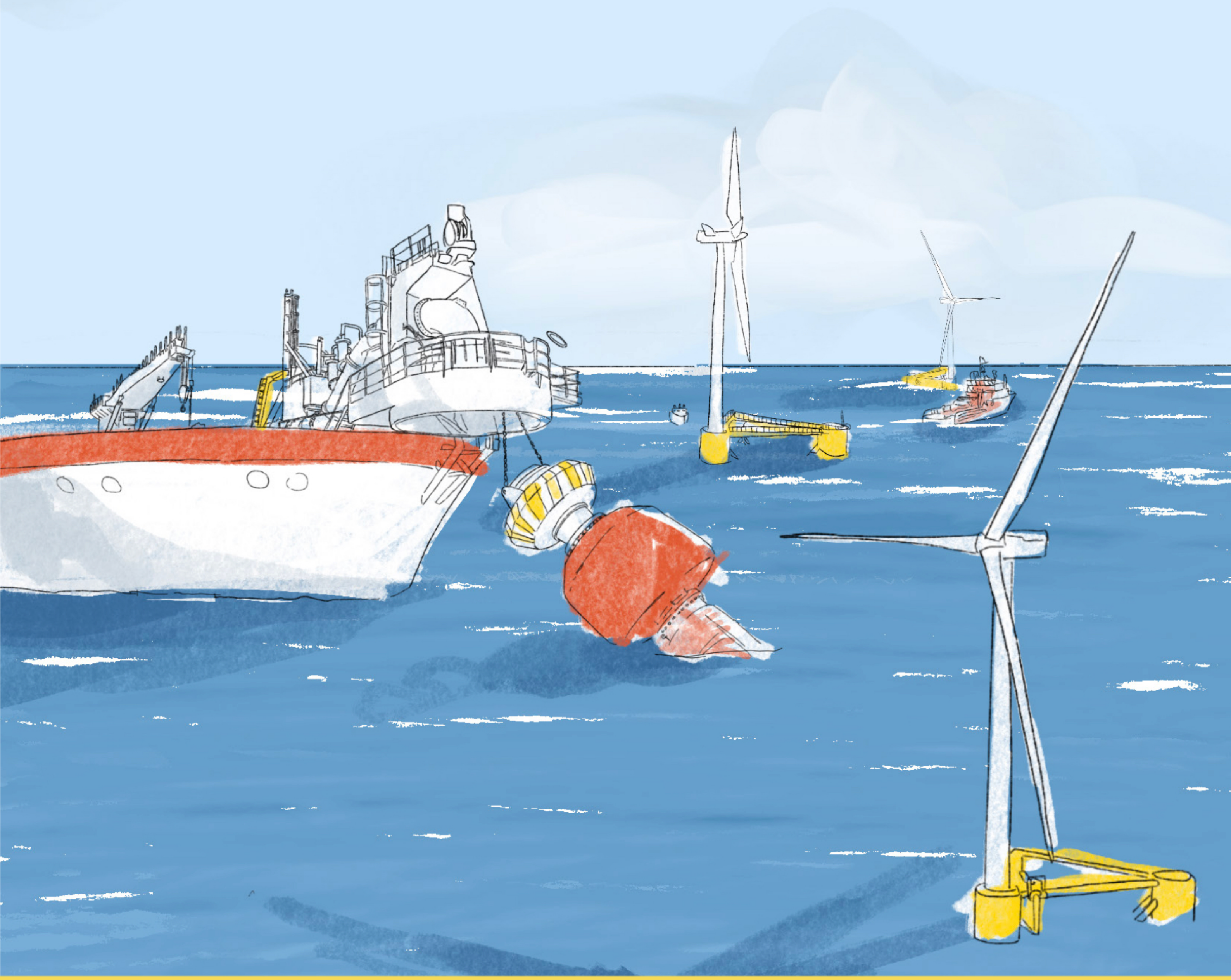
Author: H.J. van Heukelum
Dec 2022
Delft University of Technology
Boskalis



GRADUATION THESIS

Preference and Performance Based Design & Decision Systems in Offshore & Dredging Engineering

A multi-objective design/decision optimisation approach based on sound mathematical modelling of both preference and physical design performance functions

Preference and Performance Based Design & Decision Systems in Offshore & Dredging Engineering

A multi-objective design/decision optimisation approach based on sound mathematical modelling of both preference and physical design performance functions

by

H.J. van Heukelum

to obtain the degrees of ODE Master of Science and CME Master of Science at the Delft University of Technology, to be defended publicly on Friday December 16, 2022 at 3:30 PM.

Student number:	4389883	
Project duration:	November 15, 2021 – December 16, 2022	
Thesis committee:	Prof. dr. ir. A.R.M. Wolfert,	TU Delft, chair
	Dr. ir. R. Binnekamp,	TU Delft
	Dr. O.J. Colomés Gené,	TU Delft
	Dr. ir. A.C. Steenbrink,	Boskalis

TU Delft

Contents

1

Setting the Scene

Why do engineers often design what people do not want? And why do people often want solutions that are not feasible? This is because the current design and decision support optimisation methods are single-sided and ignore or fail to capture the dynamic interaction between people's preferences (subject desirability) and technical assets' performance (feasibility). Moreover, current optimisation methods are: 1) limited to the evaluation of potentially sub-optimal design alternatives (Blanchard & Fabrycky, 2011; Cross, 2021; Dym & Little, 2004; Mueller & Ochsendorf, 2015); 2) contain fundamental (aggregation) modelling errors (Barzilai, 2006, 2022); 3) do not provide a single optimal design point (Farran & Zayed, 2015; Furuta et al., 2006; Kim et al., 2022; Lee et al., 2011; Saad et al., 2018). On the other hand, the offshore dredging industry (ODE) can benefit substantially from multi-objective design/decision optimisation as projects become larger, more stakeholders are involved in concurrent design/decision-making, and new technologies emerge.

The application of optimisation in the ODE industry is not entirely new. In the tendering phase, optimisation is common and is usually done by evaluating (manually) generated design alternatives. However, it cannot be guaranteed that the optimal design alternative is part of this evaluation. Furthermore, these alternatives are generated with a bias resulting from the designer's experience. This bias may cause competing design alternatives to be disregarded. Moreover, optimisation often focuses only on cost, which is an incomplete reflection of the actual planning and engineering challenges. Finally, the client and the various stakeholders often work separately from each other, whereas they can greatly benefit from integrative design optimisation.

In the execution phase of projects in the ODE industry, especially in case of unforeseen circumstances, decision-making is often *ad hoc* and poorly aligned with the other stakeholders (i.e. made by a single actor). Moreover, the models used for optimisation are rather simplified and rely on manual input and evaluation. This is not feasible for large projects, where the impact of adjustments is difficult to oversee, and a multi-objective design/decision support optimisation system is needed.

Development statement

To overcome the aforementioned shortcomings, the following development statement has been formulated:

There is a need to develop an optimisation methodology that enables a priori human preference and asset performance systems design integration to search for the optimal, best fit-for-common-purpose, synthesis solution.

A first attempt at this was made by Zhilyaev et al. (2022), but this still had three fundamental shortcomings: 1) no generalised multi-objective design optimisation framework that includes a connection between performance, objective and preference functions; 2) no integration with the physical/mechanical object behaviour; 3) lack of a proper search algorithm for finding the optimal solution.

This thesis introduces the Open Systems Design (Odesys) optimisation methodology, the IMAP (Integrative Maximised Aggregated Preference) method, and the software tool Preferendus, which overcome the aforementioned shortcomings. This methodology is applied to two simplified exemplars and two validation cases at Dutch maritime contractor Boskalis to demonstrate its application and added value.

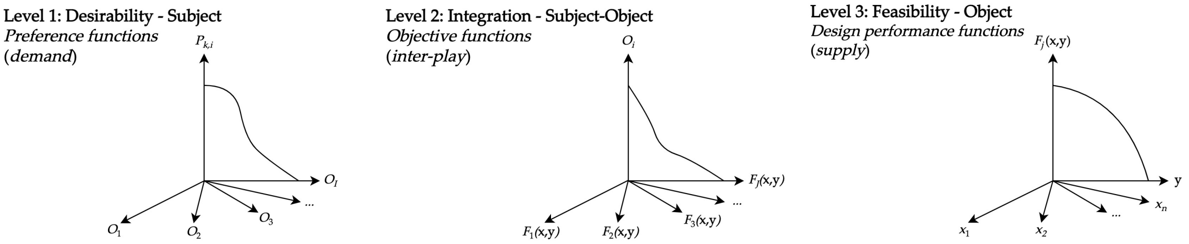


Figure 1.1: Threefold diagram of the Odesys optimisation methodology.

Results

The introduction of the Odesys methodology and the application of the Preferendus combined with the IMAP method provide a means to overcome the current shortcomings of optimisation in both the tendering and execution phases of projects in the ODE industry.

This thesis provides a mathematical framework (Figure 1.1) that allows the unification of people's preferences (subject desirability) and technical assets' performance (feasibility), capturing the dynamic interaction between these two domains. Moreover, it overcomes fundamental problems with current optimisation methodologies by combining state-of-the-art principles of preference function modelling with an intergenerational genetic algorithm (GA) optimisation solver. The application of the Preferendus in combination with the IMAP method to two (simplified) exemplars shows: 1) IMAP provides a single best fit-for-common-purpose design point, unlike a Pareto front where a system designer still has to choose the final design point through negotiation because the front does not define a single optimal design point; 2) IMAP provides the best design configuration in both examples compared to a set of single-objective design configurations and a design configuration obtained using the classical multi-objective min-max method; 3) IMAP/Preferendus truly unifies design performance functions (level 3 - supply), through the inter-play objective functions level, with stakeholders' preference functions (level 1 - demand), synthesising for the best fit-for-common-purpose solution and outperforming single-objective design approaches that focus only on the technical domain.

The application of the Odesys methodology in the tender phase of offshore floating wind development shows that the new Preferendus/IMAP can significantly improve overall tendering performance by: 1) providing initial design approaches within hours, where tender teams currently spend days working on design alternatives that, in hindsight, were sub-optimal; 2) removing the bias of tender teams from the design process and finding design solutions that were otherwise unfairly disregarded; 3) open glass-box (as opposed to black-box) modelling support for concurrent design between the asset owner and the contractor.

Finally, the application of the Preferendus and IMAP method in decision support optimisation of dredging production management during project execution showed a clear improvement over current methods, which are limited in their ability to adapt best-for-project. Preferendus/IMAP finds solutions that significantly reduce waiting time while achieving high production levels. Moreover, Preferendus/IMAP outperforms single-sided optimisation on production alone by achieving similar high production levels while improving other objectives such as CO_2 emissions and vessel efficiency.

Future outlook

The Odesys methodology and the Preferendus will be validated by other MSc and PhD studies in the near future, providing insight into its applicability in other domains. In addition, the following steps for further development have been identified for the Preferendus/IMAP:

General:

- Investigate whether a genetic algorithm is best suited for application in the Preferendus or whether other multi-objective algorithms are better suited.
- Improve the run-time of the inter-generational solver. This will benefit the application of the Preferendus in complex design environments or projects with strict time constraints.

In offshore floating wind development:

- Include the minimum breaking load of the mooring lines in the surrogate model. This addresses a problem where taut configurations are designed with excessive tension in the polyester rope.
- Include fatigue loading in the anchor design. This will add an important element to anchor design, as loads of floating wind turbines are rather dynamic, and this has a significant effect on anchor resistance.
- Include more platform designs in the surrogate model, which is currently limited to one semi-submersible platform.
- Take the delivery of the first floating wind turbine as $t = 0$ for the installation schedule.
- Improve the discrete event simulator with a focus on 1) calculating the number of anchors and mooring lines on board the installation vessels, and 2) the start of the installation of mooring lines if it takes place separately from the anchor installation.
- Improve the calculation of installation costs by including procurement and fuel costs.
- Improve calculation of CO_2 emissions by including emissions from anchor fabrication and onshore activities.

In dredging production management:

- Make fuel consumption during sailing dependent on sailing speed.
- Make it possible to set an initial time delay for vessels to reflect the time needed to resolve unforeseen downtime. If implemented, the optimisation framework (which assumes perfect conditions) can be started as soon as an unforeseen situation occurs, instead of the current situation where it can only be started when the situation is resolved.
- Investigate whether there is added value in making the waiting time of large TSHDs more important than the waiting time of smaller ones. This might already be included through the production objective, as making large TSHDs wait is not beneficial for this objective either.
- Investigate the impact and added value of including the processes on the other side of the discharge line (i.e. the beach) in the optimisation.
- Resolve the issue with different units for coordinates.

Reading guide

This thesis combines three separate documents produced during this graduation project. These three documents are included in the following three chapters.

Chapter 2 contains the scientific paper "human preference and asset performance systems design integration". This paper describes in more detail the shortcomings of current design/decision optimisation methodologies and introduces the Open Design Systems (Odesys) optimisation methodology to overcome these shortcomings. It also introduces the Integrative Maximised Aggregated Preference (IMAP) method and the Preferendus software tool, including a new inter-generational Genetic Algorithm (GA) solver, and demonstrates the applicability of the Odesys methodology in two exemplars. This paper is currently under review by the journal Structure and Infrastructure Engineering.

Chapter 3 contains the conference paper "preference based service life design of floating offshore wind structures". This paper introduces an optimisation framework, built in the Preferendus, to overcome current shortcomings in the tender phase of offshore floating wind farm developments. This optimisation considers the interaction between the wind farm developer and the maritime contractor Boskalis and focuses on optimisation of the installation schedule and mooring design. For this purpose, an integration is made with the wind turbine simulation tool OpenFAST via a surrogate model. The abstract of this paper has been accepted for publication and the paper is scheduled for presentation at IALCCE2023 in July 2023.

Chapter 4 contains the business report "dredging production management optimisation and validation". This report introduces the optimisation framework built to overcome shortcomings in the optimisation of dredge production management at large land reclamation projects. It describes the set-up of the optimisation framework and the demonstration project used to validate it with experts from Boskalis' data science, production management and project execution offices. The focus of this report is on this validation and the associated conclusions and steps for further development.

2

Human Preference and Asset Performance Systems Design Integration

This chapter includes the scientific paper that introduces the Odesys optimisation methodology. This paper is currently under review for publication[1].

In summary, this chapter introduces a new open design systems methodology and integrative optimisation method based on maximising aggregate group preference, which enables true integrative multi-objective design optimisation. This, as current optimisation methods for system design are single-sided and ignore the dynamic interaction between people's preference (demand) and engineering asset's physical performance (supply). Moreover, classical multi-objective optimisation methods contain fundamental (aggregation) modelling errors. Also, the classical multi-objective optimisation Pareto front will not provide a best-fit design point, but rather a set of design performance alternatives. This leaves designers without a single solution to their problems. Finally, current multi-objective optimisation processes are rather disconnected from design and management practices, as these lack the deep involvement of decision-makers.

The added value and use of both the Odesys methodology and the integrative optimisation method are demonstrated in two real-life infrastructure design exemplars, showing how to arrive at true best fit-for-common-purpose design points.

2.1. Introduction

The rapidly changing world of (infra)structures requires an effective and efficient design process. Multi-objective optimisation is key to making informed data-driven design decisions (Chen & Bai, 2019). However, the infrastructure design problems become increasingly complex due to challenges with environmental considerations, new types of transport and other transitions. This, in combination with the multidisciplinary nature of these problems, creates an environment in which optimisation of the design process becomes increasingly challenging and complicated where current design optimisation methods contain a number of intrinsic problems and cannot provide ready-made solutions (Omar et al., 2009).

The first problem with the current optimisation methodologies is the disconnection between the human preference domain (subject desirability) and the engineering asset physical performance behaviour domain (object feasibility). Moreover, if design optimisation is applied within the classical systems engineering context, it is usually limited to a single objective design approach and/or to an *a posteriori* evaluation of design alternatives (Blanchard & Fabrycky, 2011; Cross, 2021; Dym & Little, 2004). However, in *a posteriori* evaluation, it cannot be guaranteed that the optimal design point has been found and a choice has to be made between sub-optimal compromise solutions (even when optimisation and *a posteriori* evaluation are combined, see Mueller and Ochsendorf (2015)). Especially in complex engineering projects, the number of possible design alternatives is too large to evaluate all of them, making it possible that the optimal solution is ignored.

Secondly, most multi-objective optimisation methodologies introduce fundamental (aggregation) modelling errors, since these: 1) use undefined measurement scales and apply mathematical operations where

[1] This chapter has been sent verbatim for publication in the journal Structure and Infrastructure Engineering in December 2022 (to be published in 2023). In addition, parts of this chapter will be included verbatim in a new book "Open designs systems" (to be published in Q1 2023 by IOS Press).

these are not defined (e.g. for variables which do not have an absolute zero nor one, such as time/potential energy/preference, mathematical operations of addition and multiplication are not defined in the corresponding mathematical model which is the one-dimensional affine space, see Barzilai (2022)); 2) produce an infinite number of non-equivalent 'optimal' outcomes (e.g. the definition of the aggregation algorithm does not prerequisite having only normalised numbers); 3) outcomes are not taking into account the relative scoring impact of other design alternatives (e.g. in reality, the score of an alternative depends on the relative score towards all other alternatives, so that finding the overall score comes about by getting the best balance between all weighted relative scores for all sub-criteria given a set of alternatives). As a result, the outcomes of decision-making in engineering design may lead to sub-optimal design configurations (see Barzilai (2006)).

A third issue with many of the classical multi-objective optimisation methods is that these do not have a unified way of translating the different objective functions to a common domain to find a best-fitting aggregated optimum. To get around this problem, many times these multi-objective design methods make use of monetisation, or in other words, all objective functions are expressed in terms of money. However, according to classical decision/utility theory, decisions are not based on money but on value or preference (where expenditure minimisation or profit maximisation can form one of the objectives of course). Here, preference is an expression of the degree of 'satisfaction', and it describes the utility or value something provides. Although some researchers have incorporated preference modelling into their multi-objective optimisation frameworks (see, for example, Lee et al. (2011) or Messac (1996)), none of them use strong (preference) measurement scales or individually weighted preference functions (i.e. continuous functions linking an individually weighted preference to a specific objective). In addition, these approaches do not lead to a single optimal design point and also contain the aggregation modelling errors mentioned above.

A fourth issue with the classic multi-objective design optimisation approaches is that many of these consider the so-called Pareto front to be a common outcome (Marler & Arora, 2004). However, in addition to the fact that the Pareto front is often determined via erroneous measurement and aggregation methods (such as the weighted average mean which contains fundamental mathematical errors as already described above), the problem with this approach is that it produces an infinite set of possible, and supposedly equally desirable, design points (see for instance Farran and Zayed (2015); Furuta et al. (2006); Saad et al. (2018)). However, this is inconsistent with the fundamental basis of an engineering design process, where each design point is (subjectively) interpreted by people in terms of preference (i.e. a statement of their individual interest) and where a search is performed to find a single optimal design solution. This leaves designers without a true solution to their problems, as they cannot find such a best fit-for-common-purpose design point. The Pareto front concept is therefore of little use within an engineering design context, as also noted by e.g. Lee et al. (2011) and Kim et al. (2022).

A final issue is that current multi-objective optimisation processes are rather disconnected from design and management practices since these lack deep involvement of decision-makers (Guo & Zhang, 2022). Moreover, the dynamic nature and the interplay of human preferences are scarcely considered.

To overcome all the aforementioned issues and problems, and to enable true human preference and asset performance systems design integration, the Open Design Systems (Odesys) design methodology is introduced in this paper. Odesys builds further on the multi-stakeholder design optimisation methodology proposed by Zhilyaev et al. (2022), in which it has been shown that the only way to unambiguously solve a multi-objective engineering design/decision problem is to translate each of the objective functions into one overarching preference domain. This can be done using stakeholder preference functions (i.e. the relationship between an individual preference and a specific objective), which then allow for the maximisation of the aggregated group preference, leveraging Barzilai's theory of preference measurement (see Binnekamp (2010), where this concept was developed, and Arkesteijn et al. (2017, 2015) for its testing and validation). However, all of these recent preference-based design developments, which have only been applied in a real estate context, have three fundamental shortcomings: 1) no generalised multi-objective design optimisation framework that includes a connection between performance, objective and preference functions, 2) no integration with the physical/mechanical object behaviour, and 3) lack of a PFM-based search algorithm for finding the optimal solution (PFM is an acronym for Preference Function Modelling, see Barzilai (2005, 2022)).

The Odesys methodology allows now for full integration between subject desirability via preference functions and object feasibility via design performance functions, resulting in an automated search for the optimal synthesis solution. This makes Odesys a true systems integration methodology where human preference-based design and engineering physics/mechanics converge, offering a wide range of potential applications within a structure and infrastructure systems engineering context. As part of this Odesys methodology, a new IMAP (Integrative Maximised Aggregated Preference) optimisation method is introduced for maximising aggregated preferences. This IMAP method forms the basis of a software tool called the Preferendus and combines the state-of-the-art PFM principles with an inter-generational genetic algorithm (GA) solver developed specifically for this purpose.

Within this paper, firstly a general mathematical statement of the open design systems integration methodology has been formulated. Next, a flow chart (or concept diagram) of the Preferendus tool is described in which the Odesys methodology is operationalised. Finally, the added value of the Odesys methodology, the IMAP method and the Preferendus tool is demonstrated for two infrastructure design and management exemplars. The results are compared with single-objective design outcomes as well as with design outcomes resulting from the min-max goal attainment method.

2.2. Mathematical formulation of the Open Design Systems methodology

As described in the introduction, there is currently no optimisation framework that allows for true integration of the human preference domain (subject desirability) and the engineering asset physical performance behaviour domain (object feasibility). This disconnection will limit optimisation to sub-optimal results, as the interaction between these two levels is not considered. To overcome this, this paper introduces the following mathematical statement, that does allow for true integration of subject desirability and object feasibility and is the core of the Odesys methodology:

$$\begin{gathered} \underset{\mathbf{x}}{Maximise}\ U = T\left[P_{k,i}\left(O_i\left(F_1(\mathbf{x},\mathbf{y}), F_2(\mathbf{x},\mathbf{y}), \ldots, F_J(\mathbf{x},\mathbf{y})\right)\right), w'_{k,i}\right] \text{ for} \\ k = 1,2,\ldots,K \\ i = 1,2,\ldots,I \end{gathered} \tag{2.1}$$

Subject to:

$$g_p\left(O_i\left(F_{1,2,\ldots,J}(\mathbf{x},\mathbf{y})\right), F_{1,2,\ldots,J}(\mathbf{x},\mathbf{y})\right) \leq 0 \text{ for } p = 1,2,\ldots,P \tag{2.2}$$

$$h_q\left(O_i\left(F_{1,2,\ldots,J}(\mathbf{x},\mathbf{y})\right), F_{1,2,\ldots,J}(\mathbf{x},\mathbf{y})\right) = 0 \text{ for } q = 1,2,\ldots,Q \tag{2.3}$$

With:

- T: The aggregated preference score determined using the Preference Function Modelling (PFM) theory principles (see Barzilai (2022)).
- $P_{k,i}(O_i(F_{1,2,\ldots,J}(\mathbf{x},\mathbf{y})))$: Preference function that describes the preference stakeholder k has towards objective i.
- $O_i(F_{1,2,\ldots,J}(\mathbf{x},\mathbf{y}))$: Objective function that describes the objective i which is related to the different design performance functions.
- $F_{1,2,\ldots,J}(\mathbf{x},\mathbf{y})$: Design performance functions that describe the object, depending on one or multiple design variables x (i.e. controllable endogenous variables) and one or multiple physical variables y (i.e. uncontrollable exogenous variables).
- $\mathbf{x}$: A vector containing the (controllable) design variables $x_1, x_2, \ldots, x_N$. These variables are bounded such that $lb_n \leq x_n \leq ub_n$, where lb_n is the lower bound, ub_n is the upper bound, and $n = 1,2,\ldots,N$.
- $\mathbf{y}$: A vector containing the (uncontrollable) physical variables $y_1, y_2, \ldots, y_M$.
- $w'_{k,i}$: Weights for each of the preference functions. These weights can be broken down into weights for the stakeholders and weights for the objectives:
  - w_k: weights for stakeholders $k = 1,2,\ldots,K$. These weights represent the relative importance of stakeholders.
  - $w_{k,i}$: these weights represent the weight stakeholder k gives to objective i.

  The final weights $w'_{k,i}$ can be constructed via $w'_{k,i} = w_k * w_{k,i}$, given that $\sum w'_{k,i} = \sum w_{k,i} = \sum w_k = 1$
- $g_p\left(O_i\left(F_{1,2,\ldots,J}(\mathbf{x},\mathbf{y})\right), F_{1,2,\ldots,J}(\mathbf{x},\mathbf{y})\right)$: Inequality constraint functions, which can be either objective function and/or design performance function constraints.
- $h_q\left(O_i\left(F_{1,2,\ldots,J}(\mathbf{x},\mathbf{y})\right), F_{1,2,\ldots,J}(\mathbf{x},\mathbf{y})\right)$: Equality constraint functions, which can be either objective function and/or design performance function constraints.

To further elaborate on this formulation, several important remarks are made which are discussed below.

Remark 1: preference aggregation

In this paper, the aggregated preference scores are determined by a solver called Tetra, which is built based on the PFM principles (and which is expressed as the mathematical operator T) (Barzilai, 2005). Tetra's solving algorithm is based on finding/synthesising the aggregated preference score (i.e. the "best" fit of all weighted (relative) scores for all the decision-making stakeholders' objectives) that minimises the least-squares difference between this overall preference score and each of the individual scores (on all criteria) by computing its closest counterpart (Barzilai, 2022; Zhilyaev et al., 2022).

In this, preference is a statement of an individual stakeholder's interest and a measurement of satisfaction, which is a score that is expressed as a real number (scalar or bare quantity) on a defined scale from, for instance 0 to 100, where 0 is mapped to the 'worst' performing alternative and 100 is mapped to the 'best' performing alternative. For more information on the Tetra software, see Scientific Metrics (n.d.).

Remark 2: preference functions

Preference functions describe the relationship between an individual stakeholder's preference towards a specific objective (where a stakeholder is defined as one of the participants in the design/decision-making process). The theory of preference functions (often also called utility functions) for *a-posteriori* multi-criteria decision evaluation is a branch of the social sciences in itself. However, here the preference functions are required as input to the design/decision system to enable *a priori* multi-objective design optimisation. In this paper, the elicitation of preference functions and related stakeholders' objective weights is handled pragmatically using 'static' expert judgement whereas in practice this is by nature a dynamic and iterative process which helps stakeholders better understand the impact their input has on the optimisation outcome (see Arkesteijn et al. (2017, 2015) for elicitation specifics as part of the design cycle).

Finally, it is noted that one objective O_i can also be linked to multiple stakeholder preference functions $P_{k,i}$ (as $k \geq i$). However, it is not required that a stakeholder provides a preference for all objectives. This is modelled by giving a stakeholder's objective a weight of zero, which means that some elements of the $w_{k,i}$ matrix can be zero.

Remark 3: bound preference scores

In this paper, a preference score is bounded by $0 \leq P_{k,i} \leq 100$. A constraint can be added to the objective functions to prevent preference scores which lay outside these bounds.

Remark 4: design variables in objective functions

A design variable x can directly be linked to an objective function O. In that case, the design performance function F is just equal to the design variable x. Moreover, these design performance functions F can also only relate to an exogenous physical variable y.

Remark 5: rewrite equality constraints

Equality constraints are quite common in the object behaviour domain. However, as the Preferendus makes use of a Genetic Algorithm (GA) (Kramer, 2017), equality constraints can complicate the convergence of the optimisation, since especially the simpler constraint handlers for GAs have problems with handling equality constraints (Homaifar et al., 1994). Hence, when a system of interest is modelled, the equality constraints can be rewritten into inequality constraints, as is commonly done in literature (Coello, 2002; Kramer, 2017). For this, often the form of Equation (2.4) is used.

For the proposed open design systems methodology, it is possible to directly rewrite most equality constraints into inequality constraints, as the methodology aims at reducing "waste" in the outcome. For example, the length of a beam to support a floor will commonly have a fixed length: the length of the span. Since a longer length than the length of the span leads to more costs, material consumption, carbon emissions, etc., this equality constraint can be safely rewritten as an inequality constraint. This will make the modelling easier since the tolerance ϵ does not have to be set and tuned per problem.

$$|h_{1,2,...,M}(O_{1,2,...,I}(F_{1,2,...,J}(\mathbf{x})), F_{1,2,...,J}(\mathbf{x}))| - \epsilon \leq 0 \tag{2.4}$$

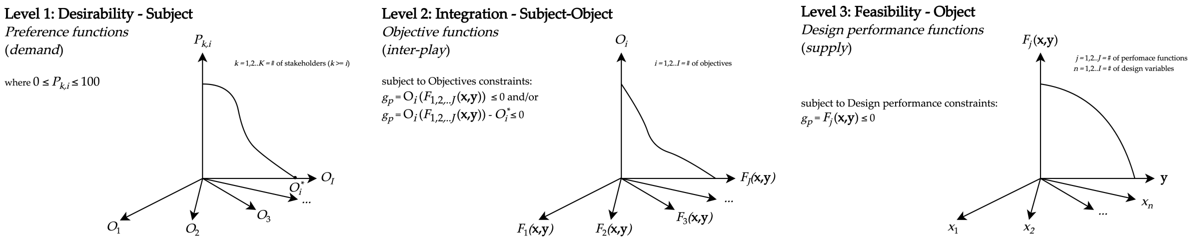


Figure 2.1: Conceptual threefold framework of the Odesys mathematical statement, where desirability-subject (preference functions, level 1) and the feasibility-object (design performance functions, level 3) are integrated subject-object (objective functions, level 2).

Remark 6: soft and hard constraints

Finally, a distinction can be made between soft and hard constraints. The former result from the sociological aspect of a design process and are negotiable. They can be adapted during the process based on discussions with other stakeholders or new insights. The latter are fixed and non-negotiable. These are given by, among others, laws of nature, material composition, environmental conditions, etc.

2.2.1. Conceptual threefold framework

The mathematical statement with the aforementioned remarks provides a general framework in which it is possible to connect the subject desirability level (preference functions) with the object feasibility level (performance functions) via the integrative subject-object interplay level (objective functions). To better understand this interaction, the mathematical formulation is conceptualised in a threefold framework, as shown in Figure 2.1. Note that the numbering of the levels is not indicating the order of setting up the design problem statement.

2.3. The Preferendus & IMAP (maximising group preference: synthesis)

In this section, the so-called Preferendus tool and its optimisation method IMAP are described as part of the Odesys methodology. Design applications using the state-of-the-art Preferendus tool will be demonstrated in the following section. Here the conceptual functioning will be introduced (as an extension and further advancement of the Preferendus as described by Zhilyaev et al. (2022)).

The Preferendus tool is based on the IMAP optimisation method, introduced within this paper. It combines proper preference aggregation with preference maximisation, as described by the mathematical formulation of the Odesys problem statement of the previous section.

2.3.1. Preference aggregation (IMAP part1)

Following the open design systems methodology, it is argued that the overarching goal of multi-objective design optimisation is to find the highest overall group preference score which represents the design synthesis. However, for these design syntheses to be possible, first the individual preference scores need to be aggregated.

As preference scores are defined in an affine space, aggregation should take place in this space too. This means that according to the basic principles of the PFM theory, the correct way of preference score aggregation is finding the aggregated preference score that provides the "best" fit to all the weighted (relative) scores of the different preference functions. Here, preference functions are the integration of objective functions and design performance functions. To perform this, the Tetra solver that incorporates the aforementioned principle of preference aggregation is used as an integral evaluation part of the overarching optimisation algorithm.

2.3.2. Preference maximisation (IMAP part 2)

To finally find the design configuration which reflects the maximum group preference aggregation, it is necessary to also use a maximisation algorithm. For this, a GA is used which is specifically adapted to work with Tetra. This is because it is not directly possible to compare one GA's generation with another as the aggregated evaluation Tetra results are only containing information about a single generation's alternatives. To overcome this, a GA is developed where broadly available elements are combined and extended with a so-called inter-generational solver. The details and the working of this solver are given in Appendix A.

As a conclusive end result, an Odesys-based design optimisation tool, the Preferendus, incorporating the IMAP method has been developed. The concept diagram of the Preferendus is shown in Figure 2.2. This tool is an open-source tool that is made available via GitHub (see data availability statement).

2.3.3. Interlude min-max goal attainment (minimising individual dissatisfaction: compromise)

To compare and validate the results and added value of the multi-objective optimisation method IMAP, the following section first compares the results with those of the single-objective optimisation. In addition, a comparison will be made with the classical min-max goal attainment multi-objective optimisation method (Marler & Arora, 2004). This method does not generate group results based on overall aggregation, but rather optimises, i.e. equalises, each individual result so that they are as close as possible to a 'utopian' design point. In other words, the min-max method tries to minimise the maximum dissatisfaction for all individual scores (i.e. expressed by the distance to a utopia point). The result of this method is a solution in which every stakeholder is equally gratified.

In order to make a like-for-like comparison between IMAP and min-max, the mathematical formulation of the Odesys problem statement will have to be modified (i.e. Equation (2.1) will have to be changed). Firstly, this means that in this case, the min-max method will try to minimise the distance to a score of 100 for all different preference scores $P_{k,i}$ (i.e. a best-scoring utopia point has been defined as 100). Subsequently, one needs to find the preference score $P_{k,i}$ that has the largest (weighted) dissatisfaction and try to minimise this, which mathematically is read as Equation (2.5).

$$\underset{\mathbf{x}}{Minimise}\ U = \max_{k,i}\left[w'_{k,i} \times \left\{100 - P_{k,i}\left(O_i\left(F_1(\mathbf{x},\mathbf{y}), F_2(\mathbf{x},\mathbf{y}), ..., F_J(\mathbf{x},\mathbf{y})\right)\right)\right\}\right] \text{ for} \\ k = 1, 2, ..., K \\ i = 1, 2, ..., I \tag{2.5}$$

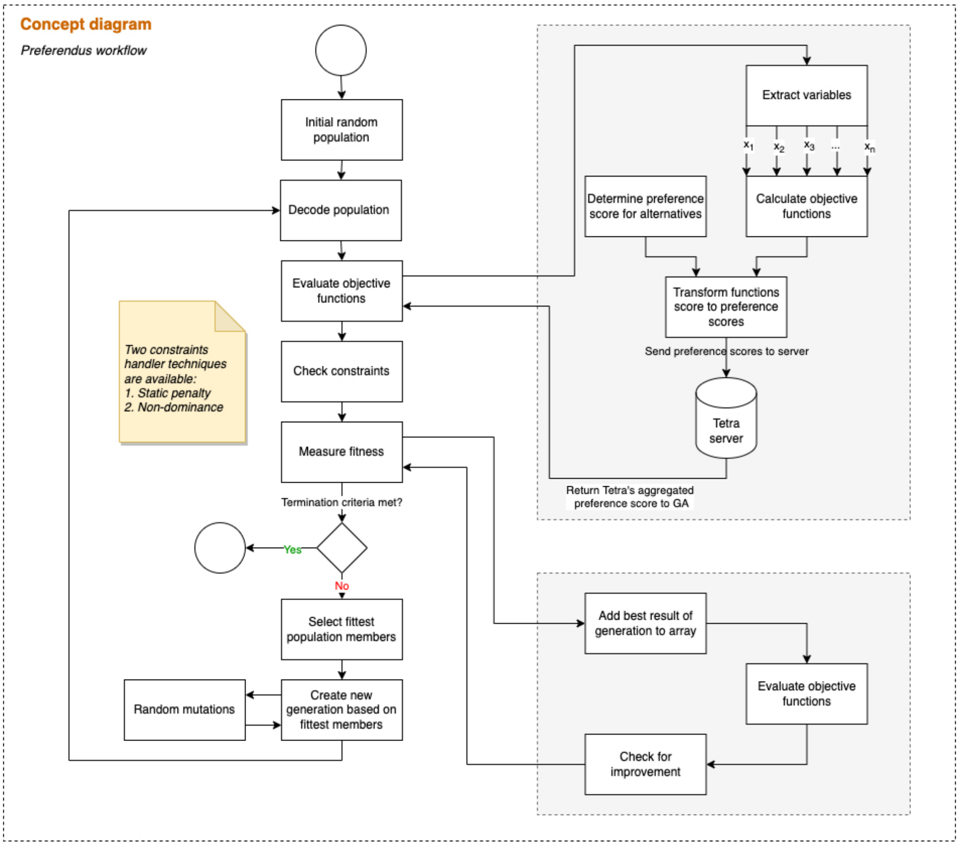


Figure 2.2: The workflow of the Preferendus, presented as a concept diagram.

It is noted that the min-max goal attainment, as part of a larger group of multi-objective optimisation methods, does not violate the PFM principles. However, this method treats the scores of all design alternatives as absolute values, ignoring the dynamic interplay between these. So, this method is focused on keeping every stakeholder as 'happy' as possible, even as this might not be beneficial for the overall group. Therefore, this optimisation is called a compromise method because it finds a design configuration based on a compromise between stakeholders rather than a synthesis.

2.4. Real-life exemplars

The open design systems (Odesys) methodology, the associated IMAP optimisation method, and the use of the Preferendus are demonstrated in two real-life infrastructure design exemplars: (1) a rail level-crossing service life design, and (2) a floating wind turbine installation. Although both problems are simplified for illustrative purposes, these still will give insight into the added value and the principles of the Odesys methodology, the IMAP method and the Preferendus tool.

2.4.1. Exemplar 1: a rail level-crossing service life design

Railways and roads cross each other commonly on so-called level-crossings. Since heavy vehicles also need to be able to cross, the railway is often cast into a concrete foundation. However, the mechanical properties of this concrete foundation are very different from the foundation of the other parts of the railroad track. As a result, transitional radiation occurs during a train passage, potentially resulting in faster local rail system degradation and/or a negative passenger travel experience due to vibrational hindrance (Metrikine et al., 1998). Therefore, a transition zone is created by varying the number of sleepers and sleeper distance to contribute to a smoother transition which should have a positive effect on both its operational service and the passenger's travel comfort. In this exemplar, a multi-objective design optimisation (MODO) of the transition zone is demonstrated based on different conflicting interests from multiple stakeholders: i.e. capital and operational expenditures and travel comfort. It is assumed that these three overall objectives are linked to three different stakeholders. Take for instance the Dutch ProRail organisation, where there is both a project delivery and a service operations department linked to the capital and operational expenditure objectives, respectively. The Dutch train passenger is depicted as the stakeholder linked to the travel comfort objective.

First, the integrative design problem is described by running through the conceptual threefold framework, see Figure 2.1, resulting in design performance-, objective- and preference functions (levels 1,2,3).

Level 3 – design performance functions

In reality, this design depends on a multitude of design variables, but for now, it will be limited to just two of them:

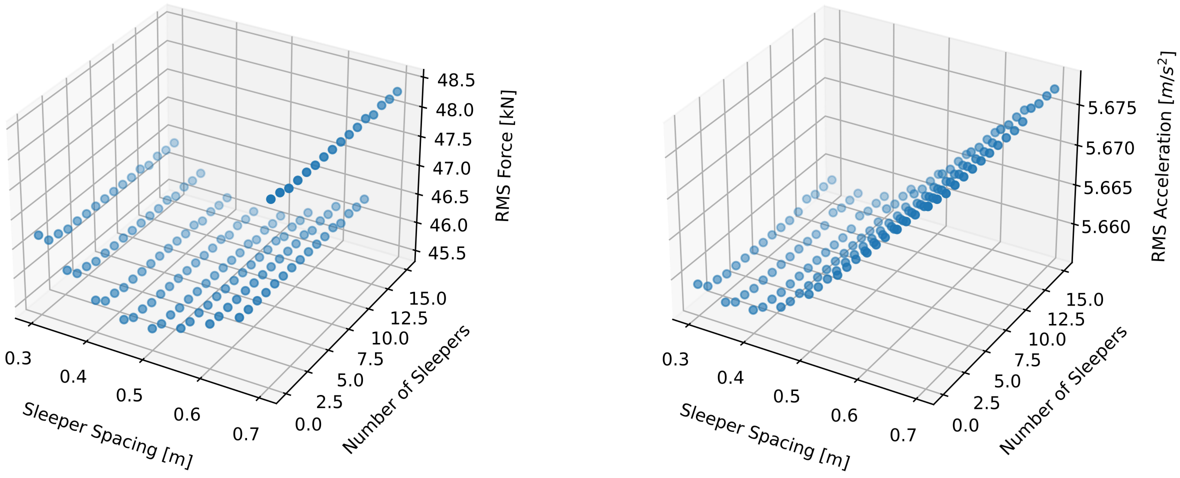
1. $F_1 = x_1 > 0$: the distance between the sleepers. Sleepers are the concrete (or sometimes wooden) beams which support the rails, as part of the ballast bed.
2. $F_2 = x_2 (\geq 1)$: the number of sleepers in the transition zone. The transition zone consists of a different type of sleeper than the rest of the rail track.

Note that (1) that to stay compliant with the general mathematical statement from section 1, here at level 3 design performance functions F_1 and F_2 are added which are equal to x_1, x_2 respectively, and (2) from the practical application context, the design variables are bounded as follows $0.3 \leq x_1 \leq 0.7$ and $4 \leq x_2 \leq 15$, which determine the design space (i.e. solution space defined by the design variables).

The key design performance functions describing the dynamic behaviour of the rail track at the level crossing transition zone, are the force $F_3 = F$ and the acceleration $F_4 = a$. Normally, these are the result of extensive numerical finite elements and/or analytical calculations. For this exemplar, the physical/mechanical relations between these variables are simplified by using interpolation of discrete numerical calculations, which follow from a state-of-the-art structural dynamic model (Shang et al., in press-a, in press-b). The outcomes of these discrete calculations which are the basis for the interpolation are shown in Figure 2.3. For this exemplar, the force and acceleration are mathematically formulated as $F_3 = F(x_1, x2)$ and $F_4 = a(x_1, x_2)$ respectively.

Level 2 – objective functions

Three objectives are investigated in this exemplar: maintenance costs, travel comfort and investment costs. Given these three objectives, the optimal design for the level crossing zone is determined.



(a) Force (b) Acceleration

Figure 2.3: Resulting force and acceleration on the rails in the transition zone, depending on x_1 and x_2.

Objective maintenance costs (OPEX)
The design of the transition zone is mainly driven by related maintenance costs. Large forces and accelerations will negatively impact the degradation of the rail track and foundations, with increasing maintenance costs as a result. Hence, the connected objective can be written as a function of the force and acceleration. To this end, the force and acceleration are normalised and combined via the root sum of the square. The final objective reads as Equation (2.6) and returns the maintenance costs per year:

$$\text{Minimise } O_M = \sqrt{F_N^2 + a_N^2} \cdot 15\,000 \tag{2.6}$$

where

$$F_N = \frac{F - F_{min}}{F_{max} - F_{min}} \tag{2.7}$$

$$a_N = \frac{a - a_{min}}{a_{max} - a_{min}} \tag{2.8}$$

and where O_M is expressed as maintenance costs per year (Euro's OPEX). Note that at level 3, it holds that $F_3 = F$ and $F_4 = a$ respectively.

Objective travel comfort
The comfort of passengers is an important factor to consider in the design of railways. When during a level-crossing passage the dynamic behaviour (accelerations) is high, this can create a negative travel experience or, in the worst case, lead to minor mishaps on the train (falling while walking or spilling drinks, etc.). To integrate this into the design problem, an objective is added that describes travel comfort as a function of the normalised acceleration:

$$\text{Minimise } O_C = 1 - a_N \tag{2.9}$$

with a_N as given in Equation (2.8).

Objective investment costs (CAPEX)
Lastly, the investment costs need to be considered. The installation of more sleepers will first of all result in higher investment costs. However, more sleepers spread out over a larger distance will also mean the investment costs for other rail parts will reduce. Hence, the objective as shown in Equation (2.10) can be constructed into:

$$\text{Minimise } O_I = 1000x_2 - 350x_1x_2 \tag{2.10}$$

where O_I is expressed in Euro's CAPEX.

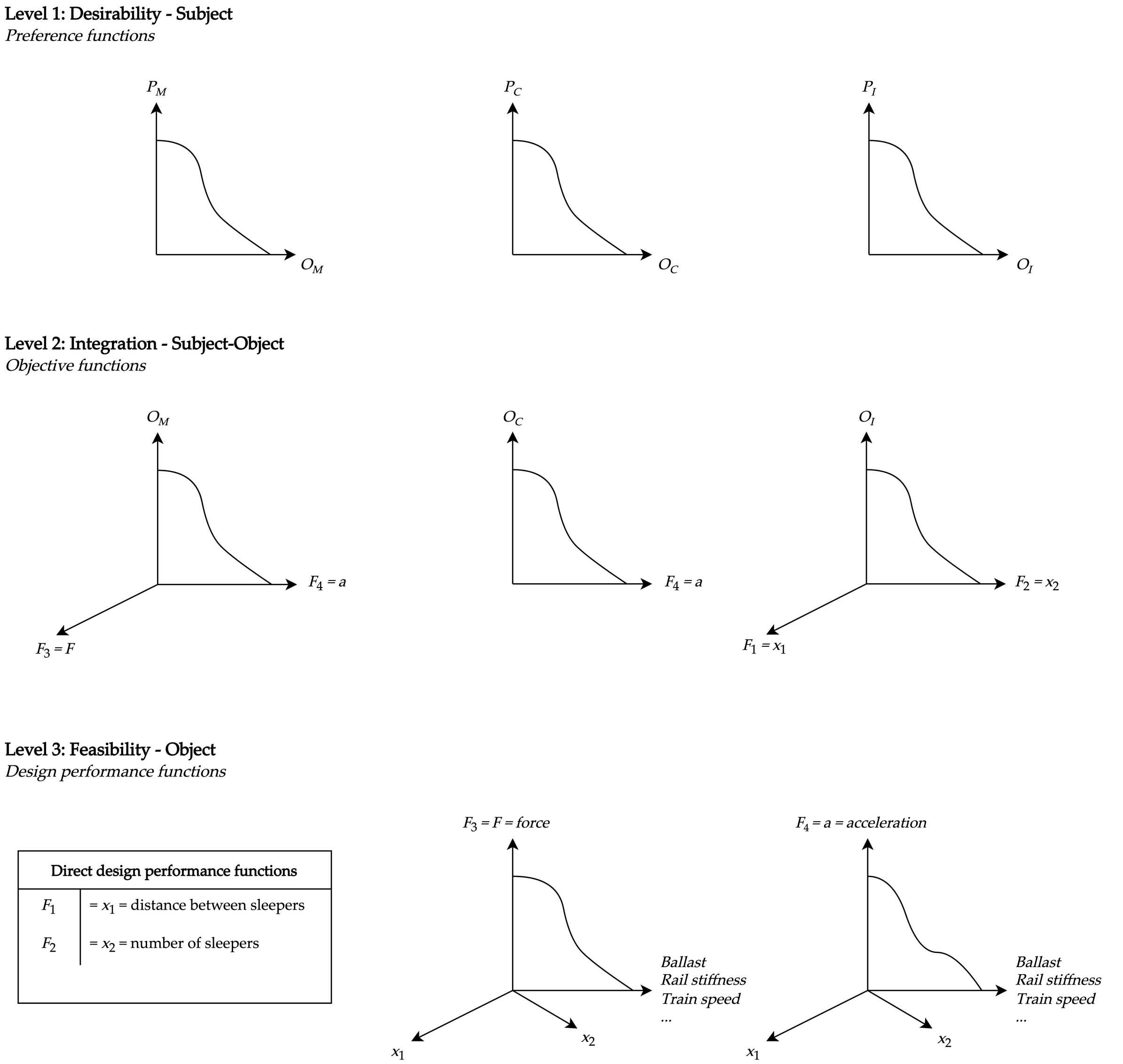


Figure 2.4: Conceptual threefold diagram, describing the systems design integration for the rail level crossing exemplar.

Level 1 - preference functions

The preference functions for this exemplar are constructed based on the input of relevant stakeholders and follow from PhD project conducted by Ms Shang, within the Engineering Asset Management group of Delft University of Technology (see Shang et al. (2021, 2020)). The resulting functions (i.e. relations between different values $P_{1..3,1..3}$ and $O_{1..3}$) are shown as the blue curves figure Figure 2.5. Note that the preference function elicitation has been done using the basics of relevant preference functions research (see Arkesteijn et al. (2017, 2015) for the PFM-based elicitation specifics as part of the design cycle, which is not the focus of this paper). Finally, the level 1,2 and 3 systems design integration problem statement is conceptualised with the threefold diagram as shown in Figure 2.4.

Design optimisation results & conspection

To generate the design points (i.e. design configuration results) for the different multi-objective optimisation methods (MODO min-max and IMAP), the weights for each objective will first have to be determined. Because in traditional (contractor) design offices a dominant weight is often given to the investment costs only and less to the quality of service (QoS) oriented interests maintenance and travel performance, here it is deliberately done "the other way round", resulting in $w_{1,M} = 0.4$ for maintenance, $w_{2,C} = 0.4$ for travel comfort and

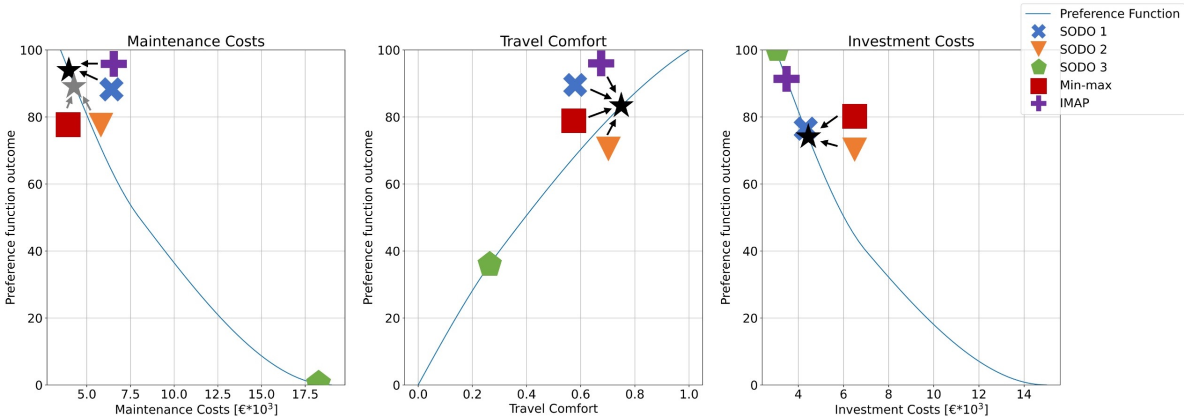


Figure 2.5: The three stakeholder preference functions ($P_{1..3,1..3}$) for different objectives ($O_{1..3}$), i.e. blue curves.

$w_{3,I} = 0.2$ for investments. For evaluative purposes, also the design points for the different single-objective optimisation methods (SODO1..3) are determined.

The outcomes of the different design points/configurations per optimisation method are first of all plotted on the different preference functions showing the different objective function values ($O_{1..3}$) and their corresponding individual preference function values ($P_{1..3,1..3}$), see Figure 2.5. Note that, the results for IMAP have been obtained with the new Preferendus tool and the other design optimisation results with specific standard Python routines (see the data availability statement for the repository containing the exemplar's code).

Secondly, the numerical results of the different design points/configurations per optimisation method (SODO and/or MODO) can be read from Table 2.1. In this table, one can also find the aggregated preference score with which the overall score/ranking was determined via the PFM-based Multi-Criteria Decision Analysis (MCDA) tool Tetra, where the resulting aggregated preference scores are rescaled between scores of 0 and 100 (here 0 reflects the 'worst' scoring configuration/alternative and 100 the 'best', see Appendix A for further details). Note that, in general, one needs at least three alternates for such an overall evaluation (e.g. a reference configuration and two MODO configurations could already suffice or, as in the following exemplar, one SODO and two MODO configurations).

Finally, because there are only two design variables in the exemplar, the two-dimensional design space (sometimes called solution space, see Dym and Little (2004)) containing the different design points / configurations per optimisation method can be plotted, see Figure 2.6.

The following three conclusions are drawn from these figures and table:

(1) It is seen that the IMAP configuration is equal or at the least distance to the best outcome on all single objectives (the SODO configurations). Only on the single-objective investment costs, IMAP is second best as it also still tries to optimise on the other two objectives O_M and O_C. For these objectives, a low spacing between the sleepers (x_1) is expected whereas the number of sleepers (x_2) has a relatively low influence on the outcome of these objectives. For this exemplar in particular, and given the different objectives and related stakeholder preferences, low spacing between sleepers (x_1) is expected to significantly affect the objectives

Table 2.1: Evaluation of different design configurations per optimisation method and their relative ranking (based on aggregated preference scores).

Optimisation methods	x_1 [m]	x_2 [#]	Aggregated preference score
Single objective O_M (SODO1)	0.39	5	84
Single objective O_C (SODO2)	0.35	5	81
Single objective O_I (SODO3)	0.70	4	0
MODO min-max	0.35	5	81
MODO IMAP	0.38	4	100

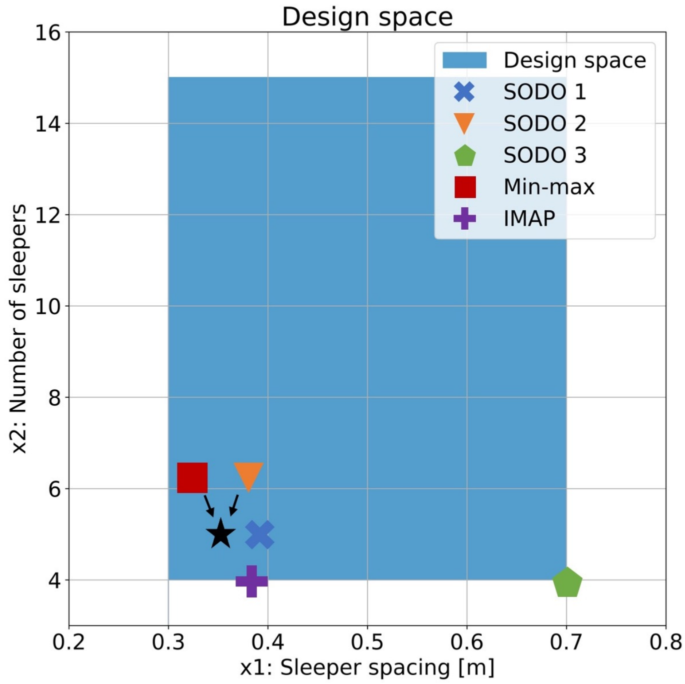


Figure 2.6: The design space and design configuration/points for the different optimisation methods.

O_M and O_C, and the number of sleepers (x_2) will do so less.

However, for objective O_I, the influence of x_2 will be substantial as the lower x_2 the lower the investment costs. Moreover, the influence of x_1 on O_I is opposite to its influence on the other two objectives. For this reason, the design configuration that only optimises investment costs is not representative. In a MODO optimisation, the ideal equilibrium in the sleeper spacing (x_1) is expected to be found, since it is expected that the outcome for the number of sleepers will be at the lower bound (i.e. $x_2 = 4$). The result of the IMAP optimisation indeed reflects this best fit-for-common-purpose balance. This allows IMAP to be characterised as a true synthesis multi-objective design method.

(2) It is seen that the IMAP configuration gets better or equal individual preference function values ($P_{1..3,1..3}$) and, more important, also scores much better overall than the MODO min-max method result. This is because, from the min-max principle, this method will never be able to score better at the individual objective result level than that single objective result which shows the maximal attainable minimal distance to 100 (i.e. minimal dissatisfaction). Thus, the min-max method by nature gives a sub-optimal compromise design outcome which for this exemplar, depending on a specific level 1-2-3 integration problem setup and its weight distributions, can at best perform equally with the synthesis IMAP method. This limits the applicability of the min-max method as a true multi-objective design optimisation method.

(3) From the design space figure, it is seen that (perhaps counterintuitively) both the SODO 1 and 2 as well as the MODO min-max results fall within the design space ($x_1; x_2$ equals 0.35/0.39 and 5 respectively), and that the MODO IMAP and the SODO 3 lie respectively on the edge and a corner point of the design space. This is because these set of design points that fall within the design space are a result of merely optimising the 'technical' performance. In other 'traditional' words, this means that without the system being able to realise this purposefully, the optimal solution moves to an optimum within the feasibility space (i.e. the solution space defined by physical engineering variables) or lies on the Pareto front (Note that in this case a possible Pareto front, which defines an edge of the feasibility space as a function of F and a, results only from the minimisation of O_M and O_C).

On the other hand, the SODO corner point shows that in that case, optimisation is done purely based on cost (read a single-sided 'management' decision) and thus, although an 'extreme' is found in the design space, it is certainly not the best fit-for-common-purpose design point. The IMAP design point ($x_1; x_2$ equals 0.38 and 4 respectively) in this case moves from a best point in the feasibility space to a best fit-for-common-purpose design point on the edge of the design space and can therefore be considered the true best fit-for-common-purpose design point.

Note that where in the design integration problem the emphasis is on the optimisation of the management process (e.g. installation planning) and no benefit can be gained from 'over-dimensioning', the direct technically driven design variables are mostly on an edge of the feasibility space (i.e. design performance constraint or a Pareto front), but that the influence of the optimal management decision determines the overall best configuration within the design space (see the following exemplar).

2.4.2. Exemplar 2: a floating wind farm installation plan

A promising solution for the extraction of wind energy in deep waters could be the use of floating wind turbines (FWT). Here the turbines are not placed on a fixed monopile, but on a platform that is moored to the seabed by anchors. In this exemplar, a multi-objective design optimisation (MODO) approach for the installation of multiple FWTs is demonstrated based on different conflicting interests from multiple stakeholders: i.e. project duration, installation costs, fleet utilisation and CO2 emissions. Given these four overall interests, an energy service provider (stakeholder one, e.g. Shell) wants a marine contractor (stakeholder two, e.g. Boskalis) to determine the optimal installation plan for a floating wind farm consisting of 36 FWTs and 108 suction anchors (i.e. 3 anchors per FWT).

Although costs are still a major driver in the offshore industry, the energy service provider will be primarily interested in a short wind farm delivery time, as it will then start generating resource income earlier. Secondly, the energy service provider will have an interest in reducing the CO2 emissions of a project, as this will benefit its carbon emission footprint and the social acceptance of the project. The marine contractor will primarily focus on reducing the costs, as this will make it more competitive. Secondly, its fleet management department can express its preference for the fleet utilisation objective, as this might lead to better fleet utilisation.

First, the integrative problem is described by running through the conceptual threefold framework, see Figure 2.1, resulting in design performance-, objective- and preference functions (levels 1,2,3).

Level 3 – design performance functions

For installing the FWTs and their suction anchors, several types of vessels are available. The number of each of these vessels used for the project are the first three design variables for this problem:

1. $F_1 = x_1 (0 \leq x_1 \leq 3)$: Small offshore construction vessels (OCV). Can store up to 8 anchors on board.
2. $F_2 = x_2 (0 \leq x_2 \leq 2)$: Large offshore construction vessels. Can store up to 12 anchors on board.
3. $F_3 = x_2 (0 \leq x_2 \leq 2)$: Self-propelled crane barges. Can store up to 16 anchors on board.

Note that the lower bound of these three design variables is equal to zero. Hence, a design performance constraint is required to ensure the sum of all vessels on the project is larger than one (reflecting that at least one vessel is required):

$$g_1 = -(F_1 + F_2 + F_3) + 1 \leq 0 \tag{2.11}$$

In this exemplar, also the design of the anchors themselves is considered. For this, design performance functions are defined that: 1) describe the resistance of the anchor to forces acting on it, and 2) the amplitude of the forces acting on the anchors.

The resistance of the anchors considered in this exemplar can be estimated via analytical design calculations (Arany & Bhattacharya, 2018; Houlsby & Byrne, 2005a; Randolph & Gourvenec, 2017). Normally, these calculations will depend on a multitude of design variables, of which in this exemplar only two are considered:

1. $F_4 = x_4 (> 0)$: Diameter of the suction anchor in meters.
2. $F_5 = x_5 (> 0)$: Penetration length of the suction anchor in meters.

For practical reasons, these variables are bounded such that $1.5m \leq x_4 \leq 4m$ and $2m \leq x_5 \leq 8m$. The other design variables are taken as uncontrollable design variables $\mathbf{y}$ in this exemplar, which here read as $\mathbf{y}$ = [working point F_a, mooring configuration, anchor type, soil conditions, mooring line properties]. As a result, the resistance of the anchor can mathematically be formulated as $F_6 = R_a(x_4, x_5, \mathbf{y})$. For the soil, clay with an undrained shear strength of $s_u = 60$ kPa and a submerged weight of $\gamma' = 9\ kN/m^3$ is assumed. The coefficient of friction between the shaft of the anchor and the soil is $\alpha = 0.64$. The mooring line consists entirely of a chain with a nominal diameter of 240 mm. This chain is attached to the anchor at a depth of 0.5 times the penetration length. Furthermore, the coefficient of friction between the seabed and the chain is taken as $\mu = 0.25$ and the active bearing area coefficient AWB= 2.5.

Although the anchor resistance can be determined by analytical calculations, this is not possible for the forces acting on the anchor. Not only because these forces depend on a great number of variables (platform type, mooring line properties, pretension, anchor radius, etc.), but also because numerous numerical time-domain calculations have to be performed to get the correct normative forces (DNV, 2021c). These calculations are, however, out of the scope of this paper. Instead, the relevant design variables are considered as uncontrollable physical variables **y**, resulting in the following (assumed) force on the anchors: $F_7 = F_a(\mathbf{y}) = 3.8MN$, where $\mathbf{y}$ = [platform type, mooring line properties, pretension, mooring line length, anchor radius].

The two design performance functions F_6 and F_7 are related to each other via a design performance constraint. This constraint describes (part of) the feasibility space of the design by defining the edge where the resistance of the anchor is larger or equal to the force on the anchor:

$$g_2 = F_7(\mathbf{y}) - F_6(x_4, x_5, \mathbf{y}) = F_a - R_a \leq 0 \tag{2.12}$$

Level 2 – objective functions

As mentioned before, four objectives are investigated in this exemplar: project duration, installation costs, fleet utilisation, and CO2 emissions. Given these four objectives, the optimal plan for installing the FWTs is determined.

Objective project duration

The project duration will depend on the number of ships on the project, their deck capacity, and the speed at which they can install anchors, which is assumed at one anchor/day/vessel. Moreover, after all the anchors on board have been installed, the ships will have to load new anchors. This process takes 1.5 days for the small OCV, 2 days for the large OCV, and 2.5 days for the barge.

To get the overall project duration, a small Discrete-Event Simulation (DES) has been added to the model, considering the vessel types and numbers (i.e. $x_1..x_3$). See the data availability statement for the code of the DES. In summary, the project duration objective function is written as:

$$\text{Minimise } O_{PD} = f(x_1, x_2, x_3) \tag{2.13}$$

where f is the DES and O_{PD} is expressed in days.

Objective installation costs

The installation costs objective of this project depends on two variables: 1) the day rates of the vessels, and 2) the costs of the anchors. For the first, the following theoretical day rates R are assumed:

1. Small OCV (x_1): R_1 = €47,000/day
2. Large OCV (x_2): R_2 = €55,000/day
3. Barge (x_3): R_3 = €35,000/day

The costs per anchor can be divided into a fixed part (€40,000/anchor) and a variable part, where the variable part is depending on the material costs (€815/mt). This leads to the following objective cost function:

$$\text{Minimise } O_C = (815M_a + 40{,}000)\,n_a + \sum_{i=1}^{3} x_i\, t_i\, R_i \tag{2.14}$$

where O_C is expressed in Euros. Here n_a is the number of anchors (i.e. $n_a = 108$); t_i the time a ship is needed (result from the DES); M_a the mass of the anchors, defined as:

$$M_a = \left(\pi x_5 x_4 t + \frac{\pi}{4} x_4^2 t\right) M_{steel} \tag{2.15}$$

with M_{steel} the mass of steel, taken as 78.5 mt.

Objective fleet utilisation
For a marine contractor, optimal fleet utilisation is a key driver. Therefore, this fleet utilisation objective is incorporated in this exemplar by examining the probability that a vessel could have been better utilised on another project (e.g. specialised vessels are preferred over multi-purpose vessels). For this, the following values for the probability that a vessel can be utilised within another project are assumed:

1. Small OCV (x_1): $p_1 = 0.7$
2. Large OCV (x_2): $p_2 = 0.8$
3. Barge (x_3): $p_3 = 0.5$

The fleet utilisation objective is then defined as Equation (2.16):

$$\text{Minimise } O_F = \prod_{i=1}^{3} p_i^{x_i} \tag{2.16}$$

where O_F is expressed as the combined chance (with a value between [0, 1]).

Objective CO_2 emissions
Sustainability becomes an increasingly important aspect of offshore (wind) project developments. Most emissions will result from the vessels, for which the following theoretical average emission rates are taken:

1. Small OCV (x_1): $E_1 = 30mt/day$
2. Large OCV (x_2): $E_2 = 40mt/day$
3. Barge (x_3): $E_3 = 35mt/day$

As other sources of emissions are neglected (e.g. the vessel speed), the emission objective is defined as Equation (2.17):

$$\text{Minimise } O_S = \sum_{i=1}^{3} x_i E_i t_i \tag{2.17}$$

where O_S is expressed in mt and with t_i the time a ship is needed (result from the DES).

Note that the Odesys mathematical statement allows for direct integration of design performance and objective functions (i.e. direct integration of level 2 and level 3 through all the design performance functions). However, as is the case for this exemplar, sometimes design performance functions will not only contribute directly to the objective functions but can also be linked via (in)equality design performance constraints. This is a form of indirect level 2 and 3 linking that will be common in design problems where, for example, force constraints play an important role. In such cases, these constraints will determine the feasibility space and they, together with directly linked design performance functions, define the design solution space.

Level 1 - preference functions

The preference functions for this exemplar are constructed in discussion with experts on floating wind projects within Boskalis, based on the input from an energy service provider. The resulting functions (i.e. relations between different values $P_{1..2,1..4}$ and $O_{1..4}$) are shown as the blue curves in Figure 2.8. Here the same approach has been used for constructing the preference functions and in eliciting weights as in Exemplar 1 (see Arkesteijn et al. (2017, 2015) for the elicitation specifics). Finally, the systems design integration problem statement is conceptualised with the threefold diagram as shown in Figure 2.7.

Design optimisation results & conspection

To generate the design points (i.e. design configuration results) for the different multi-objective optimisation methods (MODO min-max and IMAP), the weights for each objective will first have to be determined. Traditionally, installation costs are the only driver for offshore design/planning tender bids. With the new Odesys design optimisation methodology, it will become possible to still optimise with costs as a dominant objective, but now it is also possible to consider other relevant objectives that together represent the value of the joint installation plan of the energy service provider and the contractor. Therefore, the following weight distributions were chosen to model this joint plan: $w_{1,PD} = 0.30$ for project duration, $w_{1,S} = 0.20$ for sustainability (emission), $w_{2,C} = 0.35$ for costs, and $w_{2,F} = 0.15$ for fleet utilisation.

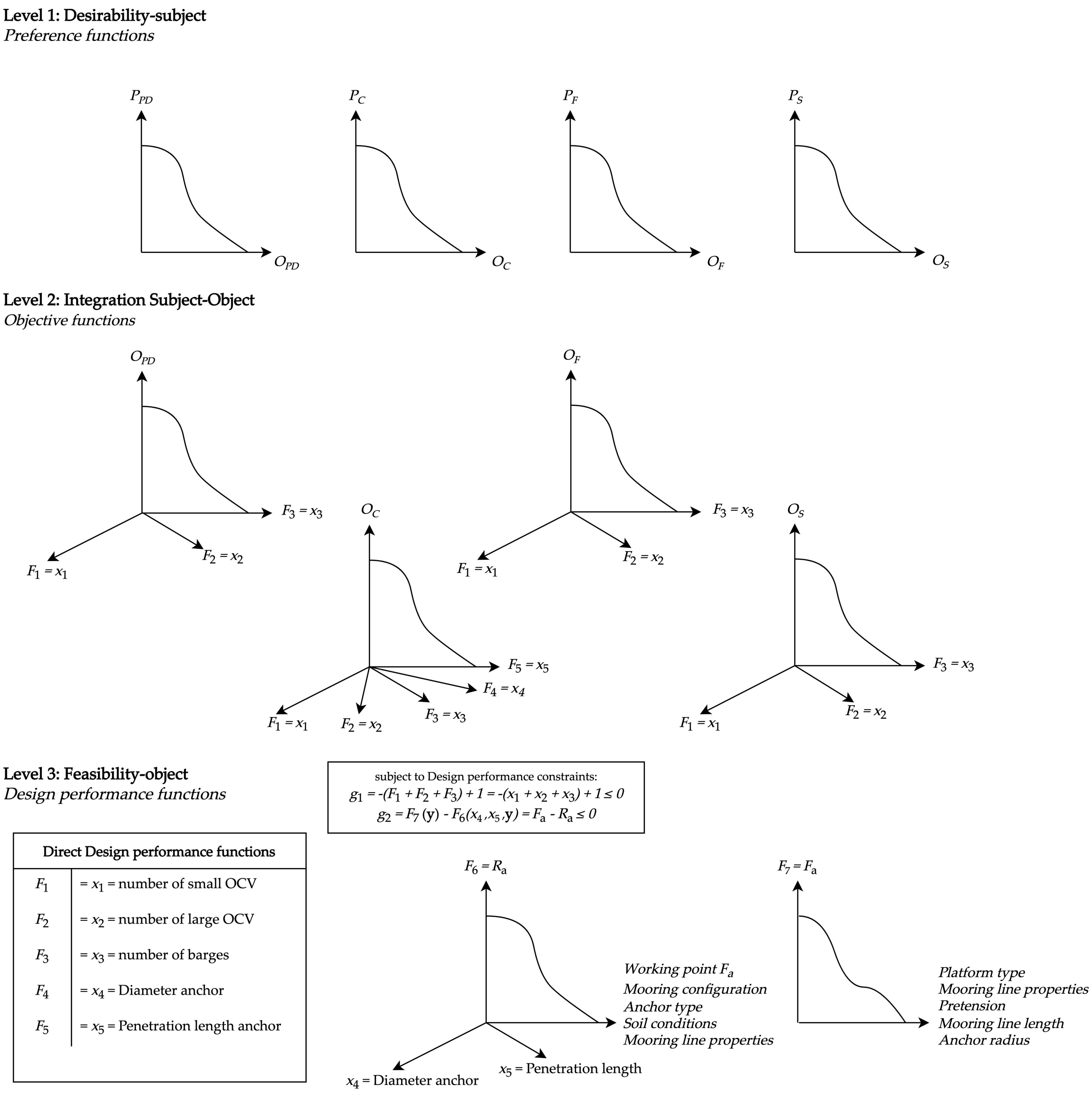


Figure 2.7: Conceptual threefold diagram, describing the systems design integration for the floating wind turbine exemplar.

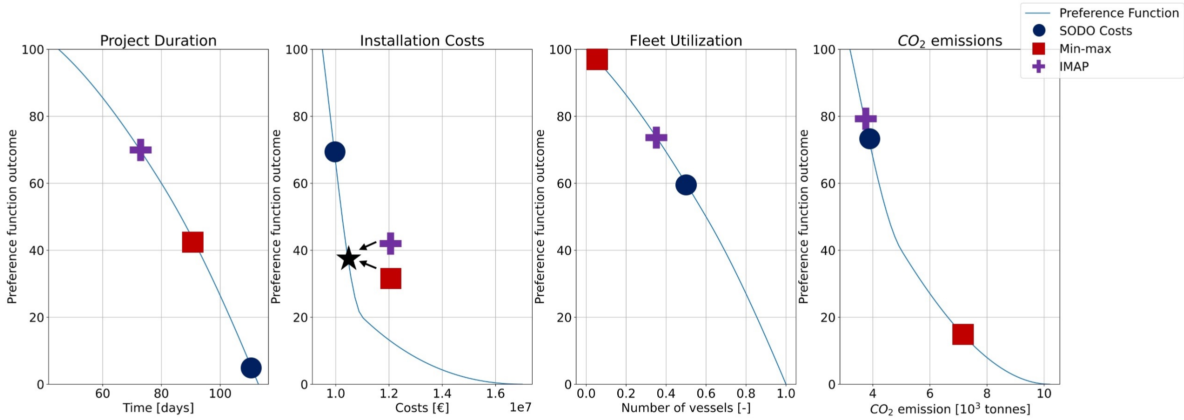


Figure 2.8: The four preference functions for the floating wind problem. The individual preference scores per objective based on the optimal design variable values are displayed in the graphs.

For evaluative purposes, the design point for the single-objective optimisation of O_C and the MODO min-max optimisation are determined too. Note that the other SODOs (single-objective optimisations on O_{PD}, O_F, and O_S) cannot be included in the integral evaluation because, in this exemplar, these do not depend on x_4 and x_5 (but only on $x_1..x_3$).

The outcomes of the different design points/configurations per optimisation method are first of all plotted on the different preference functions showing the different objective function values ($O_{1..4}$) and their corresponding individual preference function values ($P_{1..2,1..4}$), see Figure 2.8. Secondly, the numerical results of the different design points/configurations per optimisation method can be read from Table 2.2. In this table, one can also find the aggregated preference score with which the overall score/ranking was determined via the PFM-based MCDA tool Tetra, where the resulting aggregated preference scores are re-scaled between scores of 0 and 100 (here again, 0 reflects the 'worst' scoring configuration/alternative and 100 the 'best').

The following three conclusions are drawn from the figure and table:

(1) When comparing the IMAP configuration with the design point of the SODO on costs, it can be seen that IMAP outperforms the SODO on three of the four objectives. This difference is most notable when comparing the outcome of the project duration objective with the outcome of the installation cost objective. These objectives are quite opposed to each other, mostly because of the impact the number of vessels (i.e. $x_{1..3}$) has on these objectives: namely, the more vessels are deployed the faster the project is completed, but the more expensive the project becomes. Hence, a design configuration that will score well on costs will not score well on project duration, as can be seen for the SODO on costs. Hence, this result illustrates that considering costs only (single stakeholder and single objective approach) is not an accurate representation of the real-life planning challenge. IMAP on the other hand shows that it can reflect a balance between the different objectives, thereby considering both the technical design and its economics.

(2) It can be seen that the IMAP configuration scores overall much higher than the result obtained by the min-max method result. As the min-max method will try to minimise the distance to a score of 100 for all different preference scores $P_{1..2,1..4}$, it can result in very low preference scores for objectives that conflict with each other. In this exemplar, this is the case for the objectives project duration (O_{PD}) and costs (O_C). As a result, the min-max solution scores low on these two objectives. This contrasts with the IMAP design solution that can find higher preference scores $P_{1..2,1..4}$ for these two objectives. The presence of these quite conflicting

Table 2.2: Evaluation of different design configurations per optimisation method and their relative ranking.

Optimisation methods	x_1 [#]	x_2 [#]	x_3 [#]	x_4 [m]	x_5 [m]	Aggregated preference score
Single objective O_C (SODO costs)	0	0	1	2.2	8.0	69
MODO Min-max	1	0	2	2.2	8.0	0
MODO IMAP	1	0	1	2.2	8.0	100

interests limits thereby the applicability of the min-max method, as was also shown in the previous exemplar. Note that it can still score well for a "single" interest, as can be seen here for the fleet utilisation objective (it makes the use of more barges 'look' positive).

(3) From the table displayed in Table 2.2, it is seen that all three solutions have the same result for design variables x_4 and x_5. This is because this combination of x_4 and x_5 will result in the lowest costs of the anchor, without violating the design performance constraint g_2. In other words, for all three methods, there would be no difference in the optimisation if it was limited to a purely technical optimisation within the feasibility space. Still, the added value of IMAP is shown in the results for design variables x_1, x_2, and x_3, where IMAP can come to an overall better design solution compared to the other two methods by including both technical and vessel-related installation planning concerns. Note that also the best outcome within the feasibility space for x_4 and x_5 will change when objectives in the managerial (subject desirability) domain favour technical over-dimensioning of the suction anchors. Then the solution might be taken off the edge of the feasibility space (i.e. the Pareto front) as this is more beneficial for the overall planning and design performance.

2.5. Discussion

Although both exemplars are simplified for illustrative purposes, they are already showing the added value of the Preferendus/IMAP within the field of multi-objective design optimisation. However, it is also being applied and further validated within the following real-life projects: (1) the primary design and construction/production management processes of the marine contractor Boskalis; (2) the EU NRG-Storage research project (see Zhilyaev et al. (2022)); (3) several PhD/MSc thesis project applications (see van Eijck and Nannes (2022) or Shang et al. (2021)). In all projects, the decision-making stakeholders (both from the project developer and the contractor side) are predominantly positive about the unexpected design solutions which they were unable to achieve without the use of this computer-aided decision support system, the Preferendus as part of the Odesys methodology. Moreover, the Preferendus/IMAP is used for educational purposes within a novel TU Delft Systems Engineering Design course (this year 250 MSc students with 60 real-life systems exemplars).

Currently, for both exemplars (rail level crossing and floating wind turbine), a far-reaching extension of the level 1-2-3 models is taking place to better fit the design/decision problem in practice. For the floating wind exemplar, this means that OpenFAST, an open-source wind turbine simulation tool, will be connected via a surrogate model and integrated at level 3. For the level-crossing exemplar, the modelling input will be refined at all levels (focus on levels 1 and 2). In addition, for the floating wind exemplar, but also for a dredging application, validation sessions are taking place to refine the modelling inputs (especially at level 1) and evaluate the results of especially the new IMAP and the existing min-max methods. This is done in the form of a serious game, using the Preferendus as a decision support tool with the aim of increasing the internal acceptance process and connection with the engineering business.

Besides, the Preferendus and the IMAP method will be applied within other systems design and management applications such as dynamic preference and performance-based mitigation control (MitC) of large construction projects and/or optimal planning of flood defence system reinforcements (see e.g. Kammouh et al. (2022) and Klerk et al. (2021)). For application within the European NRG-Storage project (European Commission NRG-STORAGE project (project no. GA 870114)), the current Preferendus model versus the min-max optimisation approach will be evaluated within a real-life context. This will be carried out as an extension of an MSc thesis project where, within a municipality, the added value of the Preferendus within the so-called social cycle of an urban planning project was studied in more detail (van Eijck & Nannes, 2022).

Moreover, the added value within the so-called concurrent engineering and design developments in the field of 'Early Contractor Involvement' is also investigated. In particular, the Preferendus will be deployed to support and/or evaluate the new so-called two-phase contract for infrastructure projects in which the activities of the Dutch national infrastructure service provider (RWS) and its contractors are further interwoven to prevent major contract changes which were the result of the classic serial, non-participative design and engineering process.

Finally, to explore the added value of the Preferendus as soon as possible, the Odesys methodology is being educated this academic year in both the TU Delft MSc Civil Engineering and MSc Construction Management & Engineering curricula. MSc students develop a Preferendus/IMAP-based model of a self-chosen system of interest as part of the so-called Open Design Learning (ODL) response (for more detail on ODL response, see e.g. Wolfert et al. (2022)).

2.6. Conclusions

The aim of the Odesys methodology is to foster adoption of engineering artefacts in our future society by following an open space/source design and systems integration approach, which is supported by sound mathematical open glass box optimisation models as the means to achieve well-supported decision-making resulting in the best fit for socio-eco purpose open-ended solutions. Here, systems thinking and a stakeholder-oriented focus are required to search for different solutions within an open-ended optimisation process, uniting both feasibility (technics) derived from the engineering asset's performance and desirability (economics) derived from each stakeholder's preferences. This will result in an open dialogue and co-design approach that enables *a priori* best fit-for-common-purpose design synthesis dissolutions rather than *a posteriori* design compromise absolutions.

In this paper, a true *a priori* human preference and asset performance systems design integration methodology is introduced together with a new IMAP (Integrative Maximised Aggregated Preference) optimisation method. Furthermore, IMAP has been integrated within the Preferendus tool combining the state-of-the-art principles of preference function modelling (PFM) with an inter-generational genetic algorithm (GA) optimisation solver developed specifically for this purpose. Two specific engineering systems design and planning exemplars were worked out by first using the level 1-2-3 threefold diagram to formulate the mathematical problem statement. The resulting outcomes of these applications clearly highlight the added value of IMAP/Preferendus.

Firstly, it returns a single best fit-for-common-purpose design point in contrast to a Pareto front where a systems designer still has to choose the final design as the front does not define a single optimal design point. This solves another important modelling error, in addition to the fact that classical design optimisation methods leading to these Pareto fronts contain principle aggregation errors, namely that design configurations lying on the Pareto front obviously cannot all have the same preference scores.

Secondly, IMAP/Preferendus returns in all the exemplars the best design configuration compared to a set of single-objective design configurations and a design configuration as obtained by the classical multi-objective min-max method. This allows IMAP to be characterised as a true synthesis multi-objective design method which ensures a best fit-for-common-purpose point within the design space, rather than a sub-optimal single-sided corner point and/or best point in the feasibility space only.

Finally, IMAP/Preferendus truly unites design performance functions (level 3 - supply), via the inter-play objective functions level, with stakeholder's preference functions (level 1 - demand), thus synthesising for the best fit-for-common-purpose solution and outperforming single-sided design approaches that focus only on the technical domain. This means that the IMAP/Preferendus is either equal to other design methodologies in the technical domain but outperforms methodologies within the management domain (see exemplar 2: a floating wind turbine installation) or outperforms other design methodologies in both the technical and the management domain (see exemplar 1: a rail level-crossing service life design).

Acknowledgements

Thanks to Ms Shang (PhD student) for providing the necessary data for the railway infrastructure design exemplar. Thanks to Mr Zhilyaev (PhD student within the EU, NRG-Storage project) for the input on and verification of the mathematical statement. Both persons are currently PhD students at the Engineering Asset Management group at Delft University of Technology.

Data availability statement

The Preferendus software tool, including the exemplars discussed in this paper, is available via GitHub: `https://github.com/TUDelft-Odesys/Preferendus`. Note that for the Preferendus application, an API endpoint on the Tetra server is used to interact directly with the Tetra solver. This API endpoint needs authentication. For assessment purposes, credentials can be requested via the corresponding author. A limited, interactive version of the Tetra Solver can be found at `http://choicerobot.com`.

3

Preference Based Service Life Design of Floating Offshore Wind Structures

This chapter includes the conference paper describing the decision support optimisation framework built in the Preferendus to optimise the service life design of floating offshore wind farms. The abstract of this paper has been accepted for publication and the paper is scheduled for presentation at IALCCE 2023 in July 2023[1].

In summary, the conference paper presented in this chapter introduces a new optimisation framework that enables integrative design optimisation in the development of offshore floating wind farms. The design optimisation process for these wind farms is challenging due to their complex and multidisciplinary nature. Moreover, current optimisation methods 1) ignore the dynamic interplay between the managerial domain (subject desirability) and the engineering domain (object feasibility), and 2) contain fundamental issues, as introduced in the previous chapter.

The optimisation framework overcomes these shortcomings and allows the unification of the managerial and engineering domains. The framework focuses on mooring system design and installation scheduling. To enable the preliminary design of the mooring system, a surrogate model is created that interacts with the wind turbine simulation tool OpenFAST.

The application of the optimisation framework is demonstrated for an example project, showing the added value compared to a compromise solution and single-sided cost optimisation. In addition, it demonstrates the efficiency of integrative design. Finally, the framework has been validated at the Dutch maritime contractor Boskalis. This validation shows that the optimisation framework significantly improves tender performance, both in terms of removing design bias and improving process speed.

3.1. Introduction

A promising solution for wind energy production in deep waters is the development of Offshore Floating Wind Farms (OFWF), as areas with deeper water tend to have higher wind energy densities, but do not allow the economic installation of bottom-founded structures (Spring, 2020). The complexity introduced by e.g. high quality requirements, the novelty of the technology and the number of (external) stakeholders (see also Van Gunsteren (2011)), together with the multidisciplinary nature of these developments, create an environment in which modelling and optimising of the design process is of great added value, but also challenging and complicated.

In addition, classical design optimisation methods have inherent problems because they are single-sided and ignore and/or provide no insight into the dynamic interplay between the preference-dominated management domain and the object-performance-dominated engineering domain (see chapter 2). Furthermore, design optimisation is often limited to *a posteriori* evaluation of (manually) generated design alternatives, with no guarantee that the optimal design alternative is considered because the number of feasible design alternatives is too large to evaluate them all.

Moreover, to enable proper multi-objective design optimisation (MODO), all objectives must be translated into a common domain, for which the affordability domain is commonly chosen in the offshore indus-

[1]This chapter has been sent (largely) verbatim as a publication to the IALCCE 2023 conference in December 2022 (to appear in the conference proceedings in 2023).

try. However, according to classical utility theory, decisions are made based on value or preference and not based on money, as money is not a (fixed) property of objects (Barzilai, 2010). Moreover, classical MODO methods contain fundamental (aggregation) modelling errors because mathematical operations are applied without being defined (Barzilai, 2006, 2022).

Finally, ignoring preferences is also a major shortcoming of the commonly used Pareto front (Kim et al., 2022; Lee et al., 2011). Searching for the most fit-for-common-purpose design solution involves finding the most preferred solution, not a set of equally preferred solutions from which decision-makers still have to choose through negotiation.

To overcome all the aforementioned problems, this paper presents an optimisation method for the service-life design of OFWFs that integrates preference function modelling and engineering performance, allowing the unification of the managerial domain (subject desirability) with the engineering domain (object feasibility). To this end, an optimisation framework is created within the so-called Preferendus, a software tool that is part of the Odesys design methodology and uses the IMAP optimisation method (chapter 2). This paper demonstrates this framework through a demonstration project and gives insight into the applicability of the framework, which has been validated at the Dutch marine contractor Boskalis.

3.2. The OFWF service-life design demonstrator

The optimisation framework is modelled based on the Odesys mathematical statement introduced in chapter 2, see Figure 2.1. Two stakeholders are considered: 1) an energy service provider (the client) and 2) the marine contractor Boskalis. The focus of this combination is on the design of the mooring system and the installation schedule.

Four objectives are considered: project duration, installation costs, fleet utilisation and CO_2 emissions. For the client, a shorter project duration means that the wind farm will start generating revenues sooner. In addition, reducing CO_2 emissions benefits the client's carbon footprint and the social acceptance of the project. For the contractor, the focus will be on reducing costs to make it more competitive. Secondly, its fleet management department will be interested in the opportunity to improve fleet utilisation through the project.

3.3. Level 3 – design performance functions

This section introduces the relevant design performance functions and design variables in two parts: installation scheduling and mooring system design. This mooring design is restricted to Drag Embedded Anchors (DEA), Suction Piles (SP) and Anchor Piles (AP).

3.3.1. Installation schedule

The installation schedule depends on two components: the number of available vessels (and their characteristics), and the time it takes these vessels to perform a task. The available vessels are listed in Table 3.1. Whether a vessel can perform a task ($x = 1$) or not ($x = 0$) is expressed by boolean design variables (x_1-x_{21}) for all tasks except hook-up. For the hook-up, only one vessel is used (see section 3.3.1), and the integer design variable x_{22} expresses which vessel. All vessels have different properties (e.g. deck space for anchors) that affect their performance, which can be found in the input file of the framework (see the data availability statement).

In addition, each task is decomposed into building blocks that describe the time required to complete a sub-activity (e.g. the time necessary to load new anchors or transfer crew to a floating wind turbine (FWT)). During optimisation, the workable months are determined based on environmental data (see 3.3.2) and the overall schedule is constructed from these building blocks, which can be found in the input file of the framework.

Design performance constraints

To correctly model the installation schedule, three design performance constraints are added to ensure that:

1. the number of installation vessels is ≥ 0, since the definition of the design variables x_1 to x_{21} allows a total number of installation vessels equal to zero;
2. an equal number of vessels are present when both anchors and mooring lines (ML) are installed simultaneously;
3. a vessel does not perform overlapping tasks.

Table 3.1: Available vessels and the associated design variables.

Vessel	SP install	AP install	DEA install	Taut mooring install	Catenary mooring install	Stev-tensioning[2]	Hook-up
Winchester	x_1	x_5					
Atlas	x_2		x_7	x_{10}	x_{15}	x_{18}	$x_{22} = 0$
Edinburgh	x_3			x_{11}			$x_{22} = 1$
Symphony			x_8	x_{12}	x_{16}	x_{19}	$x_{22} = 2$
Legacy			x_9	x_{13}	x_{17}	x_{20}	$x_{22} = 3$
Scout	x_4	x_6		x_{14}		x_{21}	

Assumptions

In addition, Some assumptions are made in the modelling:

1. If the design force on the DEA is greater than the bollard pull of the installation vessel, stev-tensioning will be required. If this is carried out using the Scout (a heavy lift vessel), an additional anchor handling tug will be required for the same period at a day rate of €50,000.
2. The hook-up is limited by the delivery time of new FWTs, which is assumed to be one FWT every six days. As this rate is lower than the hook-up period, the number of hook-up vessels is set to one. In addition, the hook-up requires one large and one medium tug for towing and station keeping, which have a fixed day rate of €54,000 and €24,000 respectively.
3. For an AP, the ML is always installed at the same time as the anchor, as is the case for a DEA. For an SP, the ML can be installed simultaneously or separately. Stev-tensioning is always done separately.

3.3.2. Mooring system design

Most of the design variables for an OFWF mooring system are uncontrollable and result from factors like soil and environmental conditions and local marine policy. Of the controllable design variables, the following are considered in the optimisation:

- Anchor type, x_{23}: DEA, SP, or AP.
- Mooring type, x_{24}: Taut or catenary. Catenary moorings consist only of chain ($d = 0.333$m; $M = 685 kg/m^3$; $EA = 3.27e9$N), taut moorings have a lower and an upper chain with polyester rope ($d = 0.211$m; $M = 23 kg/m^3$; $EA = 3.89e9$N (BEXCO, n.d.)) in between.
- Shared anchors, x_{25}: an AP or SP can connect two or three MLs, reducing the total number of anchors to be installed.
- Anchor diameter/width, x_{26}: the diameter (for AP or SP) or width (for DEA) of the anchors.
- Anchor length, x_{27}: the length of the anchor.
- Anchor radius, x_{28}: the radius of the anchors with respect to the FWT.
- Unstretched length, x_{29}: the unstretched length of the ML.

To check that the mooring design is sufficient, a design performance constraint is added to the model, stating that the so-called utilisation factor u should be less than 1:

$$u = \frac{\textit{design force on the anchor}}{\textit{design resistance of the anchor}} = \frac{F_d}{R_d} = \frac{\gamma_f F_a}{\gamma_M R_a} < 1 \tag{3.1}$$

where γ_f is a safety factor for the anchor load; γ_M is a safety factor for the anchor resistance; F_a is the anchor load; R_a is the anchor resistance. For determining this force F_a, the open-source wind turbine simulation tool OpenFAST (NREL, n.d.-a) is used, together with the IEA 15MW reference turbine (Gaertner et al., 2020) and its semi-submersible platform (Allen et al., 2020).

[2] method to achieve higher proof-loads by vertical lifting instead of horizontal pulling (Vryhof, 2017).

Environmental conditions

TurbSim (NREL, n.d.-b) is used to simulate the wind field for the OpenFAST simulations. This software generates fully stochastic wind fields that allow the effect of turbulence on the dynamics of an FWT to be considered. The reference wind speed for the simulation is determined by statistical analysis of hourly data obtained via Hersbach et al. (2018).

The (irregular) wave field is generated by HydroDyn (Jonkman et al., 2014), where the wave spectrum is determined using the JONSWAP spectral equation (Katopodes, 2018). This is a function of both the significant wave height H_s and the peak wave period ω_m, which can be determined by statistical analysis of the hourly data obtained via Hersbach et al. (2018). Sea currents are also simulated in the HydroDyn module, using the power law (Jonkman et al., 2014). This is a function of the velocity of the sea current at the still water level U_0 and the water depth d. U_0 is obtained either from local databases (such as EMODnet (n.d.)) or from scientific papers.

Two Design Load Cases (DLC) are considered in the optimisation: DLC1.6 and the Survival Load Case (SLC) (DNV, 2021c). During DLC1.6, the turbine operates at the rated wind speed in waves with a 1/50-year H_s. During the SLC, both the 1/100-year wind speed and the 1/100-year H_s occur and the turbine is idling. The environmental conditions are simulated co-aligned (i.e. with the same heading) for a heading of 0°, 30°, and 60° relative to the FWT, where 60°is the heading parallel to a mooring line. A yaw-misalignment of ±8°is also included in the simulations.

Integration of OpenFAST in the optimisation

Due to the long runtime of OpenFAST simulations, the integration into the optimisation framework is currently done via a surrogate model. This integration consists of five steps divided into two phases: the offline phase (steps 1 to 3), which is performed separately and prior to optimisation, and the online phase, which is an integral part of the framework.

Step 1 - offline phase: determine mooring configurations

The reference mooring design (Allen et al., 2020) is scaled to different water depths (120-150 metres) and taut configurations, based on a comparison between the behaviour of the new design and the reference design under different (static) loads (via Hall et al. (2021)). For this scaling, the design variables have been limited to the anchor radius (x_{28}) and the unstretched length of the mooring line (x_{29}), which consequently become indirect design variables.

Step 2 - offline phase: run OpenFAST

OpenFAST is being run with six 700-second simulations per design scenario, each being a combination of two design load cases (DLC1.6 & SLC), three propagation directions (0°, 30°, & 60°), two mooring types (taut & catenary) and three yaw misalignments (-8°, 0°& 8°), resulting in 216 runs per water depth. The result of a simulation is a binary file containing, among other things, the time series of forces on all three anchors of the FWT.

Step 3 - offline phase: analyse the OpenFAST results

The results of the OpenFAST simulations are processed in a script, which for each design scenario:

1. eliminates the initialisation phase of the catenary mooring systems;
2. generates 60-minute time series for three FWTs by (quasi-randomly) combining the six 700-second runs;
3. calculates the net force on the shared anchors using the time series of three FWTs;
4. finds the forces F_a for one, two and three connected MLs per design scenario. All these forces are then multiplied by a safety factor (DLC1.6: γ_f = 1.35; SLC: γ_f = 1.1 (DNV, 2021c)) to give the design forces F'_d. At the same time, a script is run to determine the angles of the taut MLs with respect to the mudline.

Step 4 - online phase: determine governing forces

The final design forces F_d are determined for both catenary and taut moorings, and both shared and non-shared anchors, by taking the maximum of the design forces F'_d from the relevant design scenarios. Note: for shared anchors, F_d is the highest of either two or three connected MLs.

Step 5 - online phase: determine anchor dimensions
For all three types of anchors, the point where the chain attaches to the anchor (i.e. the padeye) is below the mudline. Because of friction with the soil, the chain will form a (so-called) inverse catenary shape below the mudline. Neubecker and Randolph (1995) describe a system of equations to determine the tension T_d and angle θ_a of the ML at the padeye, based on the design force F_d and angle θ_m at the mudline and the ML and soil characteristics. In addition, the position of the padeye is required, which for APs and SPs is set to 1/2 the anchor length below the mudline for clay and 2/3 the anchor length for sand. For DEAs, the optimum angle θ_a is determined by the manufacturer and set as a constant in the calculation for T_d. Here $\theta_{a;DEA} = 41°$ for clay and $\theta_{a;DEA} = 31°$ for sand, based on the information provided by Vryhof (2018). The anchor resistance R_d and the utilisation factor u can then be calculated, applying the safety factors γ_M according to the DNV-OS-C101 design code (DNV, 2021a):

- Drag embedded anchors: the design is limited to Vryhoff's Stevin MK3, Stevpris MK5 and Stevpris MK6 anchors. ABS (2013) describes design formulae that can be used to obtain the required mass $M_{required}$ of a DEA for a given force T_d. In addition, based on the information provided by Vryhof (2018), it is possible to determine the DEA that best matches the values for the anchor length (x_{27}) and width (x_{26}). Knowing the mass of this DEA (M_{DEA}), it is possible to calculate the utilisation factor:

$$u = \frac{F_d}{R_d} = \frac{M_{required}}{0.77 \cdot M_{DEA}} \leq 1 \tag{3.2}$$

- Suction anchors: for SPs, first the maximum suction-assisted penetration length must be determined (Houlsby & Byrne, 2005a, 2005b), in order to calculate the horizontal (H_{ult}) and vertical (V_{ult}) capacity of the anchor (eq. 42 to 49 of Arany and Bhattacharya (2018)). Finally, T_d must be decomposed into a horizontal (H_d) and vertical (V_d) component in order to calculate the utilisation factor (Randolph & Gourvenec, 2017):

$$u = \frac{F_d}{R_d} = \left(\frac{H_d}{0.83 \cdot H_{ult}}\right)^a + \left(\frac{V_d}{0.83 \cdot V_{ult}}\right)^b < 1 \tag{3.3}$$

  where $a = x_{27}/x_{26} + 0.5$ and $b = x_{27}/(3 \cdot x_{26}) + 4.5$.

- Anchor piles: for APs, the horizontal and vertical failure mechanisms are considered separately. For the horizontal failure mechanism, the 'short' pile failure mechanism can be used as described by Randolph and Gourvenec (2017), since 1) the padeye is at a significant depth below the mudline and 2) the lengths of the APs are limited compared to e.g. deepwater moorings of oil & gas platforms. Plastic hinging is therefore unlikely and only soil failure needs to be considered. The vertical failure mechanism of an AP is mainly determined by the weight of the anchor and the soil-pile friction. Therefore, the same design formulae can be used as for an SP. The utilisation factor can be calculated as:

$$u = \frac{F_d}{R_d} = \max\left[\frac{V_d}{V_{ult}}, \frac{T_d}{T_{ult}}\right] < 1 \tag{3.4}$$

Design performance constraints
In addition to Equation 3.1, the mooring system has two other design performance constraints. The first is that a DEA cannot be used for taut and shared anchor systems as it is not designed for vertical and multidirectional loads. The second restricts the L/D and D/t ratios of the APs and SPs. See ABS (2013) for reference values.

Assumptions
In the current development phase of the optimisation framework, only a preliminary design is considered, as the improvement in optimisation results that a more detailed design will entail does not currently outweigh the additional complexity of developing the necessary design calculations.

For this preliminary design, some assumptions are made:

1. All MLs can be stretched indefinitely, and the minimum breaking load (MBL) is not currently considered.

2. The effect of cyclic loading on the anchors and associated fatigue is neglected, only the ultimate limit state is considered.
3. The soil is assumed to be uniform.

The current approach to determining the force F_d for shared anchors is likely to result in the over-dimensioning of anchors with three MLs, as the net force for two MLs is often greater than the net force for three MLs. Therefore the design force F_d of anchors with three MLs will be too high. This should be addressed in further development, although the current approach overcomes problems with the reliability of shared anchors in the event of ML failure (DNV, 2021b).

3.4. Level 2 – Objective functions

The optimisation framework considers four objectives that form the link between the design performance (level 3) and the preference functions (level 1):

1. Project duration [days]: the project duration is determined by a proprietary Discrete Event Simulation (DES) combining the design variables with the task durations (see section 3.3.1).
2. Installation cost [Euro]: installation costs are primarily based on the day rates of the vessels multiplied by the time they work on the project. In addition, a daily surcharge is added for anchor installation vessels, depending on the type of anchor (x_{23}).
3. Fleet utilisation [-]: fleet utilisation is represented by normalising the number of days a vessel is booked over the next 12 months (i.e. the vessel with the lowest number of days booked has a score of 0 and the vessel with the highest number of days has a score of 1).
4. CO_2 emission [mt]: the CO_2 emission of a project depends on the fuel consumption of the vessels, related to the activity of the vessel (e.g. idling, sailing, towing), multiplied by a conversion rate (per mt MGO 3.206 mt CO_2 is emitted).

3.5. Level 1 - Preference functions

To quantify stakeholder desirability, preference functions are constructed that describe the relationship between an individual stakeholder's preference $P_{k,i}$ and a given objective O_i (where $k = 1..2$ are the two stakeholders and $i = 1..4$ are the four objectives). In addition to these functions, the weights associated with the different preference functions have to be determined, both in close cooperation with the different stakeholders. Moreover, they can change during the design process when stakeholders better understand the impact of their preference functions and associated weights on the process (Arkesteijn, 2019). Both the demonstration project and the validation described in this paper use preference functions and weights that were determined based on input from experts on floating wind projects within Boskalis. These preference functions are shown in Figure 3.1 and the weight distribution is as follows:

- Project duration: $w_{1,PD} = 0.25$
- Installation cost: $w_{2,C} = 0.50$
- Fleet utilisation: $w_{2,F} = 0.20$
- CO_2 emission: $w_{1,S} = 0.05$

3.6. Demonstration project

To demonstrate the application of the framework, a demonstration project has been set up where 45 FWTs are installed at a water depth of 120 metres. For these 45 turbines, 135 MLs are installed along with 135 anchors when no shared anchors are used or 59 anchors when shared anchors are used. At the project site, the predominant soil type is clay with a shear strength of $s_u = 50kPa$ and a submerged weight of $\gamma' = 9kN/m^3$. The optimisation aims to find the best design of the mooring system and installation schedule given the level 1, 2 and 3 specifics described in the previous sections.

The design configurations of three optimisation results have been compared: Single-Objective Design Optimisation (SODO) of the installation costs, and MODO using the IMAP and min-max method. The design variables for the three design configurations are shown in Table 3.2. The results for the objectives and the final ranking of the three design configurations are shown in Table 3.3.

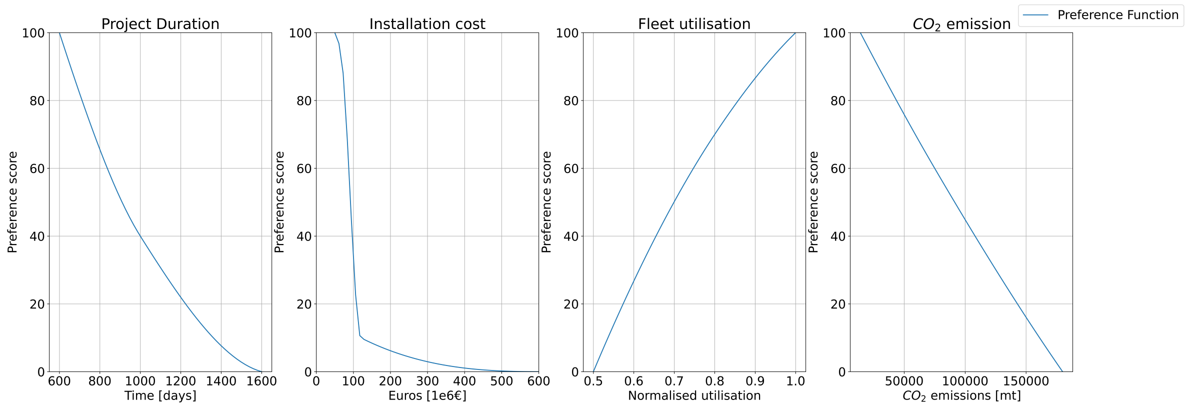


Figure 3.1: The four preference functions used in the demonstration project and validation.

Table 3.2: Table with the results of the mooring design variables.

Optimization	Installation vessels	Anchor type	Mooring system	Shared anchors	Length anchor [m]	Diameter anchor [m]
SODO Costs	Anchor: Winchester ML: Symphony Hook-up: Atlas	Suction	Catenary	Yes	19.2	5.6
MODO min-max	Anchor: Winchester ML: Symphony Hook-up: Edinburgh	Suction (integrated)	Taut	Yes	25.9	5.6
MODO IMAP	Anchor: Winchester ML: Symphony Hook-up: Atlas	Suction (integrated)	Catenary	Yes	19.2	5.6

The MODO IMAP optimisation achieves the best design configuration by balancing the four objectives to best reflect stakeholder preferences. Three other observations are made:

1) The installation cost and fleet utilisation objectives are in conflict: i.e. employing less expensive vessels lowers the fleet utilisation factor and vice versa. Since the min-max method focuses on finding the design configuration with the least dissatisfaction for all objectives, conflicting objectives limit the applicability of this method. Instead of favouring one objective over another, the min-max method finds a compromise that does not score well for either objective and does not benefit the overall design configuration, resulting in the lowest ranking of the three methods and revealing a major drawback of this method (as also concluded in the exemplars of chapter 2).

2) The lowest cost is achieved by installing the anchors and MLs separately, reducing the time one vessel has to wait for another to complete an installation task. However, this significantly increases the duration of the project, as it means that the hook-up starts a year later. It could be argued that this design configuration would never be considered because the duration of the project is unrealistically long. This shows one of the shortcomings of single-sided design optimisation: when more objectives are considered, it becomes clear that a relatively small cost increase significantly shortens the project duration. MODO IMAP is able to cap-

Table 3.3: Table with the results of the objectives and their ranking.

Optimisation	Project duration [days]	Installation cost [1e6€]	Fleet utilisation [-]	CO_2 emission [MT]	Ranking
MODO IMAP	619	56.8	0.83	21911	1
SODO costs	985	54.7	0.83	21604	2
MODO min-max	619	61.1	0.99	19720	3

ture this balance, confirming that this model is a welcome addition for design optimisation in the offshore industry.

3) The demonstration project shows the added value of integrated design optimisation. Traditionally, the mooring design is determined by the client and the contractor has to build its schedule around it. This is the so-called waterfall design process, where all tasks are performed sequentially. This disconnected design approach is likely to result in a misalignment of stakeholders' preferences, which could, for example, lead to inefficient use of vessels and delayed project delivery. This demonstration project shows that integrative design optimisation is possible, considering both the feasibility of the object and the interests of both stakeholders. This enables an overall better design, which can even result in design configurations that would not be considered from a purely engineering perspective. This is interesting, for example, for shared anchors, which are less favourable from a technical point of view because of reliability (see DNV (2021b)), but favourable from a planning and cost perspective, as the number of anchors to be installed is significantly reduced.

3.7. Validation of the optimisation framework

The optimisation framework has been validated during a meeting with offshore floating wind experts within Boskalis and demonstrated that it can be of great value to a tender team. A tender team always has a bias and especially when the design process involves evaluating design alternatives, this bias can lead to eliminating alternatives based on intuition, when in fact they are competitive. The optimisation framework removes this bias from the design process, which is in line with what Kahneman (2011) suggests when he distinguishes between thinking fast (decision-making based on intuition) and thinking slow (decision-making using, for example, mathematical decision support tools).

Moreover, the framework delivers initial results within an hour (if the surrogate model contains sufficient data), compared to one or more days in the current situation. This is a significant improvement and offers opportunities beyond the development of OFWF. One can think of 1) schedule optimisation in the first months of a project, to adjust the schedule made during the tender to the actual project conditions, or 2) improvement of the decision-making process regarding the purchase of a new vessel, as the added value for specific vessel characteristics can be modelled and demonstrated.

Furthermore, the added value for integrative design was noted. Gaining insight into why a model arrives at certain outcomes is a key element in enabling integrative design, as stakeholders can then understand how their preferences affect design outcomes. The optimisation framework provides this insight, as it is built using open-source principles and enables open glass-box modelling, unlike proprietary models where the model often acts as a black box.

3.8. Steps for further development

To improve the integration of the surrogate model, two steps for further development are identified: 1) consideration of the MBL of the MLs; 2) inclusion of fatigue loading in the design of the anchors. The first will address a shortcoming of the current model and resolves a problem with the script that calculates the taut mooring designs, which currently results in excessive tension in the polyester rope. The second will add an important element to the design of the anchors, as loads of FWTs are rather dynamic and this has a significant effect on the anchor resistance R_a. It would also be interesting to extend the surrogate model to different platforms as it is currently limited to a semi-submersible platform.

In addition, the following development steps are identified in the overall framework:

1. Take the delivery of the first FWT as $t = 0$ for the schedule.
2. Improve the discrete event simulator with a focus on 1) calculating the number of anchors and mooring lines on board the installation vessels, and 2) the start of the installation of mooring lines if it takes place separately from the anchor installation.
3. Improve the calculation of installation costs by including procurement and fuel costs.
4. Improve the calculation of CO_2 emissions by including emissions from anchor fabrication and onshore activities.

3.9. Conclusion

This paper presents an optimisation framework that enables the unification of the engineering domain (object feasibility) with the management domain (subject desirability) and a truly integrative MODO method that can accommodate conflicting objectives of multiple stakeholders whilst simultaneously considering different engineering object variables and design constraints. The applicability of the optimisation framework is shown for a demonstration project, demonstrating its added value over a compromise solution and single-sided cost optimisation, and the efficiency of integrative design. Finally, validation of the framework shows it brings significant improvement in tender performance, both in terms of removing bias from design and improving process speed. Steps for further development include improving the surrogate model and DES and extending the installation cost and CO_2 emission calculations.

3.10. Data availability statement

The optimisation framework, including the input file of the demonstration projects with all the modelling information, can be found on the GitHub repository of the Preferendus: `https://github.com/TUDelft-Odesys/Preferendus`.

4

Dredging Production Management Optimisation and Validation

This chapter contains a business report describing the second validation case within this thesis: optimisation in dredging production management. This report contains a detailed description of the validation and associated conclusions and steps for further development.

In summary, the business report presented in this chapter introduces an optimisation framework that enables multi-objective decision support optimisation in the dredging environment, in particular focusing on production management optimisation in the execution phase of (large) land reclamation projects. Current optimisation models are rather simplified and rely on manual input and evaluation. This is not feasible for large projects, where the effect of adjustments is difficult to oversee, and a multi-objective design/decision support optimisation system is needed.

The optimisation framework is built to find the optimal mitigation strategy for conflicts arising from unforeseen circumstances. It was applied to a demonstration project which has been validated with dredging, project, and data science experts from Dutch maritime contractor Boskalis. This validation showed that the optimisation framework, which utilises the IMAP method, can significantly reduce waiting time while achieving high production levels. In this, IMAP outperforms single-sided optimisation on production alone by achieving similar high production levels while improving other objectives such as CO_2 emissions and vessel efficiency.

4.1. Introduction

As one of the world's largest dredging contractors, Boskalis takes on the most challenging projects around the globe. The latest example of this is the Land Development Design and Construction of the Manila International Airport (MIA) in the Philippines, the largest project ever undertaken by Boskalis. An important part of these projects is production management, which focuses on making the best use of the discharge lines, the pipelines through which the dredged material is pumped ashore, to pump as many cubic metres of soil ashore as possible.

As the size and complexity of these projects increase, dredging production management is reaching the limits of the current planning decision support methods. At present, the available methods rely heavily on manual processes and expert judgement. However, the number of variables affecting the production planning on large projects is becoming too large to oversee their impact and manual intervention is no longer a feasible approach.

An attempt was made to overcome this problem by limiting the number of variables to only the time required to sail from the offshore borrow area back to the discharge line. This is a reasonable simplification because if something then happens in the other parts of the cycle, it will have less impact on the planning of the unloading line than if a ship is already sailing slower to compensate for something. However, this is a limitation that significantly reduces the possibilities for conflict resolution when complexity and dependencies between ships increase.

Trials have also been carried out using Discrete Event Simulation (DES) of projects. This allows for the simulation of a project to see the positions of each dredging vessel during the project and to see if conflicts will arise. However, this does not overcome the problems of finding the best mitigation strategies, as it cannot mitigate these conflicts itself, but still relies on human interaction.

Moreover, current methods focus solely on production maximisation, while dredging production management is a combination of both managerial desirability and technical feasibility involving multiple stakeholders, all with their interests and preferences.

A promising solution for truly overcoming the current shortcomings in dredging production management is the use of computer-aided Multi-Objective Decision (support) Optimisation (MODO). However, the application of MODO is not straightforward. This is because most methods ignore or provide no insight into the dynamic interplay between the managerial desirability and technical feasibility domains. In addition, there are several fundamental problems with these methods (see Barzilai (2022) and chapter 2).

This chapter presents an optimisation framework that allows for the unification of the managerial desirability domain and the technical feasibility domain in the dredging environment. This framework has been built in the Preferendus and employs the IMAP method to find the overall most preferred solution for both multiple stakeholders and a multitude of variables (see chapter 2).

In November 2022, the optimisation framework was validated. The focus of this chapter is on the results of this validation and the conclusions that can be drawn from it. It also provides insight into the steps for further development required to move from proof-of-concept to a production-ready model.

4.2. The dredging control demonstrator

To validate the optimisation framework, a demonstration project is designed that is both easy to understand and demonstrates the added value of the optimisation framework. In this project the following trailing suction hopper dredgers (TSHD[1]) are considered:

1. Willem van Oranje (capacity: 12,000 m^3)
2. Fairway (capacity: 4,500 m^3)
3. Causeway (capacity: 4,500 m^3)

These TSHDs will operate between the reclamation area (the area where the dredged material is deposited), which is located between the Dutch towns of Zandvoort and Noordwijk, and the borrow area (the area where the material is dredged), 8.75 nautical miles (NM) off the coast of Katwijk. See also Figure 4.1. The sailing distance between these two locations is 12.2 NM.

The reclamation area has a single discharge line. During the project, conflicts will arise when a TSHD has to wait for another TSHD that is discharging. The task of the optimisation framework is to find the optimal strategy for mitigating these conflicts during the project. To do this, it simulates three dredging cycles for all TSHDs and attempts to resolve the conflict during this time.

The setup of the optimisation framework follows the mathematical framework as introduced in chapter 2 and consists of three parts (see also Figure 2.1):

1. Design variables and design performance functions (level 3).
2. Objective functions (level 2).
3. Preference functions (level 1).

These three parts are discussed briefly below.

Level 3 - design variables and design performance functions

A dredging cycle consists of four tasks: 1) sailing to the borrow area; 2) loading; 3) sailing to the reclamation area; 4) unloading. The duration of all four tasks can be adjusted using the following design variables:

1. Sailing speed empty: the sailing speed from the reclamation area to the borrow area, the outbound leg.
2. Sailing speed loaded: the sailing speed from the borrow area to the reclamation area, the inbound leg.
3. Loading time: the time the TSHD is loading soil at the borrow area. Note that this means the loading process can be capped off before the TSHD is fully loaded.

[1] `https://boskalis.com/about-us/fleet-and-equipment/dredgers/trailing-suction-hopper-dredgers`

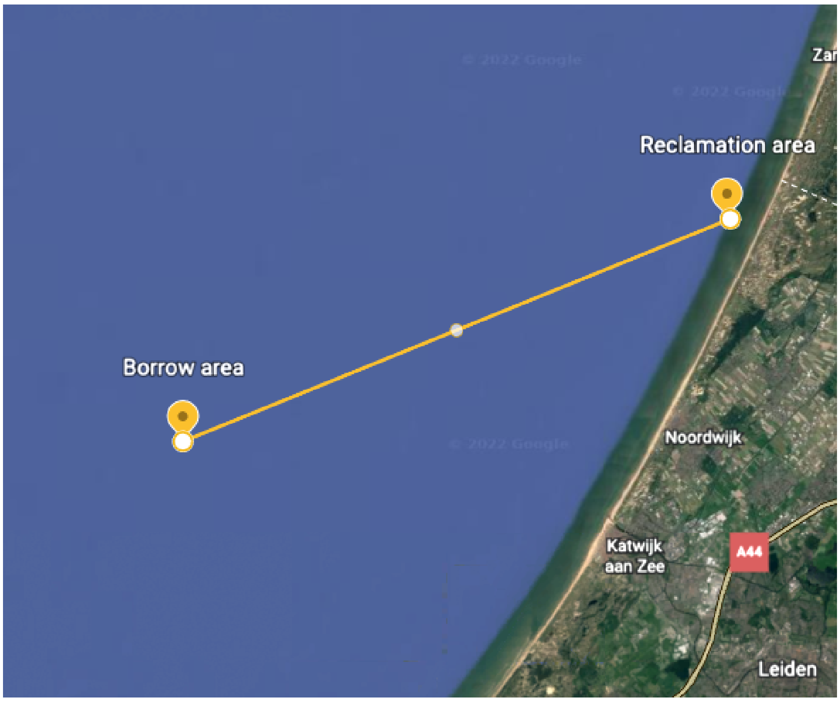


Figure 4.1: Overview of the reclamation and borrow area of the demonstration project. Source: Google Earth (n.d.).

4. Unloading time: the time the TSHD is discharging soil at the reclamation area. Note that this means the discharge process can be capped off before the TSHD is fully empty.

By adjusting the values of these design variables, a production manager can set the arrival time at the discharge line of a TSHD. This planning is manageable for one TSHD, but since the values of these design variables are determined per TSHD and per dredging cycle, the planning becomes quite challenging for large projects.

The relevant design performance functions that determine the feasibility of the optimisation are described in Appendix B.

Level 2 - objective functions

The link between the technical feasibility domain and the managerial desirability domain is provided by objective functions. In this optimisation framework, the following four objectives are considered:

1. Waiting time: the discharge line cannot be used by more than one TSHD at a time. Therefore, if a TSHD arrives at the reclamation area and the discharge line is still in use, it will have to wait. This objective is the sum of all the time TSHDs have to wait
2. Production: for land reclamation projects, production (i.e. cubic metres of soil transported) is an important measure. It determines how long the project takes and therefore how much it costs. Production is included in the optimisation as the amount of soil discharged per hour through the discharge line.
3. TSHD utilisation: the efficiency of TSHDs, expressed as the ratio of the volume of soil transported by a TSHD (P_{actual}) to the maximum volume that this TSHD could have transported (P_{max}).
4. CO_2 emissions: sustainability is becoming an increasingly important factor in dredging projects, and by including CO_2 emissions as an objective, it gives stakeholders a way to consider sustainability in optimisation. The objective is defined as the sum of the metric tonnes of CO_2 emitted collectively by the TSHDs. This is correlated one-to-one with fuel consumption, which is broken down by activity.

A more detailed description of these objectives can be found in Appendix C.

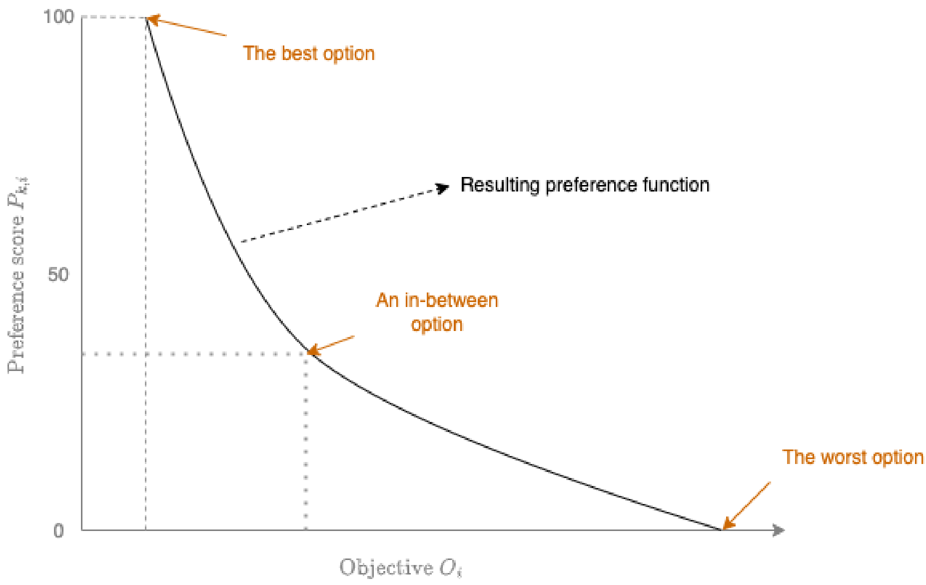


Figure 4.2: The preference function describes the relationship between a preference score $P_{k,i}$ and an outcome of objective O_i.

Level 1 - preference functions

To allow stakeholders to express their desirability, preference functions are constructed that describe the relationship between an individual stakeholder's preference and the outcome of a specific objective (i.e. the relationship between a preference score $P_{k,i}$ and an outcome of objective O_i, where k is the stakeholder and i is the objective). See also Figure 4.2.

In addition to these functions, the weights of the different preference functions should also be determined, both in close cooperation with the different stakeholders. Furthermore, they can change during the design process when stakeholders better understand the impact of their preferences on the process. For more details on the construction of preference functions, the reader is referred to chapter 2.

4.3. Validation

The optimisation framework is validated in a meeting with a production management expert, a project execution expert, and a modelling expert. This section describes the validation process and its results.

4.3.1. Set-up of validation meeting

Since the optimisation framework has a run-time of 20-30 minutes, it was not possible to interact with it in real-time during the meeting. Therefore, a specific scenario was prepared for the demonstration project in which a significant waiting time would occur without intervention.

In this scenario, the Freeway (fully loaded) has just arrived at the discharge line and the Willem Van Oranje (also fully loaded) is on its way back from the borrow area. If no action is taken, the total waiting time will be 3.5 hours over three cycles.

During the meeting, the participants had the opportunity to first try to manually mitigate the conflict, as is often done in reality. The result of this manual mitigation was then compared with four different optimisation results obtained via the optimisation framework:

1. Single-Objective Decision (support) Optimisation (SODO) of the 'production' objective.
2. MODO using the IMAP method, considering only the design variable 'sailing speed loaded' for all TSHDs and cycles.
3. MODO using the min-max method (alternative to the IMAP method, see chapter 2), considering all design variables.
4. MODO using the IMAP method, considering all design variables.

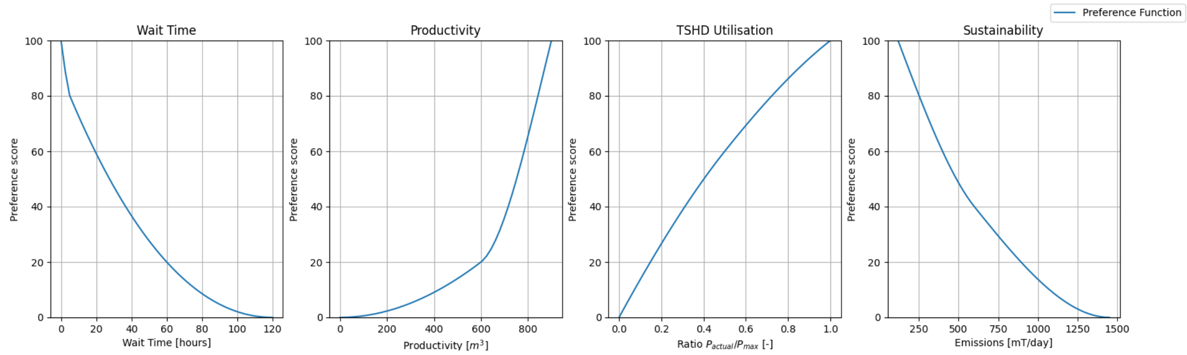


Figure 4.3: Preference functions showing the relationship between preference scores and objective outcomes.

Before discussing the results of the validation, some notes need to be placed:

- Since the optimisation results were obtained before the validation meeting took place, the preference functions and weight distributions were determined in advance. Both result from discussions with people involved in the dredging management process within Boskalis. The resulting preference functions can be found in Figure 4.3 and the following weights were used:
  1. Objective waiting time: $w_{1,WT} = 0.20$.
  2. Objective production: $w_{2,P} = 0.40$.
  3. Objective TSHD utilisation: $w_{3,VP} = 0.20$.
  4. Objective CO_2 emissions: $w_{4,S} = 0.20$.
- Due to a modelling error with the coordinates, the location of the Willem van Oranje as shown on the map did not match the user input. This is due to a problem with the conversion of degrees, minutes, and seconds into decimal coordinates. As a result, the Willem van Oranje was 14NM away from the reclamation area, instead of the 6.5NM it was thought to be.

  After the meeting, the optimisation framework was rerun with the correct coordinates. Although the numerical values are different, the impact on the validation is expected to be small. This is because the differences are minor and the error was already noticed at the meeting, although the cause of the error was thought to be something else.
- During the manual mitigation exercise, the visual representation of changes in design variables was limited to new numerical results of the objectives. Feedback on the changes would have been better if something like a Gantt chart had been shown and this might have improved the result.

4.3.2. Manual mitigation of the conflict

The challenge with manual mitigation is that it is difficult to foresee the effect of changing the value of a single design variable. Changing the sailing speed of a TSHD may resolve one conflict but introduce a new one in the next cycle. With 36 design variables to tune, this cascading effect makes manual mitigation difficult, if not impossible.

This problem was also encountered during the validation. Mitigating the first conflict always introduced another, and the overall production was always lower than if nothing had been done. The dredging production expert confirmed that this is also the challenge in real projects, giving this (still theoretical) exercise the validity of the situations encountered in projects.

4.3.3. Comparing the current way of working with the optimisation results

The results of the various optimisations described in subsection 4.3.1 are shown in Table 4.1. In this table, the optimisation while considering only the variable 'sailing speed loaded' is taken as the base case and all other results are shown relative to it. This is the fairest comparison between the current way of working and the optimisation results.

These results reaffirmed that optimisation is a welcome and essential addition to production management. The optimisation framework can capture the cascading effect of changes in design variables and finds

Table 4.1: Relative outcomes of the different optimisations. Green values represent an improvement, red values a decline.

Method	Waiting time	Production	TSHD utilisation	CO_2 emissions[2]	Aggregated preference
MODO IMAP, design variables 'sailing speed loaded' only (base case)	0.0%	0.0%	0.0%	0.0%	23
No intervention	+272.8%	-0.4%	+0.0%	-1.6%	0
SODO production	+16.3%	+4.6%	-1.0%	-5.7%	94
MODO min-max	+154.3%	+3.1%	-7.1%	-8.9%	46
MODO IMAP	-66.3%	+4.5%	-1.0%	-5.7%	100

a solution that would be unattainable with a manual approach. This is visible when the two IMAP optimisations are compared. Considering all design variables, compared to only the sailing speed of the inbound leg, yields an improvement of 66.3% in waiting time and 4.5% in production.

Moreover, the results show that a single-sided focus on production is not the best optimisation strategy. Indeed, the SODO of production shows the highest improvement in production (4.6%), but at the expense of waiting time. The MODO IMAP result, with all design variables considered, shows an almost identical improvement in production (4.5%) and is able to significantly reduce waiting time. Since the optimisation framework does not consider real-world influences, in reality, there will be a discrepancy between the performance of the TSHDs and what the optimisation framework prescribes. Therefore, the difference between the SODO and MODO IMAP improvements in production is negligible. However, this is not the case for the difference in waiting time improvement, where the MODO IMAP outperforms the SODO.

During the validation meeting, it was noted that the distribution of weights used in the MODOs does not fully reflect reality. In a project, the emphasis will be even more on production and CO_2 emissions (since the latter reflects fuel consumption) than on waiting time and TSHD utilisation. The weights were already quite skewed towards $w_{2,P}$ and $w_{4,S}$, but these would increase further, while the other weights would decrease.

This observation is interesting when looking at the results of the optimisations shown in Table 4.1. Even with these weights, the result of the IMAP method, considering all design variables, already shows the highest possible production and a similar decrease in CO_2 emissions, while the waiting time decreases by more than 66%.

4.3.4. Comments on modelling limitations and future additions

The validation also provided insight into the limitations and future improvements of the optimisation framework.

Firstly, when unforeseen events occur, the captain of the TSHD usually calls the production managers with an estimate of the duration. Currently, the optimisation framework assumes that everything is working as it should at the start of the simulation. A good addition to the optimisation framework would be the possibility of setting initial delays for the TSHDs so that the expected duration of downtime can be considered at the start of optimisation. This way, the optimisation framework does not have to wait for the situation to be resolved but can immediately start working on finding the best mitigation strategy.

Secondly, the optimisation framework assumes that the waiting time for each TSHD is equally bad. As the meeting showed, this is not the case. The waiting time of a large-capacity TSHD is more valuable than that of a smaller-capacity TSHD. It needs to be investigated whether this difference should be included in the waiting time objective or whether it is already included through the production objective, as keeping large TSHDs waiting is not beneficial for this objective either.

Thirdly, the optimisation framework currently considers fuel consumption while sailing as a constant. This is an oversimplification and will lead to an overestimation of the CO_2 emissions.

Fourthly, the optimisation framework does not consider any processes at the other end of the discharge line. The optimisation framework could benefit from this addition, especially if, for example, a TSHD cannot start discharging because they are not ready at the other end of the discharge line.

[2]Note that emissions during sailing are currently considered independent of sailing speed. Consequently, emission results may be the same while production figures differ. This is a shortcoming that needs to be addressed in the further development of the model.

4.4. Conclusions & next steps

Based on the validation, it can be concluded that the optimisation framework can overcome the shortcomings of the current way of working and will be of great added value to production management during projects.

Firstly, the optimisation framework is a correct representation of the logic behind the management of dredging production. Although the optimisation framework is simplified, it follows the current way of working and correctly reflects the preferences. In addition, although some of the limits of the design variables are not entirely consistent with common practice, the results of the optimisation framework make sense.

Secondly, the optimisation framework is not only able to oversee the impact of all design variables but is also able to find better mitigation strategies compared to the current way of working. Especially the MODO IMAP optimisation is reaching an improvement that is unattainable with the current methods.

Thirdly, the results show that a single-sided focus on production alone is not the best optimisation strategy. The SODO of production indeed shows the highest improvement in production, but the difference between the SODO and MODO IMAP improvements on this objective is negligible where this is not the case for the difference in waiting time improvement, where the MODO outperforms the SODO.

Finally, there is a clear delta when compared to a simple Discrete Event Simulation (DES) of a project. A DES alone is no more than a visualisation of the project, which still contains the problems currently encountered in production planning where the best strategies for TSHDs is depending on manual input. The optimisation framework can overcome this shortcoming by removing the dependency on human input for finding the best strategies and replacing it with computer-aided optimisation. However, as the run-time of the optimisation framework is still rather high, real-time simulation of projects is not recommended. Combining a DES with the optimisation framework is therefore of great added value during a project. The DT can simulate a project's real-time progress, and when conflicts arise, the optimisation framework can be run to resolve them.

4.4.1. Steps for further development

In the further development of the optimisation framework, the following points should be considered:

- Currently, fuel consumption during sailing is considered independent of the sailing speed. This is an oversimplification and should be corrected.
- Make it possible to set an initial time delay for vessels to reflect the time needed to resolve unforeseen downtime. If implemented, the optimisation framework (which assumes perfect conditions) can be started as soon as an unforeseen situation occurs, instead of the current situation where it can only be started when the situation is resolved.
- Investigate whether there is added value in making the waiting time of large TSHDs more important than the waiting time of smaller ones. This might already be included through the production objective, as making large TSHDs wait is not beneficial for this objective either.
- Investigate the impact and added value of including the processes at the other end of the discharge line in the optimisation.
- The issue of different units for coordinates needs to be resolved.

These points contain important steps for further development that can be implemented in the current version of the optimisation framework. With proper verification and validation on real-life projects, it is possible to develop the optimisation framework from current proof-of-concept to production-ready. This report shows that this development can be of great added value to Boskalis, and it is strongly recommended that these next development steps are taken as soon as possible.

Data availability statement

The Preferendus can be found on GitHub: `https://github.com/TUDelft-Odesys/Preferendus`. Due to its confidentiality, the optimisation framework described in this report cannot be made public. For inspection purposes, access can be requested via the chair of the graduation committee (Prof. dr. ir. Wolfert, R.Wolfert@tudelft.nl) or the company supervisor (Dr. ir. A.C. Steenbrink, sander.steenbrink@boskalis.com).

References

ABS. (2013). Offshore anchor data for preliminary design of anchors of floating offshore wind turbines. *American Bureau of Shipping*.

Aires, R. F. d. F., & Ferreira, L. (2018). The rank reversal problem in multi-criteria decision making: a literature review. *Pesquisa Operacional*, *38*, 331–362.

Allen, C., Viselli, A., Dagher, H., Goupee, A., Gaertner, E., Abbas, N., … Barter, G. (2020). *Definition of the UMaine VolturnUS-S reference platform developed for the IEA Wind 15-megawatt offshore reference wind turbine* (Tech. Rep.). International Energy Agency. NREL/TP-76773.

Arany, L., & Bhattacharya, S. (2018). Simplified load estimation and sizing of suction anchors for spar buoy type floating offshore wind turbines. *Ocean Engineering*, *159*, 348–357.

Arkesteijn, M. (2019). *Corporate real estate alignment: a preference-based design and decision approach.* Doctoral thesis TU Delft.

Arkesteijn, M., Binnekamp, R., & De Jonge, H. (2017). Improving decision making in CRE alignment, by using a preference-based accommodation strategy design approach. *Journal of Corporate Real Estate*.

Arkesteijn, M., Valks, B., Binnekamp, R., Barendse, P., & De Jonge, H. (2015). Designing a preference-based accommodation strategy: a pilot study at Delft University of Technology. *Journal of Corporate Real Estate*.

Barzilai, J. (2005). Measurement and preference function modelling. *International Transactions in Operational Research*, *12*(2), 173–183.

Barzilai, J. (2006). *Preference modeling in engineering design.* In K. E. Lewis, W. Chen, and L. C. Schmidt, (eds.), *Decision Making in Engineering Design.* ASME Press.

Barzilai, J. (2010). *Preference function modelling: the mathematical foundations of decision theory.* In M. Ehrgott et al. (eds.), *Trends in multiple criteria decision analysis.* Springer.

Barzilai, J. (2022). *Pure economics.* FriesenPress.

BEXCO. (n.d.). *Deeprope polyester* (Tech. Rep.). Author.

Binnekamp, R. (2010). *Preference-based design in architecture.* IOS Press.

Blanchard, B. S., & Fabrycky, W. J. (2011). *Systems engineering and analysis.* Pearson/Prentice Hall,.

Camp, T. R. (1946). Sedimentation and the design of settling tanks. *Transactions of the American Society of Civil Engineers*, *111*(1), 895–936.

Chen, L., & Bai, Q. (2019). Optimization in decision making in infrastructure asset management: A review. *Applied Sciences*, *9*(7), 1380.

Coello, C. A. C. (2002). Theoretical and numerical constraint-handling techniques used with evolutionary algorithms: a survey of the state of the art. *Computer methods in applied mechanics and engineering*, *191*(11-12), 1245–1287.

Cross, N. (2021). *Engineering design methods: strategies for product design.* John Wiley & Sons.

DNV. (2021a). *Design of offshore steel structures, general - LRFD method* (Tech. Rep.). DNV-OS-C101.

DNV. (2021b). *Floating wind turbine structures* (Tech. Rep.). DNV-ST-0119.

DNV. (2021c). *Loads and site conditions for wind turbines* (Tech. Rep.). DNV-ST-0437.

Dym, C. L., & Little, P. (2004). *Engineering design : a project-based introduction.* Wiley,.

EMODnet. (n.d.). *Emodnet physics.* EMODnet. `https://map.emodnet-physics.eu`

Farran, M., & Zayed, T. (2015). Fitness-oriented multi-objective optimisation for infrastructures rehabilitations. *Structure and Infrastructure Engineering*, *11*(6), 761–775.

Furuta, H., Kameda, T., Nakahara, K., Takahashi, Y., & Frangopol, D. M. (2006). Optimal bridge maintenance planning using improved multi-objective genetic algorithm. *Structure and Infrastructure Engineering*, *2*(1), 33–41.

Gaertner, E., Rinker, J., Sethuraman, L., Zahle, F., Anderson, B., Barter, G., … others (2020). *Definition of the IEA Wind 15-megawatt offshore reference wind turbine* (Tech. Rep.). NREL/TP-5000-75698.

Google Earth. (n.d.). *Google earth.* `https://earth.google.com/`

Guo, K., & Zhang, L. (2022). Multi-objective optimization for improved project management: Current status and future directions. *Automation in Construction*, *139*, 104256.

Hall, M., Housner, S., Sirnivas, S., & Wilson, S. (2021). *Moorpy: Quasi-static mooring analysis in python.* National Renewable Energy Laboratory.

Hersbach, H., Bell, B., Berrisford, P., Biavati, G., Horányi, A., Muñoz Sabater, J., … Thépaut, J.-N. (2018). Era5 hourly data on single levels from 1959 to present. *Copernicus Climate Change Service (C3S).*

Homaifar, A., Qi, C. X., & Lai, S. H. (1994). Constrained optimization via genetic algorithms. *Simulation*, *62*(4), 242–253.

Houlsby, G., & Byrne, B. (2005a). Design procedures for installation of suction caissons in clay and other materials. *Proceedings of the Institution of Civil Engineers-Geotechnical Engineering*, *158*(2), 75–82.

Houlsby, G., & Byrne, B. (2005b). Design procedures for installation of suction caissons in sand. *Proceedings of the Institution of Civil Engineers-Geotechnical Engineering*, *158*(3), 135–144.

Jonkman, J., Robertson, A., & Hayman, G. (2014). *HydroDyn user's guide and theory manual* (Tech. Rep.).

Kahneman, D. (2011). *Thinking, fast and slow.* Macmillan.

Kammouh, O., Nogal, M., Binnekamp, R., & Wolfert, A. R. M. (2022). Dynamic control for construction project scheduling on-the-run. *Automation in Construction*, *141*, 104450.

Katopodes, N. (2018). *Free-surface flow: Shallow water dynamics.* Butterworth-Heinemann.

Kim, S., Frangopol, D., & Ge, B. (2022). Probabilistic multi-objective optimum combined inspection and monitoring planning and decision making with updating. *Structure and Infrastructure Engineering*, *18*(10-11), 1487-1505.

Klerk, W., Kanning, W., Kok, M., & Wolfert, A. R. M. (2021). Optimal planning of flood defence system reinforcements using a greedy search algorithm. *Reliability Engineering & System Safety*, *207*, 107344.

Kramer, O. (2017). *Genetic algorithm essentials.* Springer International Publishing AG.

Lee, S., Park, W., Ok, S., & Koh, H. (2011). Preference-based maintenance planning for deteriorating bridges under multi-objective optimisation framework. *Structure and Infrastructure Engineering*, *7*(7-8), 633–644.

Marler, R., & Arora, J. (2004). Survey of multi-objective optimization methods for engineering. *Structural and multidisciplinary optimization*, *26*(6), 369–395.

Messac, A. (1996). Physical programming-effective optimization for computational design. *AIAA journal*, *34*(1), 149–158.

Metrikine, A. V., Wolfert, A. R. M., & Dieterman, H. A. (1998). Transition radiation in an elastically supported string. abrupt and smooth variations of the support stiffness. *Wave motion*, *27*(4), 291–305.

Miedema, S. (2008). An analytical approach to the sedimentation process in trailing suction hopper dredgers. *Terra et Aqua*, *112*, 15–25.

Miedema, S. (2019). Production estimation of water jets and cutting blades in drag heads. *Dredging summit & expo '19 proceedings.*

Miedema, S., & Ramsdell, R. (2016). *Slurry transport: Fundamentals, a historical overview and the delft head loss & limit deposit velocity framework.* SA Miedema/Delft University of Technology.

Miedema, S., & Rhee, C. v. (2007). A sensitivity analysis on the effects of dimensions and geometry of trailing suction hopper dredges. *Wodcon Orlando, USA.*

Mueller, C. T., & Ochsendorf, J. A. (2015). Combining structural performance and designer preferences in evolutionary design space exploration. *Automation in Construction*, *52*, 70–82.

Neubecker, S., & Randolph, M. (1995). *Performance of embedded anchor chains and consequences for anchor design* (Vol. All Days). (OTC-7712-MS)

NREL. (n.d.-a). *OpenFAST.* National Renewable Energy Laboratory. `https://www.nrel.gov/wind/nwtc/openfast.html`

NREL. (n.d.-b). *TurbSim.* National Renewable Energy Laboratory. `https://www.nrel.gov/wind/nwtc/turbsim.html`

Omar, M., Trigunarsyah, B., & Wong, J. (2009). Infrastructure project planning decision making: challenges for decision support system applications. *Proceedings of the 7th Asian Pacific Structural Engineering and Construction Conference & 2nd European Asian Civil Engineering Forum*, 146–152.

Randall, R. E. (2022). Fluid dynamics of dredging. *Physics of Fluids*, *34*(1), 013304.

Randolph, M., & Gourvenec, S. (2017). *Offshore geotechnical engineering.* CRC press.

Saad, D. A., Mansour, H., & Osman, H. (2018). Concurrent bilevel multi-objective optimisation of renewal funding decisions for large-scale infrastructure networks. *Structure and Infrastructure Engineering*, *14*(5), 594–603.

Scientific Metrics. (n.d.). *Tetra.* `https://scientificmetrics.com/`

Shang, Y., Nogal, M., Teixeira, R., & Wolfert, A. R. M. (in press-a). Optimal design of rail level crossings and associated transition zones using adaptive surrogate-assisted optimization. *Engineering Structures*.

Shang, Y., Nogal, M., Wang, H., & Wolfert, A. R. M. (2021). Systems thinking approach for improving maintenance management of discrete rail assets: a review and future perspectives. *Structure and Infrastructure Engineering*, 1–19.

Shang, Y., Nogal, M., & Wolfert, A. R. M. (in press-b). A co-simulation solution for vehicle-track interaction dynamics problems. *The Fifth International Conference on Railway Technology: Research, Development and Maintenance*.

Shang, Y., van den Boomen, M., de Man, A., & Wolfert, A. R. M. (2020). Reliability-based life cycle costing analysis for embedded rails in level crossings. *Proceedings of the Institution of Mechanical Engineers, Part F: Journal of Rail and Rapid Transit*, *234*(8), 821–833.

Spring, M. (2020). Global expansion of offshore wind power depends on overcoming significant challenges facing floating wind turbines. *Offshore Technology Conference*.

van Eijck, S., & Nannes, R. (2022). *Preference based decision support system for waelpolder: An a priori design optimization approach (PDOA) as decision support system, applied to the urban development of waelpolder*. [Master's thesis, Delft University of Technology]. `http://resolver.tudelft.nl/uuid:36146902-4c0c-4d50-8643-59c067008978`

Van Gunsteren, L. A. (2011). *Stakeholder-oriented project management: Tools and concepts* (Vol. 6). IOS Press.

Van Rhee, C. (2002). Modelling the sedimentation process in a trailing suction hopper dredger. *Terra et Aqua*, 18–27.

Vryhof. (2017). *Stevtensioner: enabling installations*.

Vryhof. (2018). *Anchor manual 2018: The guide to anchoring*.

Wang, Y.-M., & Luo, Y. (2009). On rank reversal in decision analysis. *Mathematical and Computer Modelling*, *49*(5-6), 1221–1229.

Wolfert, A. R. M., van Nederveen, S., & Binnekamp, R. (2022). Fit for purpose building information modelling and systems integration (BIMSI) for better construction projects management. *The Journal of Modern Project Management*, *10*(1), 174–187.

Zhilyaev, D., Binnekamp, R., & Wolfert, A. R. M. (2022). Best fit for common purpose: A multi-stakeholder design optimization methodology for construction management. *Buildings*, *12*(5), 527.

Nomenclature

α	Coefficient of friction between the shaft of the anchor
ϵ	Tolerance for equality constraint
γ	Specific weight of the soil
γ'	Submerged weight of soil
γ_f	Safety factor for F_a
γ_M	Safety factor for R_a
μ	Coefficient of friction between the seabed and the chain
ω_m	Peak wave period
θ_a	Angle of the ML at the padeye
θ_m	Angle of the ML at the mudline
d	Nominal mooring line diameter
E	CO_2 emission per day in mt
EA	The mooring line stiffness
F_a	Force action on an anchor
F_d	Design force on an anchor
F_j	Design performance function
G_n	Generation n of a GA
g_p	Inequality constraint
h_q	Equality constraint
H_s	Significant wave height
H_{ult}	Ultimate horizontal capacity of an anchor
M	Mass mooring line per meter
M_a	Mass of an anchor
M_{DEA}	Mass of the DEA
$M_{required}$	Required mass of a DEA
M_{steel}	Mass of steel
O_i	Objective function
p	Probability
P^*	Threshold value for the re-evaluation in the inter-generational solver
P_2	Gauge pressure (pressure relative to ambient)

P_a	Ambient pressure
P_v	Vapour pressure
P_{actual}	Actual production of a TSHD
$P_{k,i}$	Preference function for stakeholder k and objective i
P_{max}	Maximum production of a TSHD
R	Day rate of a vessel
R_a	Resistance of an anchor
R_d	Design resistance of an anchor
s_u	Shear strength of clay
T	Aggregated preference score
t	Time a vessel is required on the project
T_d	Design tension on the padeye
U	Objective function to minimise/maximise
u	Utilisation factor
U_0	Sea current velocity at the still water level
V_2	Fluid velocity at the pump entrance
V_{ult}	Ultimate vertical capacity of an anchor
$w_{k,i}$	Weight for preference function $P_{k,i}$
x	Design variable
y	Uncontrollable physical variables
AP	Anchor Pile
AWB	Active bearing area coefficient
DEA	Drag Embedded Anchor
DES	Discrete Event Simulator
DLC	Design Load Case
FWT	Floating Wind Turbine
GA	Genetic Algorithm
IMAP	Integrative Maximised Aggregated Preference
MBL	Minimum Breaking Load
MCDA	Multi-Criteria Decision Analysis
ML	Mooring Line
MODO	Multi-Objective Design Optimisation / Multi-Objective Decision Optimisation
NM	Nautical Mile
NPSHA	Net Positive Suction Head Available

OCV	Offshore Construction Vessel
Odesys	Open Design Systems
ODL	Open Design Learning
OFWF	Offshore Floating Wind Farm
PFM	Preference Function Modelling
QoS	Quality of Service
SLC	Survival Load Case
SODO	Single-Objective Design Optimisation / Single-Objective Decision Optimisation
SP	Suction Pile
TDS	Tonnes Dry Soil
TSHD	Trailing Suction Hopper Dredger

APPENDICES

A
The Inter-Generational GA Solver

To find the design configuration which reflects the integrative maximum preference aggregation (Preferendus/IMAP), it is necessary to use an optimisation algorithm. Moreover, this IMAP algorithm will also need to be able to interoperate with Tetra, which is the Preference Function Modelling (PFM) based multi-criteria decision analysis (MCDA) software tool. The algorithm of the non-linear Tetra solver is based on minimising the least-squares difference between the overall preference score and each of the individual scores (on all decision criteria) by computing its closest counterpart (for more information on the Tetra software, see Scientific Metrics (n.d.)).

For this purpose, a Genetic Algorithm (GA) has been developed that is specifically tailored to interoperate with Tetra and its specific features of normalised scores and relative ranking. First, these features are described.

A.1. Normalised scores

Preference scores are expressed as numbers on a defined scale, here ranging from 0 to 100, where 0 reflects the 'worst' scoring design configuration/alternative and 100 the 'best'. This means that when aggregated preference scores are normalised, the best alternative will always get a score of 100 and the worst alternative will always have a score of 0. As a GA will typically check whether the best score of the current generation (G_n) outperforms the previous one (G_{n-1}), normalised scores will lead to problems in convergence because the GA cannot determine whether improvement is occurring since the best alternative always scores 100.

Also, in the case of constrained problems, where the alternative with a score of 100 might be unfeasible and should be taken out of consideration, problems with convergence persist. As a result, it might be possible that the best feasible design alternative will have a lower preference score in generation G_n compared to generation G_{n-1}. This is because, due to normalisation, the score of one alternative always depends on the performance of all other alternatives. This needs to be accounted for within the GA solver.

A.2. Rank reversal

Rank reversal, the notion that ranks might change when an alternative is added or removed, is commonly encountered in different MCDA models and is also present in Tetra (Aires & Ferreira, 2018; Wang & Luo, 2009). This phenomenon is commonly observed when a non-competitive (i.e. irrelevant) alternative is added or removed from the population (Aires & Ferreira, 2018). In short, especially when extreme or 'irrelevant' (i.e. no real-life meaning) alternatives are added/removed, rank reversal can occur, potentially leading to convergence problems in finding the best solution by evaluating whether generation (G_n) outperforms the previous one (G_{n-1}). Moreover, as an initial population is generated (quasi) randomly, it is not unlikely that extreme or irrelevant alternatives will be part of the first generation evaluated by the GA. These alternatives would never be considered in reality, creating a discrepancy between the GA solver and real-life design alternatives that should be mitigated to achieve convergence.

A.3. Modifications to the GA

To solve the aforementioned issues resulting from normalisation and/or rank reversal, the following modifications were applied resulting in a so-called inter-generational GA solver:

(1) an additional step must be added in the evaluation of a generation. After determining the aggregated preference scores for the complete population, the member with the highest rank is added to a list. This list contains the best members of all generations ($G_n, G_{n-1}, ..., G_0$) and is evaluated separately to acquire an aggregated preference score for all members of this list. In case the aggregated preference score of generation G_n yields a lower score than G_{n-1}, no improvements are made. However, if the score of generation G_n equals 100, the GA has either improved or, if the score of generation G_{n-1} also equals 100, a temporary optimum has been found.

(2) the initial population can be built from user-defined initialised solutions. These solutions can be arbitrarily chosen or guided by the single objective and/or min-max design optimisation outcomes. Thereby, the initial population is not (quasi) random anymore because it reflects true potential design points, reducing the probability of non-convergence from the start. After this first starting evaluation, mutation will start diversifying the population, making it again possible to reach another optimal solution even though the initial population is directionally determined.

Note that this implementation of 'arbitrary' initialised solutions is also of great benefit for the validation of the results. Running the same problem with different starting points can confirm that the result is indeed optimal.

(3) at the evaluation of the function U (see Equation (2.1)), always an additional specific re-evaluation is introduced by feeding the GA as much as possible with potential real-life design points. Here, a re-evaluation of the population is implemented so that the very worst alternatives are left out, which reflect irrelevant non-competitive alternatives. This means that after this population is evaluated, only alternatives with an aggregated preference score higher than a specific lower limit P^* (which can be set by the designer, here fixed at 20) will be re-evaluated a second time, improving GA convergence.

The three aforementioned modifications have been added to a fit-for-purpose inter-generational solver GA, where key elements from standard available GA Python packages have been integrated enabling comparing the aggregated results of one generation with another. See the data availability statement for the code of this solver.

Note that the aforementioned modifications are the result of pragmatic engineering judgement using the principle of reflection and after validation of a multitude of example problems. As a possible specific step for further research, it may be of interest (partly from the perspective of improved solving speeds) to investigate whether other optimisation algorithms than a GA might be more suitable for this specific purpose.

B

Design Performance Functions for Dredging Production Management

The feasibility of the solutions proposed by the optimisation framework is governed by the physical limitations of the dredging processes and TSHDs. These limitations can be divided into three separate parts:

1. limitations in sailing speeds
2. limitations during loading
3. limitations during discharging

These parts are discussed separately in the following sections.

B.1. Limitations during sailing

The maximum speed at which a TSHD can travel the distance between the reclamation area and the borrow area depends on several characteristics of the TSHD, the most important of which is its draft. This draft contributes significantly to the TSHD's resistance and depends mainly on the mass/volume of dredged material on board the TSHD.

In the optimisation framework, TSHDs will sail with different volumes of dredged material on board. Thus, for fully correct integration of this behaviour in the optimisation framework, the maximum sailing speeds should become a function of the draught, which in turn should be a function of the dredge volume. However, this relationship becomes quite complex because it depends on parameters such as the density of the material and the volume of water in the TSHD, as well as weather influences such as wave heights.

Consequently, the relationship between dredged volume on board a TSHD and its sailing speed is simplified for application in the optimisation framework. For the upper limit of the sailing speed, i.e. the maximum speed that a TSHD can have, the following assumptions are made:

1. On the route from the reclamation area to the borrow area (the outbound leg), the TSHD cannot sail faster than its normal empty sailing speed (even though the TSHD may not be empty).
2. On the return journey from the borrow area to the reclamation area (the inbound leg), the TSHD cannot sail faster than its normal fully loaded sailing speed (even though the TSHD may not be fully loaded).

The lower limit of the sailing speed is currently taken as an experience-based fraction of the upper limit. Further development of the optimisation framework should improve the determination of the lower limit.

The consequence of these assumptions is that it can lead to solutions where the sailing speed is too high or too low for the given volume of dredged material in the TSHD. This is a shortcoming of the optimisation framework. However, the impact of these assumptions is likely to be small since, based on the objectives, utilisation of the TSHD can be expected to be high: i.e. the volume of dredged material on the inbound leg will be close to the maximum and on the outbound leg close to the minimum.

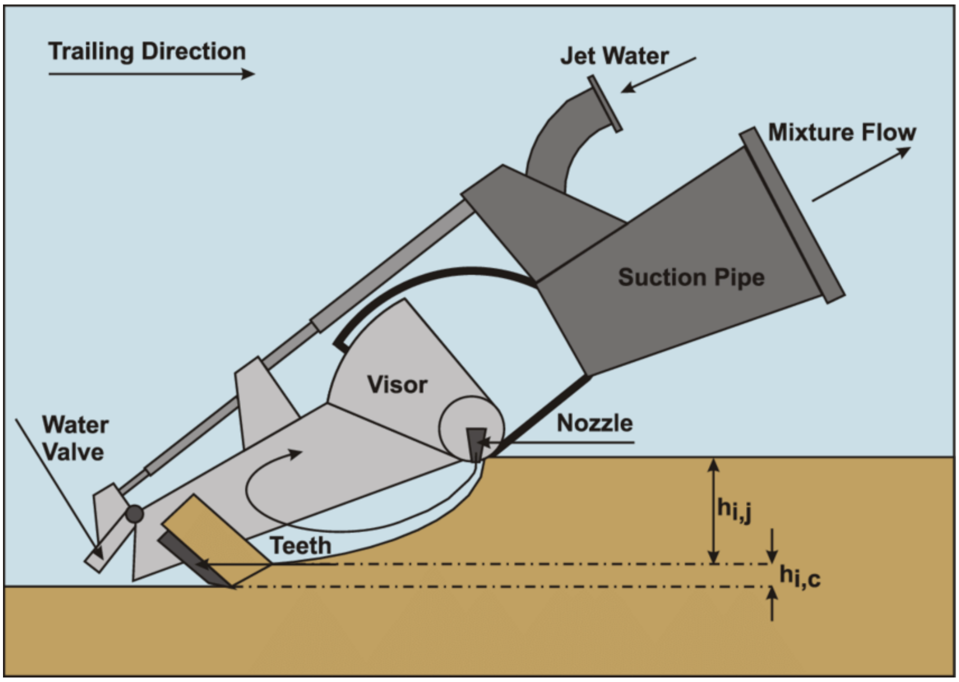


Figure B.1: Working principle of a drag head on the seabed. Source: Miedema (2019).

B.2. Limitations during loading

Loading the TSHD is done by lowering a so-called drag head onto the seabed. As the TSHD will move forward, the drag head will cut the material (by teeth and jets, see also Figure B.1). This material will subsequently mix with water and is pumped on board via a large suction pipe at the top of the drag head. The drag head of the Fairway, including the arm to which it is connected to the vessel, is shown in Figure B.2.

The production rate (i.e. m^3/s soil) of the drag head can be described by the model introduced by Miedema (2019). In his article, Miedema introduces an equation that describes the production rate of a drag head as a function of both the soil conditions, and the properties of the TSHD.

In addition, the drag head production rate is constrained by the occurrence of cavitation. Cavitation occurs when the pressure at the pump inlet becomes too low and leads to the continuous formation and collapse of air bubbles (Randall, 2022). This will reduce the efficiency of the pump and damage it over time.

To prevent cavitation, the pressure at the pump inlet must be kept lower than the Net Positive Suction Head Available (NPSHA) (Randall, 2022):

$$NPSHA = \frac{P_a}{\gamma} + \frac{P_2}{\gamma} + \frac{V_2^2}{2g} - \frac{P_v}{\gamma} \tag{B.1}$$

where P_a is the ambient pressure; γ is the specific weight of the soil; P_2 is the gauge pressure (pressure relative to ambient); V_2 is the fluid velocity at pump entrance; P_v is the vapour pressure, the pressure at which cavitation will occur, which depends on temperature. Thus, the production rate that can be achieved will depend on project specifications such as what soil is dredged and the temperature of the water.
On board, the mixture is pumped into one of the hoppers (large open holds in the TSHD). Here, the soil begins to settle while the excess water flows overboard. This process continues until the maximum amount of soil has been taken on board, after which the TSHD takes the drag head back on board and sails back to the reclamation area.

This settling of the soil is constrained by the settling speed of the mixture, as described by Miedema (2008). Figure B.3 shows a snapshot of the loading process. Here, the mixture flows into the hopper in the upper left corner and there is already some sedimentation at the bottom. At the top right is the overflow, where excess water can flow out of the hopper. However, in addition, also part of the mixture will flow overboard. This is because the flow velocity across the sedimentation bed is too high for every particle to settle before the flow reaches the overflow (Camp, 1946; Miedema, 2008; Van Rhee, 2002). Note that small particles settle more slowly than larger ones, causing mainly the finer particles to flow back out through the overflow. As a

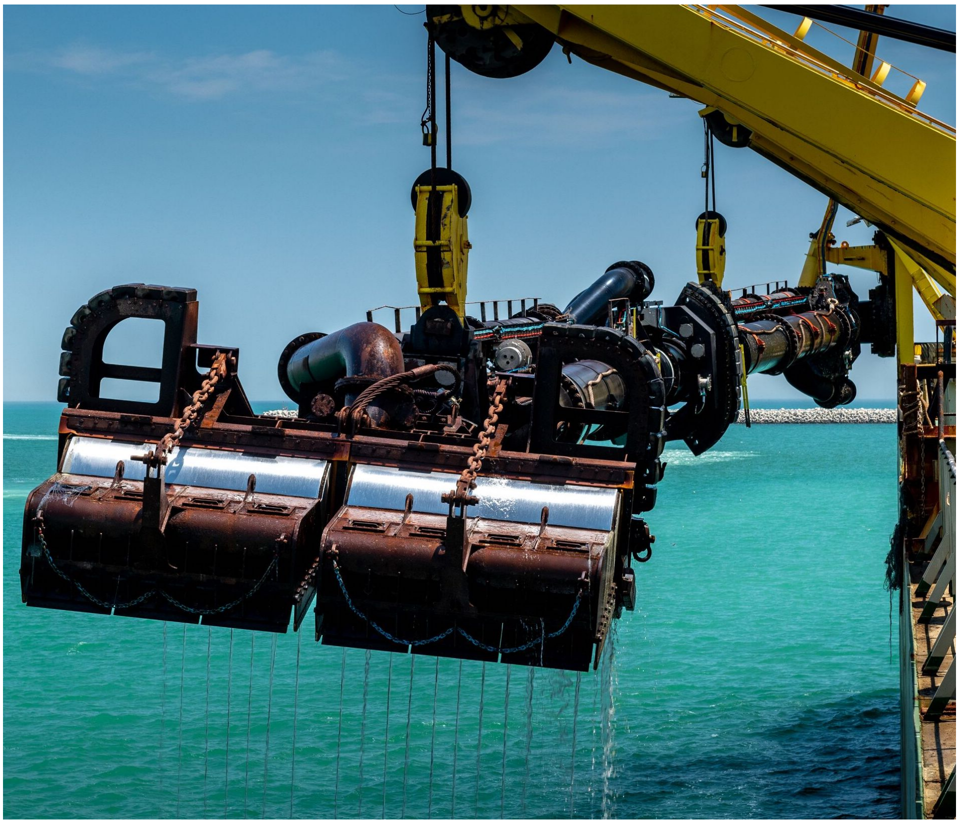


Figure B.2: Drag head of the Fairway. Source: Media library Royal Boskalis N.V.

consequence, the sedimentation bed will have a coarser particle size distribution[1] than the dredged material originally had.

As the sedimentation level increases, the flow velocity across the bed will further increase, causing additional erosion: particles that had already settled are resuspended in the water. As a result, the loading productivity, expressed in cubic metres of soil settling per hour, will gradually decrease until it reaches zero: the point at which sedimentation and erosion are in equilibrium and the volume of dredged material in the hopper will no longer increase.

As a result, the time needed to fill a hopper is highly dependent on soil properties. The finer the particle size distribution, the slower the particles settle and the more susceptible the process is to erosion during the final stage of loading. For these finer particle distributions, the loading time is therefore longer than for coarser ones, since either the overflow losses are greater or the loading rate needs to be reduced.

[1]The particle size distribution describes the relative quantity of each particle size present in the soil.

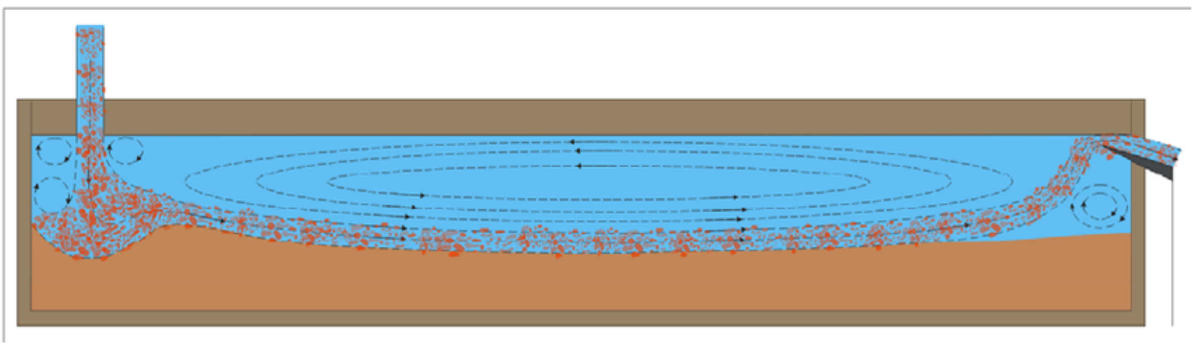


Figure B.3: Snapshot of the hopper of a TSHD during the loading process. Source: Miedema (2008).

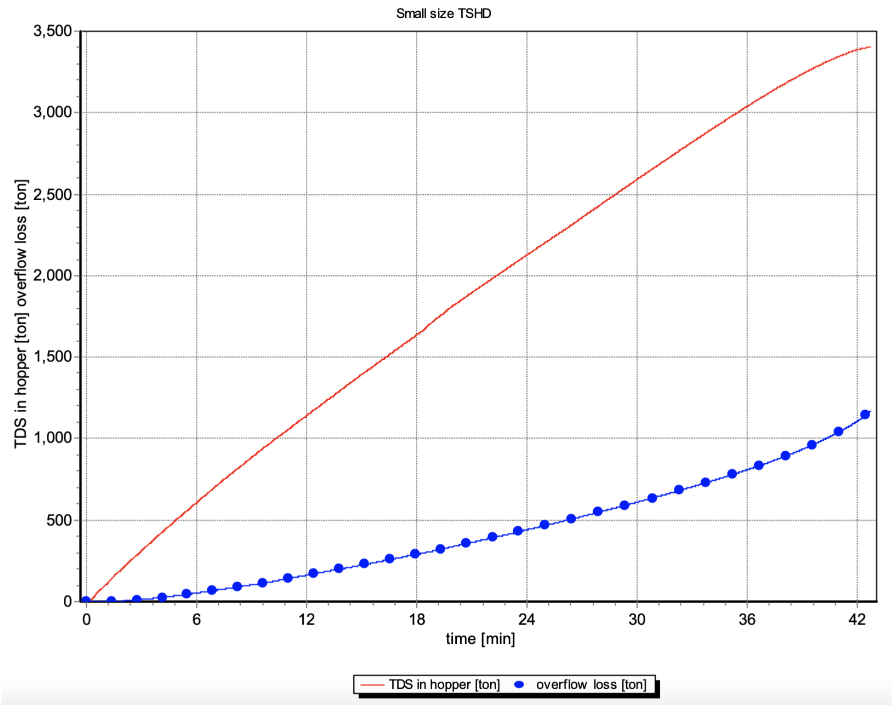


Figure B.4: Sample graph of a loading curve of a TSHD, showing the loaded Tonnes of Dry Soil (TDS) and overflow losses over time. Source: Miedema and Rhee (2007).

The implementation of the load production rate in the optimisation framework is done through the so-called loading curves of the different TSHDs. These loading curves describe the volume of soil that has settled in the TSHDs over time and are created with Tendertools, an internally developed simulation tool of Boskalis. These curves can be created in advance for different soil conditions and fed into the optimisation framework. An example of a loading curve can be found in Figure B.4.

These loading curves take into account drag head production, pump power limitations due to cavitation, and settling speed in the hopper. Considering these processes separately increases the complexity significantly, while the improvements in optimisation results are limited. Moreover, since Tendertools was developed internally by Boskalis, it contains a more accurate description of the relevant TSHDs that may not be feasible with customised development models. Therefore, integration via loading curves is detailed enough for the current stage of development of the optimisation framework.

In the further development, these load curves can be improved by analysing the load production data obtained by TSHDs on a project. Currently, the load curves are constructed in a theoretical model that assumes perfect conditions, such as similar soil conditions throughout the borrow area. In reality, this is not the case and load curves can vary significantly. This variation can be extracted from the production data and is ideally considered in the model.

In addition, it could be explored whether pump power could be part of the optimisation framework. Currently, it is assumed that pumps always operate at their maximum power, given the limitations of cavitation. However, it could be interesting to reduce the pump power (and consequently fuel consumption) such that loading takes longer, allowing the TSHD to arrive at the discharge line at a better time. This could reduce fuel consumption more efficiently than reducing the sailing speed, since pumping the mixture on board also has a significant fuel consumption. Moreover, a reduction in pumping power also results in a lower flow rate in the hopper and could reduce overflow losses, thus improving loading efficiency.

Finally, it should be noted that the design variable for loading time in the optimisation framework is the time the TSHD is allowed to load. Given the initial level in the hopper and this allowed loading time, the optimisation framework will determine where it has ended on the loading curve and returns that value as the level in the hopper when it starts sailing to the reclamation area. It is thus not the case that the TSHD is by definition fully loaded when it starts sailing to the reclamation area.

B.3. Limitations during discharging

At the reclamation area, water is pumped into the hopper to liquefy the soil, and this mixture of water and soil is then pumped to the beach through the so-called discharge pipeline. This process is mainly limited by the critical velocity of the mixture, as below this velocity, the soil in the pipeline begins to settle and can clog the pipe.

It is important to note that the way the mixture flows through the discharge pipe can vary greatly and depends on, for example, the particle diameter and the flow velocity. Five flow regimes can be distinguished (see also Figure B.5 and Miedema and Ramsdell (2016)):

1. Homogeneous (I): all particles are fully suspended and equally distributed throughout the cross-section of the pipe.
2. Heterogeneous: the particles are not equally distributed over the cross-section. Two versions can be identified:
    (a) Fully suspended heterogeneous flow (II)
    (b) Heterogeneous flow with rolling bed (III)
3. Sliding bed (IV): at the bottom of the pipe, a bed layer forms that moves at a smaller velocity than the water in the pipe. Only a small number of particles are still suspended in the water.
4. Fixed bed (V): a fraction of the bed layer no longer moves. If this fraction becomes too large, the pipe becomes clogged.

The lower the velocity of the mixture and the larger the particle size, the more the flow regime moves towards a fixed bed.

As the mixture moves through the pipe, it loses energy due to friction with the pipe wall. In other words, the speed of the mixture decreases as it moves through the pipe. Consequently, after a certain distance, a fixed bed regime will then develop and clogging of the pipe might become a problem. Keeping the flow rate high enough depends mainly on the head (i.e. pressure) that a dredge pump can deliver. This head depends on the power and design of the pump, the soil conditions and the concentration of the mixture. The interested reader is referred to Miedema and Ramsdell (2016) for the governing equations.

Since the distance between the connection point of the TSHDs and where the soil is needed can be quite large, additional booster pumps may be installed. These pumps are placed in the discharge line and can further increase the head so that a sufficiently high flow rate is achieved even with long discharge lines.

It would be interesting, for optimisation purposes, to make the specifics of the flow rate through the discharge line a function of the pumping power. This would give more control over fuel consumption during unloading. However, this integration is quite complex and was not feasible for the current proof-of-concept. Instead, it is assumed that clogging of the pipe is not a problem. This is a safe assumption since the optimisation framework is applied to projects that are already underway. Thus, if clogging was a problem, it has already been addressed.

Instead, the discharge production rate is assumed to depend solely on the density of the mixture. For a fully loaded TSHD, the production rate is highest at the beginning of discharging. During this phase, there is enough soil in the hopper to reach the optimum mixture concentrations when water is added. However, as the volume of soil in the hopper decreases, the mixture concentrations and production rate will also decrease.

In reality, the production rate will gradually decrease. However, as is often the case in dredge management and also here, the discharging process is divided into two phases: 1) maximum production rate and 2) clean-up production rate. During these two phases, the production rate is assumed to be constant.

Only a part of the volume of dredged material can be pumped at the maximum production rate. For example, if the threshold for clean-up production is $5,000m^3$ and the volume of soil in the hopper is $7,000m^3$, only the first $2000m^3$ can be discharged at the maximum production rate and the rest is discharged at the clean-up production rate. The optimisation framework takes this into account and determines the discharge production of a TSHD based on the volume of soil in the hopper of the TSHD and the time it is allowed to discharge.

Note that, besides the mixture concentration, the production rate also depends on the vertical distance between the top of the soil and the pump inlet. During the validation meeting, it became clear that this influence is difficult to model and is not considered in current modelling tools. So this has also been omitted in the optimisation framework.

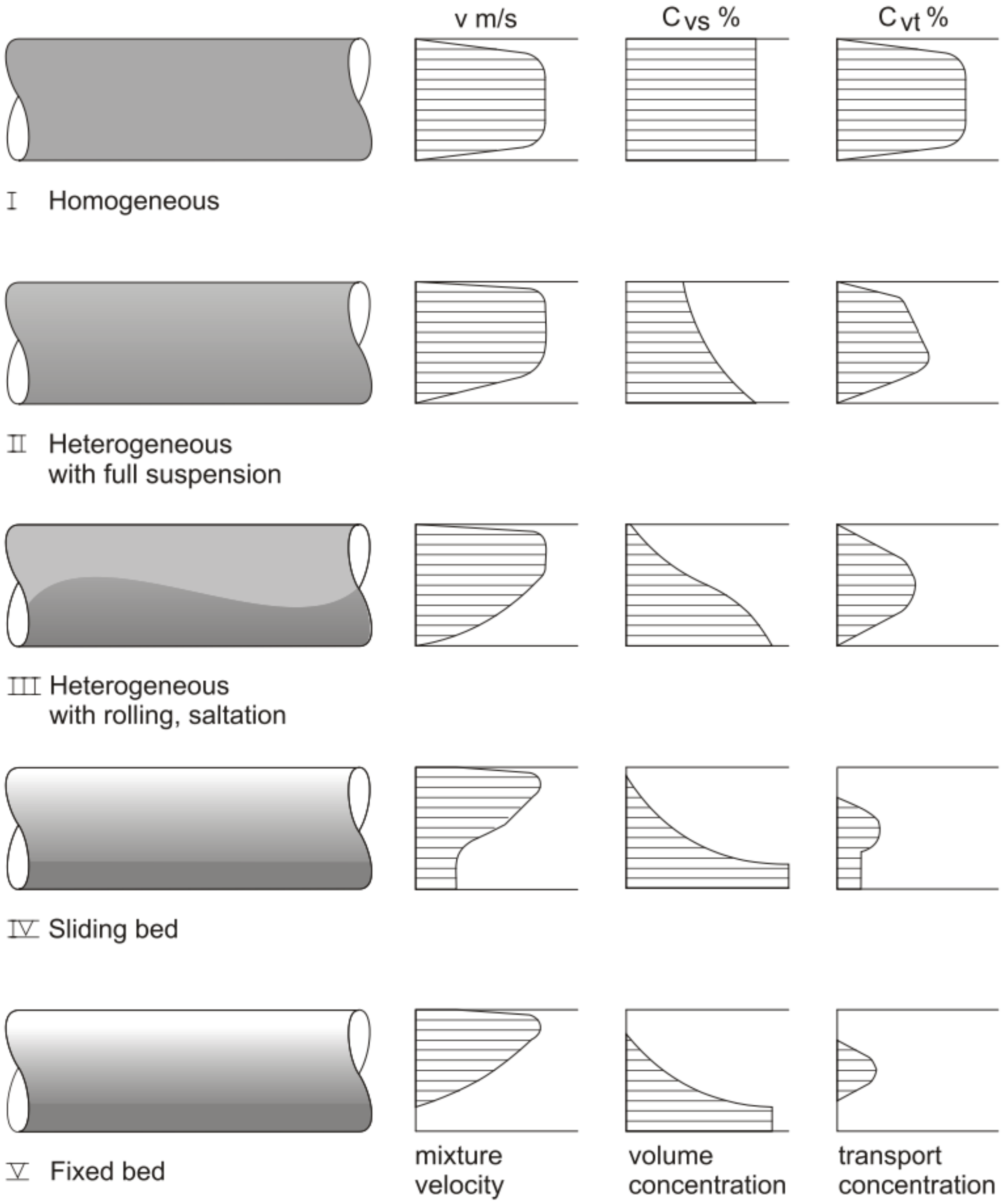


Figure B.5: Different flow regimes of the mixture in a discharge line. Source: Miedema and Ramsdell (2016).

C

Objective Functions for Dredging Production Management

Objective functions are the link between the preference functions (level 1) and the design performance functions (level 3). For this optimisation framework, four objectives are considered in finding the optimal mitigation strategy: waiting time, production, TSHD utilisation, and CO_2 emissions. Each of these objectives is discussed separately below.

C.1. Objective waiting time

The discharge line cannot be used by more than one TSHD at a time. Therefore, if a TSHD arrives at the reclamation area and the discharge line is still in use, it will have to wait. This objective is the sum of all the time TSHDs have to wait.

If a TSHD has to wait, it is an inefficient use of the vessel, which is not preferred. Moreover, at the start of a project, the dredging cycles of all TSHDs are planned so that the waiting time is limited. Unforeseen circumstances disrupt this planning and cause additional waiting time. By taking waiting time into account during optimisation and trying to minimise it, a new conflict is less likely to arise immediately after the last dredging cycle included in the optimisation ends. Instead, the project can hopefully continue as if nothing had happened. For both reasons, waiting time should be an objective in this optimisation framework.

C.2. Objective production

For land reclamation projects, production (i.e. cubic metres of soil transported) is an important measure. It determines how long the project takes and therefore how much it costs. Production is included in the optimisation as the amount of soil discharged per hour through the discharge line.

Note that the production of a project is limited by the load and discharge production of the individual TSHDs, which are determined by the design performance functions/processes described in section B.2 and section B.3.

C.3. Objective TSHD utilisation

Besides waiting time, the efficiency of TSHDs can also be expressed in terms of TSHD utilisation. This measure is the ratio of the volume of soil transported by a TSHD (P_{actual}) to the maximum volume that this TSHD could have transported (P_{max}).

As the optimisation framework tries to find the best mitigation strategy, it may decide on rather resolute measures and allow a TSHD to load only a fraction of its normal volume. Especially for captains, this is not desirable. The addition of this objective gives them a way to express this preference.

Further development should explore the added value of this objective. This objective may already be indirectly included in the combination of the objectives production and CO_2 emissions, as a partially filled hopper is not beneficial for these objectives.

C.4. Objective CO_2 emissions

Sustainability is becoming an increasingly important factor in dredging projects, and by including CO_2 emissions as an objective, it gives stakeholders a way to consider sustainability in optimisation. The objective is defined as the sum of the metric tonnes of CO_2 emitted collectively by the TSHDs. This is correlated one-to-one with fuel consumption, which is broken down by activity.

As the objective is an indicator of fuel consumption, it is the most important objective to consider alongside the production objective, especially for projects where the fuel is paid for by Boskalis.

Note that currently, fuel consumption for sailing is a constant value, independent of sailing speed. This is an oversimplification that needs to be addressed in further development of the optimisation framework.