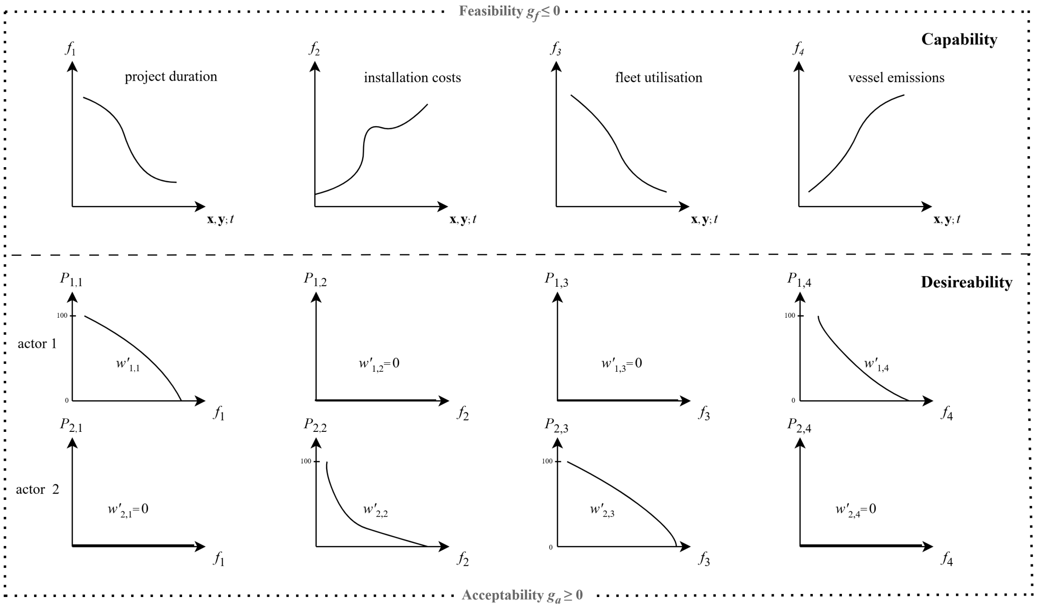

Figure 1: ODESYS problem schematization

(2) Allocation decision problem – Dynamic Vessel Allocation (AlloDyn)

Within Boskalis, the ODESYS methodology has been applied to a dynamic vessel allocation problem, resulting in the development of the *AlloDyn* decision-support tool. AlloDyn is embedded within the Vessel Operations Management System (VOMS) of a Marine Services business unit managing a global fleet of approximately 30 vessels. The system allocates new commercial tasks or projects, obtained by the commercial department, to the available vessels worldwide, balancing multiple criteria such as voyage distance, location, vessel capabilities, maintenance, mobilisation, and operational priorities.
The focus of this demonstrative problem is not on the operational outcomes produced by AlloDyn, but on formally describing the underlying multifaceted decision problem and its multi-constrained solution space. The emphasis is therefore on managerial decision-making related to vessel allocation, rather than on the design or modification of physical assets. For

simplicity, the problem is considered with a single actor ($k = 1$) representing the decision-making business unit, with multiple performance interests, and is formulated as an ODESYS synthesis operator:

$$\mathrm{OD}\Big(P_{1,i}\big(\mathbf{F}(\mathbf{x},\mathbf{y})\big);\ w'_{1,i}\Big), \qquad (\mathbf{x},\mathbf{y}) \in \mathcal{S}_{f,a}, \quad i = 1..4. \tag{8}$$

This formulation represents an integrative vessel allocation decision problem, simultaneously addressing decision variables related to vessel management (e.g. selection, scheduling) within an operational fleet context under multiple constraints. The system performance vector $\mathbf{F}(\mathbf{x},\mathbf{y})$ captures the relevant system performances, while the aggregated actor preferences $\mathbf{A}\big(P_{1,i}(\mathbf{F}); w'_{1,i}\big)$, expressed through the ODESYS framework, determine the final allocation decisions. The full problem formulation, including all variables, parameters, and constraints, is provided in the Appendix; here, only the main structures in FIVES are outlined.

Note: This formulation represents a highly constrained combinatorial decision problem, characterised by tightly coupled temporal, spatial, and resource constraints. In practice, such problems are typically solved using constraint programming (CP) techniques. In this work, however, they are embedded within the ODESYS framework to enable pure preference-based group decision-making, rather than hierarchical or purely numerical multi-objective optimisation, across multiple actors and performance dimensions. In other words, conventional CP approaches are limited to numerical constructs and optimisations, and consequently miss the opportunity to treat the problem as a true decision game, where actors' preferences and interests are fully integrated.

Capability The system capability is described by a four-dimensional performance vector

$$\mathbf{F}(\mathbf{x},\mathbf{y}) = \big[f_1(\mathbf{x},\mathbf{y}), f_2(\mathbf{x},\mathbf{y}), f_3(\mathbf{x},\mathbf{y}), f_4(\mathbf{x},\mathbf{y})\big],$$

representing total mobilisation distance $f_1(\mathbf{x},\mathbf{y})$, total mobilisation cost $f_2(\mathbf{x},\mathbf{y})$, total fuel consumption $f_3(\mathbf{x},\mathbf{y})$, and total sailing time $f_4(\mathbf{x},\mathbf{y})$, respectively. The controllable design–decision vector is given by $\mathbf{x} = (x_1..x_5)$, while the uncontrollable parameter vector is given by $\mathbf{y} = (y_1..y_{14})$. The full definitions of the decision variables, parameters, their domain constraints $g_f^{(0)}(\mathbf{x},\mathbf{y})$ and analytical expressions of f_1–f_4 are provided in the Appendix.

Feasibility System feasibility is enforced through a set of feasibility constraints that ensure domain validity, temporal consistency, vessel assignment feasibility, sequencing correctness, and path continuity. The feasible system solution space is defined as

$$\mathcal{S}_f = \Big\{(\mathbf{x},\mathbf{y}) \;\Big|\; g_f^{(i)}(\mathbf{x},\mathbf{y}) \le 0,\ i = 0..15\Big\}.$$

Here, $g_f^{(0)}$ represents the domain constraints for the decision vector $\mathbf{x}$ and the parameter vector $\mathbf{y}$, while constraints $g_f^{(1)}$–$g_f^{(15)}$ capture all remaining activity, sequencing, and path feasibility constraints. All individual constraints are explicitly specified in the Appendix.

Desirability System desirability is evaluated using preference functions over each performance dimension. Here, the actor-defined lower and upper bounds f_i^{loc} and f_i^{upl} coincide with the minimum and maximum performance values of f_i, defining the endpoints of the preference function:

$$P_{1,i}(f_i) = 0 \quad \text{at} \quad f_i = f_i^{\text{loc}}, \qquad P_{1,i}(f_i) = 100 \quad \text{at} \quad f_i = f_i^{\text{upl}}.$$

Intermediate values are scaled linearly, giving $P_{1,i} \in [0, 100]$. This approach ensures that system performance within the actor-defined acceptable bounds is fully represented in the preference space, while all details of the functional expressions are provided in the Appendix. In the present formulation, a single decision actor ($k = 1$) is assumed, who assigns equal importance to all four performance dimensions. Consequently, the local preference weights are uniformly distributed as $w_{1,i} = 0.25$ ($i = 1..4$). In practical applications, however, decision-making typically involves multiple actors representing different organizational perspectives, such as commercial and operational departments. In such cases, global actor weights (e.g. 0.5 per actor) are introduced, within which actor-specific local preference weights can be distributed across the performance dimensions. The extension to multi-actor preference aggregation is supported by the ODESYS framework but is not further elaborated here, as the present example focuses on illustrating the underlying problem formulation rather than stakeholder negotiation.

Acceptability Acceptability is imposed directly on the preference values. In the present case, the minimum acceptable preference level is set to $\overline{P}_{1,i} = 0$ for all performance dimensions, implying

$$P_{1,i} \geq 0, \quad i = 1, \ldots, 4.$$

As a result, the acceptability constraints do not further restrict the feasible space beyond feasibility, and the combined feasible–acceptable solution space reduces to $\mathcal{S}_{f,a} = \mathcal{S}_f$.

Solvability The resulting integrated multi-actor preference (IMAP) problem is solved using an intergenerational genetic algorithm, yielding a best-fit-for-common-purpose design–decision vector $\mathbf{x}^*$ through linear aggregation of z-normalized preference scores.

4. Conclusions

The demonstrative examples above illustrate that conventional multi-objective approaches, when applied without integrated preference modelling, cannot guarantee a unique, consistent, and mathematically valid group decision outcome. In contrast, the ODESYS structure in FIVES implements a pure performance–preference paradigm, where (1) capability (system performance), (2) feasibility (hard constraints), (3) desirability (stakeholder preferences) and (4) acceptability (negotiable constraints), are fully integrated within a single associative decision space, while (5) solvability is achieved by integratively maximising the aggregated preference (IMAP). For this, preferences are mapped into a single preference domain and aggregated via a uniquely defined, PFM-consistent linear aggregation operator, ensuring that all relative differences are preserved and that the resulting group-optimal solution simultaneously satisfies the four MOO–MCDM conditions—Preference-Key, Integration, Association, and Uniqueness—yielding a single, consistent, and fully decision-valid outcome. By contrast, all other methods reviewed in the references cited in this paper—including CP-, MIP-, and conventional MOO approaches—do not satisfy the four MOO–MCDM conditions and therefore cannot guarantee a decision-valid solution, as also independently noted in (Ferdous et al., 2024; Pajasmaa et al., 2025). ODESYS overcomes these limitations through its integrated preference-based framework. Moreover and importantly, the framework preserves individual design-decision freedom within the feasible and acceptable solution space, enabling actors to express their priorities while contributing to a collective search for a best-fit-for-common-purpose synthesis.

Through its structure-in-FIVES formulation, ODESYS operationalises this methodology for complex, multi-system design and decision problems, rigorously enforcing both hard feasibility constraints and soft acceptability conditions. IMAP identifies the unique best-fit-for-common-purpose design–decision vector using a intergenerational genetic search algorithm (GA), accommodating multiple actors with diverse preferences. In doing so, it finds the outcome with maximum aggregated preference, maintains full traceability and participatory engagement and enables forward-looking design decision-making rather than selecting from a curated numeric set, which unveils the illusion of free choice in conventional MCDM.

Taken together, these results establish the IMAP solver and ODESYS/FIVES framework as a rigorous, preference-consistent, and operationally validated methodology for multi-objective, multi-actor design–decision-making. It demonstrates how system performance *capability*, stakeholder preference *desirability*, and *feasibility* versus *acceptability* can be coherently integrated to produce decisions that are simultaneously transparent, associative, and *solvable* as a best-fit-for-common-purpose. Consequently, when individual actors are willing to give in on their pure self-interests, the group outcome achieves a higher aggregated preference, transforming creative conflicts into a shared ‘yes’ — without deceiving the realities of the physical system. This sets the stage for the final conclusions, highlighting both the theoretical and practical contributions of the ODESYS to confronting complex, socio-technical system developments. In doing so, ODESYS turns MOO-MCDM upside down and right side up, leveraging the synergy of ’systems-thinking-social’ and ’design-thinking-slow’ to deliver a best-fit-for-and-from-the-whole within reach!

Disclosure Statement

The author declares that there are no competing interests.

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Data Availability

The Preferendus software tool, including the design applications discussed in this paper, is publicly available via GitHub: `https://github.com/TUDelft-Odesys/Preferendus`. Preferendus employs the A-Fine-Aggregator for preference-based optimisation; the algorithm is available here: `https://github.com/Boskalis-python/a-fine-aggregator`. One of the demonstrative examples, the floating wind farm, is also accessible in accordance with confidentiality agreements via this repository: `https://github.com/Boskalis-python/ODYCON`.

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Appendix

Let the (vessel) allocation decision problem be defined by the ODESYS system structure in FIVES as:

$$\mathrm{OD}\Big(P_{k,i}\big(\mathbf{F}(\mathbf{x},\mathbf{y})\big);\ w'_{k,i}\Big), \qquad (\mathbf{x},\mathbf{y}) \in \mathcal{S}_{f,a} \tag{A1}$$

Here, $\mathrm{OD}(\cdot)$ is the ODESYS synthesis operator, $\mathcal{S}_{f,a}$ represents the feasible and acceptable system solution space, and $\mathbf{F}(\mathbf{x},\mathbf{y})$ is the system performance (capability) vector. The functions $P_{k,i}(\cdot)$ define actor specific preference functions over performance dimension i for actor k, while $w'_{k,i}$ denote the associated local preference weights.

(1) Capability

The multi-system performance vector is defined as

$$\mathbf{F}(\mathbf{x},\mathbf{y}) = \big[f_1(\mathbf{x},\mathbf{y}), f_2(\mathbf{x},\mathbf{y}), f_3(\mathbf{x},\mathbf{y}), f_4(\mathbf{x},\mathbf{y})\big]. \tag{A2}$$

Mobilization distance is defined as:

$$f_1(\mathbf{x},\mathbf{y}) = \sum_{r\in R}\sum_{r'\in R} y_{r,r'} \cdot D_{\ell_{\mathrm{end}}(r,\lambda),\, \ell_{\mathrm{start}}(r',\lambda)},$$

while mobilization cost is given by::

$$f_2(\mathbf{x},\mathbf{y}) = \sum_{r\in R}\sum_{r'\in R}\sum_{v\in V} \mathbf{1}[y_{r,r'} = 1 \wedge x_r = v] \cdot c_v \cdot \theta_{r,r',v}.$$

Fuel consumption is modelled as:

$$f_3(\mathbf{x},\mathbf{y}) = \sum_{r\in R}\sum_{r'\in R} y_{r,r'} \cdot f_{x_r}(\sigma_{r,r',x_r}) \cdot \theta_{r,r',x_r},$$

and total sailing time is expressed as:

$$f_4(\mathbf{x},\mathbf{y}) = \sum_{r\in R}\sum_{r'\in R} y_{r,r'} \cdot \theta_{r,r',x_r}.$$

The controllable decision vector is defined as:

$$\mathbf{x} = (T, \lambda, x, y, z)$$

where the individual components correspond to timing, location, vessel assignment, sequencing, and sequence initiation decisions. The associated domain constraints for the simplified decision vector $\mathbf{x} = (x_1, \ldots, x_5)$ are summarised in Table 2:

Table 2: Domain constraints for the simplified decision vector $x = (x_1, \ldots, x_5)$

x	**Description**	$g_f^{(0)}(x_i)$
x_1	Start time of activity $a \in A$	$\underline{T}_a \le x_1[a] \le \overline{T}_a$
x_2	Location choice for maintenance activity $a \in A_{maint}$	$x_2[a] \in L_a$
x_3	Vessel assigned to role $r \in R$	$x_3[r] \in \mathcal{D}_r$
x_4	Sequencing variable: role r' follows r	$x_4[r, r'] \in \{0, 1\}$
x_5	Sequence start indicator: role r is first in sequence	$x_5[r] \in \{0, 1\}$

The uncontrollable parameter vector is defined as:

$$\mathbf{y} = \left(d_a,\ [\underline{T}_a, \overline{T}_a],\ \ell_a^{start},\ \ell_a^{end},\ L_a,\ p_a,\ \alpha(r),\ \mathcal{D}_r,\ R_a,\ D_{\ell,\ell'},\ [T_{v,\ell,\ell'}^{min}, T_{v,\ell,\ell'}^{max}],\ [s_v^{min}, s_v^{max}]\right)$$

where each parameter captures exogenous system characteristics such as activity durations, time windows, spatial information, precedence relations, vessel capabilities, and sailing characteristics. The domains and feasibility constraints associated with the parameter vector are listed in in Table 3:

Table 3: Parameter vector $\mathbf{y} = (y_1, \ldots, y_{12})$ and their domain constraints

y	**Description**	$g_f^{(0)}(y_i)$
y_1	Duration of activity a	$y_1[a] = d_a \ge 0$ (Days)
y_2	Start time window for activity a	$[\underline{T}_a, \overline{T}_a] \ge 0$
y_3	Start location for towing activity $a \in A_{tow}$	$y_3[a] = \ell_a^{start} \in$ Locations
y_4	End location for towing activity $a \in A_{tow}$	$y_4[a] = \ell_a^{end} \in$ Locations
y_5	Allowed locations for maintenance activity $a \in A_{maint}$	$y_5[a] = L_a \subseteq$ Locations
y_6	Predecessor of activity a	$y_6[a] = p_a \in A \cup \{\emptyset\}$
y_7	Parent activity of role r	$y_7[r] = \alpha(r) \in A$
y_8	Vessel domain for role r	$y_8[r] = \mathcal{D}_r \subseteq V$
y_9	Set of roles belonging to activity a	$y_9[a] = R_a = \{r \in R \mid \alpha(r) = a\}$
y_{10}	Sailing distance from location ℓ to ℓ'	$y_{10}[\ell, \ell'] = D_{\ell,\ell'} \ge 0$
y_{11}	Min and max travel time for vessel v	$y_{11}[v, \ell, \ell'] = [T_{v,\ell,\ell'}^{min}, T_{v,\ell,\ell'}^{max}] \ge 0$
y_{12}	Min and max sailing speed for vessel v	$y_{12}[v] = [s_v^{min}, s_v^{max}] \ge 0$
y_{13}	Daily mobilisation rate for vessel v	$y_{13}[v] = c_v \ge 0$
y_{14}	Fuel consumption rate function for vessel v	$y_{14}[v](s) = f_v(s) \ge 0, \forall s \in [s_v^{min}, s_v^{max}]$

Notes:

- $\theta_{r,r',v}$ is the sailing duration for vessel v from role r to r', determined by time gaps and vessel limits.

- $y_{r,r'}$ is the sequencing variable indicating if role r' immediately follows r.
- x_r is the vessel assigned to role r.
- $D_{\ell,\ell'}$ is the sailing distance between locations ℓ and ℓ'.
- Sailing speed σ_{r,r',x_r} is defined by

  $$\sigma_{r,r',x_r} = \frac{D_{\ell_{\text{end}}(r,\lambda),\,\ell_{\text{start}}(r',\lambda)}}{24 \cdot \theta_{r,r',x_r}}$$

  and determines the vessel's speed between consecutive roles.

(2) Feasibility

We write all feasibility constraints (activity, sequencing, and path) as a feasibility function $g_f^{(i)}(\mathbf{x},\mathbf{y}) \leq 0$. Then the feasible system solution space is defined as

$$\mathcal{S}_f = \left\{(\mathbf{x},\mathbf{y}) \;\middle|\; g_f^{(i)}(\mathbf{x},\mathbf{y}) \leq 0,\ i = 1,\ldots,15\right\} \tag{A3}$$

Activity Constraints No vessel may be assigned to more than one role within the same activity:

$$g_f^{(1)}(\mathbf{x},\mathbf{y}) = x_r - x_{r'} \leq 0, \quad \forall a \in A,\ \forall r,r' \in R_a,\ r \neq r'.$$

An activity cannot start before its predecessor has finished:

$$g_f^{(2)}(\mathbf{x},\mathbf{y}) = T_a - \left(T_{p_a} + d_{p_a}\right) \leq 0, \quad \forall a \in A:\ p_a \neq \emptyset.$$

If the same vessel is assigned to two roles in different activities, sufficient completion and travel time must exist:

$$g_f^{(3)}(\mathbf{x},\mathbf{y}) = T_{\alpha(r')} - \left(T_{\alpha(r)} + d_{\alpha(r)} + T^{\min}_{x_r,\,\ell_{\text{end}}(r,\lambda),\,\ell_{\text{start}}(r',\lambda)}\right) \leq 0,$$
$$g_f^{(4)}(\mathbf{x},\mathbf{y}) = T_{\alpha(r)} - \left(T_{\alpha(r')} + d_{\alpha(r')} + T^{\min}_{x_{r'},\,\ell_{\text{end}}(r',\lambda),\,\ell_{\text{start}}(r,\lambda)}\right) \leq 0,$$

for all $r \neq r'$ such that $\alpha(r) \neq \alpha(r')$ and $x_r = x_{r'}$.

Sequencing Constraints In the sequence of activities there can be at most one successor:

$$g_f^{(5)}(\mathbf{x},\mathbf{y}) = \sum_{r' \in R} y_{r,r'} - 1 \leq 0, \quad \forall r \in R,$$

and at most one predecessor

$$g_f^{(6)}(\mathbf{x},\mathbf{y}) = \sum_{r \in R} y_{r,r'} - 1 \leq 0, \quad \forall r' \in R.$$

There can not be self-loops:

$$g_f^{(7)}(\mathbf{x},\mathbf{y}) = y_{r,r} \leq 0, \quad \forall r \in R.$$

There can not be intra-activity sequencing:

$$g_f^{(8)}(\mathbf{x}, \mathbf{y}) = y_{r,r'} \leq 0, \quad \forall r, r' \in R: \ \alpha(r) = \alpha(r').$$

Transitions between roles of the same activity are prevented, as such roles are performed simultaneously rather than sequentially:

$$g_f^{(9)}(\mathbf{x}, \mathbf{y}) = y_{r,r'} - \mathbf{1}[x_r = x_{r'}] \leq 0, \quad \forall r, r' \in R.$$

There can not be temporal precedence in sequences

$$g_f^{(10)}(\mathbf{x}, \mathbf{y}) = T_{\alpha(r)} - T_{\alpha(r')} \leq 0, \quad \forall r, r' \in R: \ y_{r,r'} = 1.$$

There should be sufficient travel-time for consecutive roles:

$$g_f^{(11)}(\mathbf{x}, \mathbf{y}) = T_{\alpha(r')} - \Big(T_{\alpha(r)} + d_{\alpha(r)} + T^{\min}_{x_r,\, \ell_{\text{end}}(r,\lambda),\, \ell_{\text{start}}(r',\lambda)} \Big) \leq 0,$$

for all $r, r' \in R$ such that $y_{r,r'} = 1$ and $x_r = x_{r'}$.

Path Constraints There can be at most one predecessor per role

$$g_f^{(12)}(\mathbf{x}, \mathbf{y}) = \sum_{r \in R} y_{r,r'} - 1 \leq 0, \quad \forall r' \in R.$$

Similarly, each vessel can have at most one sequence start:

$$g_f^{(13)}(\mathbf{x}, \mathbf{y}) = \sum_{r \in R} \mathbf{1}[x_r = v]\, \mathbf{1}\left[\sum_{r' \in R} y_{r',r} = 0 \right] - 1 \leq 0, \quad \forall v \in V$$

and at most one sequence end:

$$g_f^{(14)}(\mathbf{x}, \mathbf{y}) = \sum_{r \in R} \mathbf{1}[x_r = v]\, \mathbf{1}\left[\sum_{r' \in R} y_{r,r'} = 0 \right] - 1 \leq 0, \quad \forall v \in V.$$

For each vessel, the assigned roles must together form exactly one continuous path (path cardinality condition):

$$g_f^{(15)}(\mathbf{x}, \mathbf{y}) = \sum_{r \in R} \sum_{r' \in R} y_{r,r'} \cdot \mathbf{1}[x_r = v] - \max\left(0,\ \sum_{r \in R} \mathbf{1}[x_r = v] - 1 \right) = 0, \quad \forall v \in V.$$

(3) Desirability

Within the vessel allocation problem, we consider a single decision maker ($k = 1$). For confidentiality reasons, we provide only the general formula for constructing linear preference functions[1]. A linear preference function for performance i is defined by mapping the observed minimum and maximum values of f_i to a preference scale of 0 to 100:

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[1] Within Boskalis, where this ODESYS system operates as part of the *AlloDyn* software, one uses different business-specific and customized preference functions including business-specific thresholds.

$$P_{1,i}\big(f_i(\mathbf{x},\mathbf{y})\big) = 100 \cdot \frac{f_i(\mathbf{x},\mathbf{y}) - f_i^{\min}}{f_i^{\max} - f_i^{\min}}, \quad i = 1,\dots,4, \tag{A4}$$

where

$$f_i^{\min} = \min_{\mathbf{x}\in\mathcal{S}_{f,a},\mathbf{y}} f_i(\mathbf{x},\mathbf{y}), \qquad f_i^{\max} = \max_{\mathbf{x}\in\mathcal{S}_{f,a},\mathbf{y}} f_i(\mathbf{x},\mathbf{y}).$$

This linear mapping ensures that the relatively worst performance (minimum: least preferred) and best performance (maximum: most preferred) correspond to 0 and 100, respectively, and intermediate preference values are scaled proportionally. This results in linear preference functions over the four performance dimensions.

(4) Acceptability

Acceptability constraints are formulated exclusively in preference space and act on the normalized preference values rather than directly on the performance functions. In this case, no explicit minimum acceptable preference levels are imposed. Consequently, for each performance dimension i, the preference function spans its full range:

$$P_{1,i}\big(f_i(\mathbf{x},\mathbf{y},t)\big) \in [0,100], \qquad f_i(\mathbf{x},\mathbf{y}) \in \big[f_i^{\text{loc}} = f_i^{\min};\, f_i^{\text{upc}} = f_i^{\max}\big] \qquad i = 1,\dots,4.$$

This implies that the corresponding performance functions naturally range between their minimum and maximum feasible values, which coincide with the endpoints of the preference functions. In the absence of acceptability constraints ($g_a \geq 0$), all feasible system performances are admissible and included in the acceptable solution space.
When acceptability constraints are introduced—by specifying minimum acceptable preference levels $\overline{P}_{1,i}$ for one or more performance dimensions—only solutions satisfying

$$g_a^{(i)}\big(P_{1,i}(\mathbf{F})\big) \geq \overline{P}_{1,i}, \quad i = 1,\dots,4$$

are retained[1]. These constraints do not affect system feasibility but restrict the acceptable solution space by excluding solutions with insufficient preference levels.
The resulting design–decision solution space is therefore defined as

$$\mathcal{S}_{f,a} := \big\{\mathbf{x} \mid g_f(\mathbf{x},\mathbf{y}) \leq 0 \ \wedge\ g_a\big(P_{1,i}(\mathbf{F})\big) \geq 0,\ i = 1,\dots,4\big\}. \tag{A5}$$

(5) Solvability

The resulting preference-performance based optimisation problem is now formulated as follows:

$$\max_{\mathbf{x}} Z(\mathbf{x}) = \mathbf{A}\Big(P_{1,i}\big(\mathbf{F}(\mathbf{x},\mathbf{y})\big);\ w'_{1,i}\Big), \qquad i = 1,\dots,4, \tag{A6}$$

where $w'_{1,i}$ are business-specific weights reflecting the relative importance of each performance dimension for the decision-making unit.
The operator $\mathbf{A}$ denotes the *a-fine aggregator*, implemented as a linear aggregation (weighted centroid) of the z-normalised preference scores. The resulting solution

$$\mathbf{x}^* = \arg\max_{\mathbf{x}} Z(\mathbf{x}), \qquad Z(\mathbf{x}) = \sum_{i=1}^{4} w'_{1,i}\, z_{1,i}(\mathbf{x}), \qquad \sum_{i=1}^{4} w'_{1,i} = 1,$$

defines the unique design–decision vector $\mathbf{x}^*$ corresponding to the maximum aggregated stakeholder preference.

Solvability is achieved by searching for the *best-fit-for-common-purpose* design–decision vector $\mathbf{x}^*$ using ODESYS' Preferendus intergenerational genetic algorithm (GA) (see Data Availability section and (van Heukelum et al., 2024)). A Biased Random-Key Genetic Algorithm (BRKGA) represents candidate solutions as random-key vectors in $[0, 1)^n$, with a deterministic decoder that maps these vectors to complete schedules while explicitly enforcing complex constraints (e.g., assignment uniqueness and temporal precedence) during evolution. Biased inheritance accelerates convergence by preferentially propagating elite solutions. This extended intergenerational GA explores the feasible and acceptable solution space $\mathcal{S}_{f,a}$ and evaluates candidates via the IMAP A-Fine aggregation structure.