

A FRAMEWORK FOR COLLABORATIVE FRONT-LOADED DESIGN SPACE EXPLORATION

IMPROVING COLLABORATION ACROSS THE AERONAUTICAL
SUPPLY CHAIN

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SUPPLY CHAIN

by

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SUMMARY

In the contemporary aircraft design process, the design and integration of the various (sub)systems is distributed over multiple organisations. This results in a distribution of knowledge, where collaborations between organisations are required to effectively design one product. In the design process, the Original Equipment Manufacturer (OEM) takes the central role of aircraft designer, who aims to deliver the best aircraft to suit market demands. The process starts with the conceptual design phase, where OEMs wish to identify feasible technologies for their new aircraft. To do so, they perform design space exploration (DSE) using their own, typically lower-fidelity, design methods. When the OEM is unable to assess a certain technology themselves, Tier-1 suppliers are consulted to assist the OEM in their DSE. Currently, these consultations are done on a one-at-a-time basis, preventing an in-depth exploration of the design space.

A closer collaboration would be beneficial for both the OEM and the supplier. The OEM would then be able to achieve the goal of the collaboration faster, reducing lead times of the design process. A supplier is able to consolidate their market position, by offering this service to the OEM, gaining an advantage over competitors.

However, a number of obstacles restrict such a collaboration in industry use. The collaboration is often done ad-hoc and is unstructured. Licensing and IP regulations prevent design tools from directly being shared. The suppliers design tools are often higher-fidelity and computationally expensive to run. Furthermore, they often require more input than the OEM has available in the conceptual design phase. This results in a reliance on assumptions, often leading to iterations later in the design process.

Following this problem definition, the research question is formulated as: *How can a collaborative workflow between an OEM and a Tier-1 supplier be enabled and exploited to enhance design space exploration in the conceptual design phase?*

To answer the research question, certain research projects, such as AGILE, IDEaliSM, and AGILE 4.0 are investigated. These research projects explored a closer than state-of-the-art collaboration between aircraft organisations through enabling Multidisciplinary Design Analysis and Optimisation (MDAO) workflows. In such workflows, computer aided engineering (CAE) tools, such as Knowledge Based Engineering (KBE) applications, are used to optimally exploit interactions between several (coupled) disciplines. Although the developed frameworks were successfully applied in R&D use cases, they rely on all involved partners to collaborate with one another. Instead, the methodology of this work revolves around a one-on-one collaboration between an OEM and a supplier.

Taking inspiration from the aforementioned research projects, three methods to enable the cross-organisational (in)direct usage of design tools were identified. The first of these technology sharing methods (TSMs) is for the supplier to share the results of a design study, specified by the OEM, in a tabular form. Secondly, the supplier can train a surrogate model (SM) that the OEM can use for their DSE. A surrogate model is an ana-

lytical model able to predict a more expensive model, based on a collected data set and an approximation function. The SM hides the underlying methodology of the suppliers design tool. Moreover, they are significantly cheaper to evaluate than the original tool, making them attractive to use in MDAO workflows. Lastly, the supplier can facilitate remote access (RA) to the design tool. The OEM can then use the design tool by remotely providing the input, and receiving the output remotely as well.

In addition, to reduce the lead times of design studies, front-loading principles are applied. Front-loading was a fundamental aspect of IDEaliSM, and plays a key role in DEFAINE, the research project in which this thesis is performed. Through front-loading, the suppliers are able to perform preemptive design studies, reducing the required work when an OEM issues a request. To apply front-loading to the DSE process, a database was included, which can be filled when a project starts. Moreover, the database can be exploited to support the DSE process. In this thesis, three types of post-processing were proposed: visualisation to quickly identify trends in the data, sensitivity analysis (SA) to assess the most influential parameters, and a complementary sampling (CS) strategy to generate sampling plans that avoid already evaluated samples. The proposed complementary sampling strategy relies on adaptive sampling methods used in surrogate model training.

Using KE-chain as a basis and extending its functionalities with Python scripts where necessary, the author implemented the framework in a collaborative environment. The environment enables rapid instantiating of pre-configured workflow templates, streamlining the request for new design studies. Furthermore, the results from completed design studies are automatically collected and can be analysed in the environment.

The framework was applied to two cases. The first case, based on the SSBJ design problem, was used to determine the feasibility of the three identified TSMs. As all methods resulted in errors below 4% when compared to direct usage of the design tool, all methods were deemed technically feasible for the conceptual design phase. Furthermore, a CS grid generated using the proposed strategy, resulted in a more efficient exploration of the design space in a follow-up study when compared to an ordinary sampling method. Lastly, SA was successfully applied to identify the most influential parameter in the problem.

The second case was a use case in DEFAINE, concerning the structural design of a movable, and was used to showcase the framework to the DEFAINE consortium. The consortiums feedback was gathered using a questionnaire, which revealed that RA is considered infeasible in industry use due to strict IT policies. There was no unanimous opinion on which of the other methods was preferable over the other, but IP regulations were still mentioned as a major challenge to overcome in enabling closer collaborations. However, the framework could also be envisioned inside of an organisation, implying that its use is not limited to collaborative scenarios.

Overall, the framework was well received, but can be improved and expanded to increase its benefit. Firstly, the methodology can be expanded to consider optimisation workflows as well. Furthermore, the CS strategy can be improved to reduce clustering in the new sampling plan. Lastly, a SA method that can assess both numerical and categorical variables would greatly improve the benefit of SA in mixed-variable design problems.

CONTENTS

Acknowledgements	v
Summary	vii
List of Figures	xi
List of Abbreviations	xiii
1 Introduction	1
I State of the Art	5
2 Collaborative workflows	7
2.1 Formalising cross-organisational workflows	8
2.2 Facilitating cross-organisational tool usage	10
2.2.1 Direct sharing of results	10
2.2.2 Sharing a surrogate model	11
2.2.3 Offering remote access.	12
2.3 Incomplete data definitions.	12
3 Reducing design lead times and costs	13
3.1 Front-loading	13
3.2 Sensitivity analysis	14
4 Enabling technologies	17
4.1 Collaboration Platform	17
4.2 Automated Workflow Formulation	18
4.3 Workflow Execution.	19
4.3.1 Process Integration and Design Optimisation	19
4.3.2 Surrogate modelling	19
4.3.3 Remote access	20
4.4 Common Data Standards	21
4.4.1 Product definition: CPACS	21
4.4.2 Workflow definition: CMDOWS	21
II Methodology and Implementation	23
5 A methodology for collaborative front-loaded design space exploration	25
5.1 Collaborative design space exploration	26
5.1.1 A general DOE workflow	27
5.1.2 Technology sharing methods	27

5.2	Applying front-loading principles	30
5.2.1	Inclusion of a database.	30
5.2.2	Exploiting the database for design space exploration	32
5.3	Framework overview	36
5.3.1	Build	37
5.3.2	Operate	38
5.3.3	Analyse	39
6	Implementation	41
6.1	Case description	41
6.2	Build phase	42
6.2.1	Data schema specification	44
6.2.2	Workflow template creation	44
6.3	Operate phase	45
6.4	Analyse phase.	46
6.4.1	Visualisation	46
6.4.2	Sensitivity analysis.	47
6.4.3	Surrogate modelling and complementary sampling	49
6.5	Alternative scenarios	50
III	Verification and Validation	53
7	Test case: Supersonic Business Jet	55
7.1	Case description	56
7.2	Comparison of technology sharing methods	58
7.3	Complementary sampling	60
7.4	Sensitivity analysis	62
7.5	A critical reflection on the test case	65
8	DEFAINE use case: UAV movable design	67
8.1	Sensitivity analysis	67
8.2	Qualitative assessment	68
9	Conclusions and Recommendations	71
9.1	Recommendations	73
A	Implementation of Panair in the SSBJ test case	81
B	Test case diagrams	85

LIST OF FIGURES

1.1	The impact design decisions have is greatest early in the design process. . .	2
2.1	The AGILE paradigm: a blueprint for collaborative MDO systems.	9
2.2	The IDEaliSM Framework Architecture.	10
3.1	Front-loading enables a higher design maturity in shorter lead times. . . .	14
4.1	Example of remote access using BRICS.	20
5.1	The steps taken in design space exploration using DOEs.	28
5.2	A collaborative DSE where the results are shared in tabular form.	28
5.3	A collaborative DSE where a surrogate model is built by the supplier and shared with the OEM.	29
5.4	A collaborative DSE where remote access enables direct usage of the supplier owned tool by the OEM.	29
5.5	The inclusion of a database to the design space exploration process.	31
5.6	Methods for a supplier to front-load future design studies by performing preemptive design studies.	31
5.7	A parallel plot generated in AGILE, based on an optimisation study.	32
5.8	A scatterplot matrix based on the movable design case.	33
5.9	An overview of the proposed framework for collaborative front-loaded design space exploration.	37
5.10	An overview of steps taken in the Build phase.	38
5.11	An overview of the steps taken in the Operate phase.	39
5.12	An overview of the steps taken in the Analyse phase.	40
6.1	Overview of the steps taken in a design study in the movable use case. . .	43
6.2	Interface for the specification of a data schema in the collaborative environment.	44
6.3	Interface for the generation of Design Study Configuration files.	45
6.4	Interface for creating a new design study instance.	46
6.5	Overview of the parameters after the collection of results.	47
6.6	Visualisation window in the front-loaded environment.	48
6.7	Sensitivity analysis window in the front-loaded environment.	48
6.8	Surrogate modelling window in the front-loaded environment.	50
6.9	Complementary sampling window in the front-loaded environment. . . .	50
7.1	XDSM of a DOE workflow in the SSBJ problem.	57
7.2	XDSM of the SSBJ DOE workflow with the higher-fidelity solver implemented. .	58

7.3	Interface for the requested design study in the KE-chain environment. . .	59
7.4	Histogram showing the relative error of Scenario 1 and 2.	61
7.5	Comparison of the sampling grids evaluated in the sequential DOE.	63
7.6	The effect of the ratio of evaluated samples to samples in the new grid. . .	64
A.1	Overview of the wing planform used in the SSBJ test case.	82
A.2	Examples of generated 3D geometries to be analysed by Panair.	83
A.3	Flow chart of the higher fidelity aerodynamic solver implemented in the SSBJ test case.	84
B.1	XDSM of the original SSBJ problem.	86
B.2	XDSM of Scenario 1	87
B.3	XDSM of Scenario 2	88
B.4	XDSM of Scenario 3	89

LIST OF ABBREVIATIONS

CAE	Computer Aided Engineering
CS	Complementary Sampling
DEFAINE	Design Exploration Framework based on AI for front-loaded Engineering
DOE	Design of Experiments
DSE	Design Space Exploration
GUI	Graphical User Interface
HDMR	High Dimensional Model Representation
I/O	Input/Output
IP	Intellectual Property
LHS	Latin Hypercube Sampling
MDAO	Multidisciplinary Design Analysis and Optimisation
OEM	Original Equipment Manufacturer
PIDO	Process Integration and Design Optimisation
QOI	Quantity of interest
RC	Refinement Criterion
SA	Sensitivity Analysis
SM	Surrogate Model
TLARs	Top Level Aircraft Requirements
TSM	Technology Sharing Method
XDSM	eXtended Design Structure Matrix

1

INTRODUCTION

The contemporary aircraft design process and manufacturing process is distributed over multiple companies[1]. The many disciplines and various subsystems present in aircraft make it economically unfeasible for one party to completely design and manufacture an entire aircraft: the labour required and associated risk are too great. Central to the design process is the Original Equipment Manufacturer (OEM), who aims to deliver aircraft to best suit market demands. Based on a market research or customer requests, the OEM specifies the top level aircraft requirements (TLARs) that will drive the design of the new (fleet of) aircraft. It is the OEMs challenge to integrate the various components and (sub)systems into one coherent design that meets the TLARs. To do so, the design process starts with the conceptual design phase. Here, the best available design options to meet the TLARs are sought out and identified, and if deemed viable, design space exploration (DSE) is performed: a set of design parameters is varied in order to study and quantify the effects on the requirements, in order to find the optimal set of designs for the aircraft (sub)systems. The collection of solutions of all systems present in the aircraft forms the conceptual design, and the basis for the more detailed preliminary design.

The design space exploration is primarily done using the OEMs own design methods. These design tools are typically low-fidelity in nature, such as low level physics and empirical methods. Such tools are used because they are quick to evaluate, can explore a wide range of options, and depend only on basic high-level input. At some point, the OEM may realise that their own design tools are inadequate for the current design problem. For instance, they may wish to explore novel technologies that cannot be analysed using their own analysis tools. Another reason may be that they wish to increase the detail of the design, and use a higher-fidelity method to verify the estimations made earlier in the design process. In such cases, the OEM can consult potential Tier-1 suppliers to involve them in the design process. The Tier-1 suppliers have higher-fidelity analysis tools that are able to provide the knowledge that the OEM desires. However, higher-fidelity tools often require more detailed input than is available in the conceptual design phase. Moreover, they are computationally more expensive to run. Because of these characteristics, these consultations are currently done on a one-at-a-time basis, where the OEM

provides a single design to be evaluated by the supplier.

In the context of DSE, where the OEM considers a large number of options, this is not an effective approach. The requirements on which the provided design is based may change. This would then result in a design iteration, where the supplier is contacted again to evaluate the updated design. Moreover, if the analysis tool requires more input parameters than the OEM has available, the uncertainty in the unknown parameters may render the results unusable. The consultations are then not worth the efforts, and are not performed at all. Innovative concepts that can only be investigated using the higher-fidelity are thus not properly assessed early on, and are often dismissed due to their associated risks and uncertainties[2]. Correspondingly, the cost of implementing a novel technology increases as the design matures, and more changes are needed to proceed with the implementation[3]. This is schematically visualised in Figure 1.1. This increased cost may outweigh the benefits of switching design options, obstructing a more optimised design. For this reason, a proper assessment of novel technologies early in the design process is extremely beneficial.

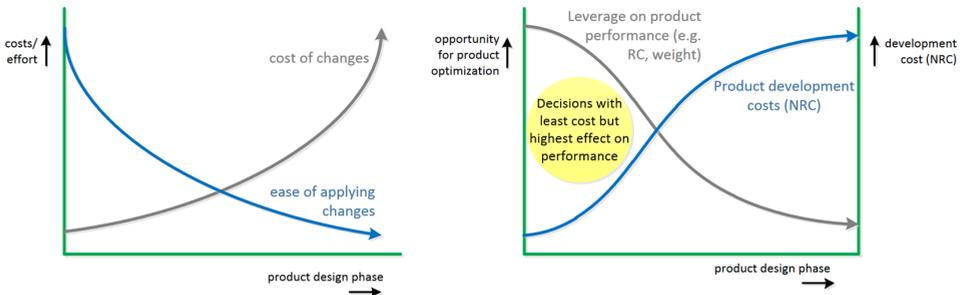


Figure 1.1: The impact design decisions have is greatest early in the design process[3].

A closer collaboration has the potential to enable the usage of Tier-1 supplier tools in the design space exploration. Such a collaboration would be favourable for both the OEM and the supplier. By using the higher-fidelity design tools in the DSE, the OEM can achieve a higher level of detail at an earlier stage. This prevents design iterations due to incorrect assumptions, thereby shortening the project lead time. Furthermore, novel technologies can be properly explored, allowing the OEM to make a more informed design choice. The supplier can also bring up newer technologies that the OEM is not yet aware of, ensuring that the most novel technologies are considered in the design. Finally, by offering the service of performing DSE for OEMs, the supplier gains an edge over competitors, strengthening their market position.

The concept of a closer collaboration between OEMs and their Tier-1 suppliers is not new, and has been explored in recent research projects [4–6]. Despite these (successful) efforts, such collaborations are not yet state-of-the-art. The aim of this thesis is to bridge the gap between collaborations encountered in literature and the current state-of-the-art. The scope is limited to design space exploration in the conceptual design phase, because if successful, this collaboration could result in shorter project lead times as well

as proper assessment of novel technologies. This in turn has the potential to improve both the aircraft development process and resulting aircraft design. Furthermore, only one interaction between a supplier and an OEM is considered. If successful, the OEM can establish multiple of such interactions to enhance their design process. The research question of this thesis can thus be formulated as:

How can a collaborative workflow between an OEM and a Tier-1 supplier be enabled and exploited to enhance design space exploration in the conceptual design phase?

The research question can be divided into the following two sub-questions:

- *How can a workflow where an OEM and a Tier-1 supplier collaboratively perform design space exploration be enabled?*
- *How can the supplier provide the OEM with high quality data in a reduced lead time?*

In order to answer the posed questions, the report is divided into three parts. Part I describes the current state of the art of collaborative workflows. This includes an overview of recent research projects that explored a closer collaboration in aircraft design. Relevant solutions found in these research projects are reused and applied in the methodology proposed in this work. Part II describes the main deliverable of this work: a framework to facilitate front-loaded collaboration in design space exploration. An implementation of the framework used in this thesis is also presented. Finally, Part III describes the application of the proposed framework on two cases: a test case to simulate the effects of different collaboration strategies, and a use case within the ongoing DEFAINE (Design Exploration Framework based on AI for front-loaded Engineering)[7] project, to assess the applicability of the framework to industry use. The part ends with the conclusion of the thesis and recommendations for future work.

I

STATE OF THE ART

2

COLLABORATIVE WORKFLOWS

The first goal of this thesis is to enable a closer collaboration between the OEM and their suppliers in the conceptual design phase. As mentioned in the introduction, the concept of such a closer collaboration has been explored in recent research projects. This chapter provides an overview of the hurdles encountered in cross-organisational collaborations, how they have been mitigated in academic work, and how the solutions can be translated to state-of-the-art industry.

One recent research project investigating a closer collaboration in the aerospace industry, was AGILE (Aircraft 3rd Generation MDO for Innovative Collaboration of Heterogeneous Teams of Experts)[4]. The goal of this project was to *"achieve a significant reduction in aircraft development costs through a more competitive supply chain able to reduce the time to market of innovative aircraft products"*. The AGILE project was considered very successful and has received the ICAS Award for Innovation in Aeronautics, *"for outstanding and innovative contributions to the development of advanced aeronautical systems"*[8]. The AGILE project was succeeded by AGILE 4.0, which aimed to incorporate the upstream aspects of systems engineering, such as requirement management and certification, into the process[9, 10].

To identify the obstacles in setting up any collaborative workflow, a questionnaire was performed at the start of the project[11]. The obstacles most relevant to this thesis can be categorised as:

- Lack of formalised cross-organisational workflow.
- Protection of IP: limited tool availability/shielding of trade secrets.
- Incomplete or unclear input and output (I/O) definitions.

These hurdles, as well as the solutions provided, are described in the sections below. This gives an overview of the existing solutions that were considered in this thesis.

2.1. FORMALISING CROSS-ORGANISATIONAL WORKFLOWS

The AGILE project focused on setting up and executing collaborative MDAO workflows. In Multidisciplinary Design Analysis and Optimisation (MDAO)[12] systems, disciplines that have strong interactions with each other are strategically ordered and executed to exploit these interactions. The methodology originated in the 1970s after numerical optimisation was performed on the structural design of a wing[13]. Due to the multidisciplinary nature of aircraft design, MDAO is considered a powerful methodology in the field. However, several technical and non-technical barriers have limited the adoption of MDAO in industry use[14].

To perform a collaborative MDAO study, a framework was developed for setting up a "3rd generation" MDO system[15], characterised by the distribution of not only the analysis, but the complete discipline, including its specialists[16]. This framework was described as the AGILE paradigm, and is visualised in Figure 2.1. Three levels in the blueprint can be distinguished:

- At the lowest level, the design competences are present. These represent the individual analyses and disciplines relevant to the design problem at hand. An example of an analysis is the sizing of a wings primary structures, or the computation of block fuel mass. The specialists involved are responsible for facilitating the analysis and, together with the collaborative engineers, making the tools required in the analysis available to the framework.
- In the design and optimisation layer, the MDAO workflow is formulated and eventually executed by the integrator. The integrator chooses a suitable MDAO architecture and specifies the execution order of the disciplines. Depending on the chosen MDAO architecture, the workflow is enriched with a convergence loop or consistency constraints[17].
- In the development process, the overall development process is defined by the architect. This consists of defining the requirements, identifying the necessary design competences to solve the problem, and bounding of the design space.

Another research project that explored a collaborative workflow, was IDEaliSM (Integrated and Distributed Engineering Services framework for MDO)[5]. This project had the goal to "drastically reduce the time-to-market and development cost of high-tech structures and systems, by delivering a novel product development framework"[3]. The proposed solution was an integrated and distributed framework, that allows different parties to practice their disciplines remotely in a collaborative network. The framework is schematically represented in Figure 2.2, and has the following structure[18]:

- The *Engineering Language Workbench* (ELW) is the environment which holds all technical knowledge required to create or modify engineering services. It contains the high level programming languages in which the engineering services are built, and the specific domain knowledge. Together, these are used to create so called engineering services, i.e. the customised tools to be used in the engineering problems. The ELW is used in the "build" phase, i.e. in preparation of future design problems.

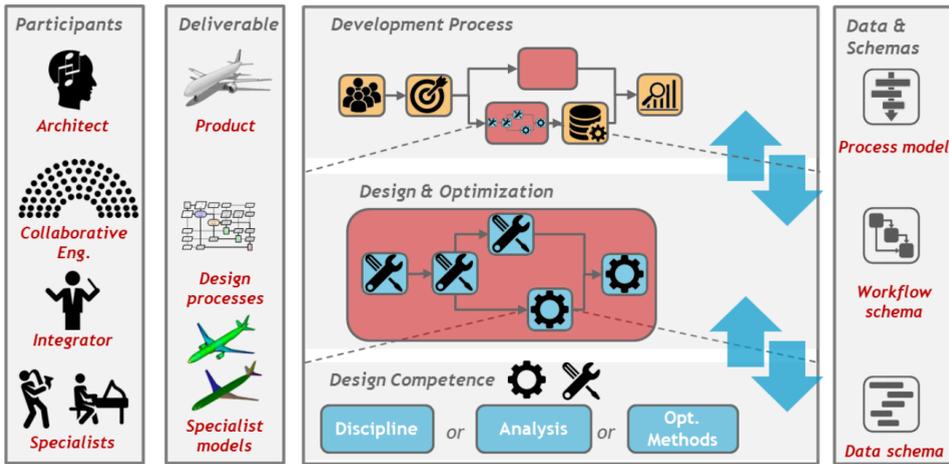


Figure 2.1: The AGILE paradigm: a blueprint for collaborative MDO systems[4].

- The *Engineering Library* is the environment where the engineering services are stored. Examples of engineering services are Knowledge Based Engineering (KBE) applications, that enable the automation of certain engineering processes and thus inclusion in MDAO workflows. It also holds a database of already existing solutions and workflow templates. The EL is thus the central module that stores the ingredients to be used in the generation of engineering solutions.
- The *Advanced Integration Network* is the environment where the design processes are executed. Here, the engineering services and workflow templates are imported from the Engineering Library, allowing them to be used by end-users. It consists of several layers:
 - The business process layer provides the interface that end-users will interact with.
 - The simulation process layer is invoked by the business process layer, and executes MDAO workflows.
 - The tool layer hosts all the tools that are used in the workflows.
 - The execution infrastructure defines the physical location where the tools are executed, such as local computer clusters or cloud-based services.

The methodologies for collaborative workflows proposed by these projects were formulated with different intentions. Whereas AGILE focused on how to formulate and execute a collaborative MDAO workflow, IDEaliSM directed its efforts towards preparing and (re)using standardised processes. Despite these differences, the methodologies share some similarities as well. For instance, both methodologies rely on methods to enable cross-organisational analysis tool usage, and on data standards to ensure consistency. These elements are explored in more depth in the upcoming sections.

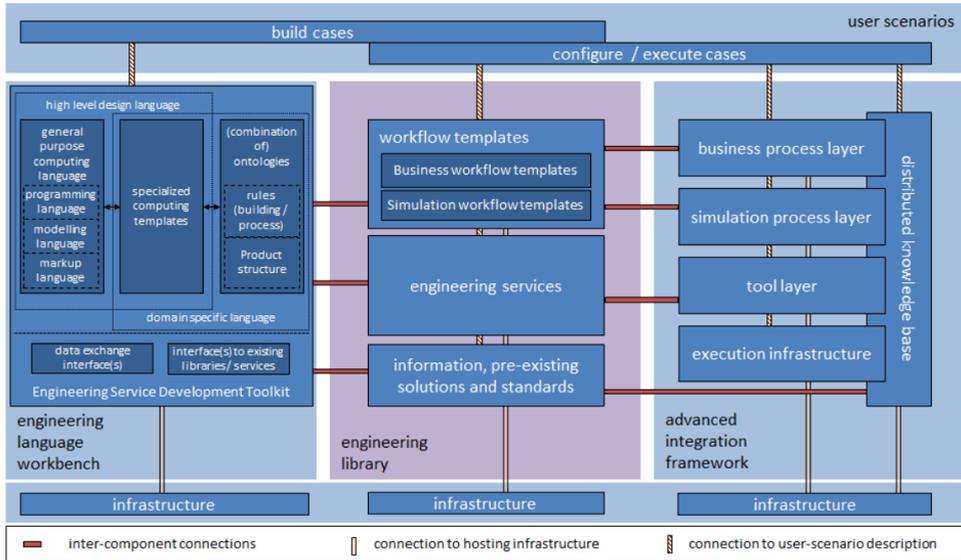


Figure 2.2: The IDEalISM Framework Architecture[19].

2.2. FACILITATING CROSS-ORGANISATIONAL TOOL USAGE

A commonality found in the research projects described above, is the distribution of disciplines across different organisations. In order to realise the collaborative workflows using these disciplines, the required analysis tools must become available for users outside of the owned organisation. However, directly sharing the tool is not an option due to Intellectual Property (IP) policies and/or licensing constraints. Analysis tools take considerable resources to develop, and as such, are not readily shared. Furthermore, if any proprietary software under a commercial license is used, the tool cannot be shared at all.

To facilitate the use of analysis tools across organisations, three methods were identified, henceforth called *technology sharing methods* (TSMs). Their principles are described below in the context of this thesis, where an OEM requests the assistance of a Tier-1 supplier for design space exploration. It is assumed here that the tool in the suppliers possession is of higher-fidelity than the OEMs current methods, and takes more computational time to run. The technologies used to enable these methods are described in Chapter 4.

As these TSMs form a key aspect in enabling a collaborative workflow, it was chosen to assess them in more depth. The goal of this assessment was to determine which (if any) TSM is preferable over the others, and in what situation. The setup of the assessment is part of the methodology of this work, presented in Chapter 5.

2.2.1. DIRECT SHARING OF RESULTS

The first strategy is to share a table of results of the analysis tool. This can be considered the state-of-the-art consultations described in Chapter 1, where instead of only one design, a collection of designs is requested to be evaluated. In this method, the OEM and

supplier formulate and agree on the design space to be explored, after which the supplier executes the study and shares the results. The OEM can then use the data for their design purposes. This strategy is straightforward to implement, since the results are simply collected from the analysis tool and shared in a tabular format. Sensitive information generated by the analysis tool can be excluded from sharing, thereby respecting IP regulations. However, there are several limitations. The first is that this method cannot straightforwardly be used in MDAO workflows. One of the key benefits of MDAO is the ability to deal with coupled disciplines, where certain disciplines depend on each others I/O, by means of a convergence loop. This can result in multiple calls to the involved disciplines even for evaluation of a single design. The waiting time due to back-and-forth communication renders this method unfeasible for tools within convergence loops.

2.2.2. SHARING A SURROGATE MODEL

Another possibility is for the supplier to build a surrogate model (SM) of the analysis tool and share it with the OEM. A surrogate model is an analytical model that can replace a more complex model by modelling its outcome. Surrogate models can be classified in two ways: physics-based and data driven[20]. The scope here is limited to data driven surrogate models, because physical reduction is not always an option to replace a complex analysis tool.

To create a data driven SM, also known as response surface model, a Design of Experiments (DOE) must be set up to generate the data. After the data is generated, it can be used to train and validate the SM. Several data fitting algorithms exist, such as polynomial fitting, radial basis functions, or kriging[21]. Generally, data fitting algorithms can be divided in two categories: interpolation and approximation[20]. The former method ensures that the model fits the sampled points exactly, the latter method approximates them as well as the space in between. Which data fitting algorithm is viable, depends largely on the data and is not trivial. The choice of algorithm requires expertise and is traditionally a manual process, although efforts have been made to automate the algorithm selection[22, 23].

Several aspects make the use of surrogate models attractive in collaborative design studies[24]. First and foremost, since a SM is essentially a black box that only models the output, it allows suppliers to share the model without compromising the underlying methodologies, thus respecting their IP[25]. Furthermore, a SM requires less computational time to run than the tool (or cluster of tools) that it models[20]. This is important if the analysis tool is used in a convergence loop, and can be called multiple times in analysing a single design. Additionally, SMs are only valid for the subset of the design space explored in the DOE. The use of a SM is thus limited, preventing the model from becoming a one-to-one copy of the original tool. The AGILE project proved that SMs can be used as accurate substitutes in MDAO workflows while greatly saving on computational efforts[26]. Within the DEFATINE project, the Surrogate Advisory System (SAS)[23] was developed to identify (clusters of) disciplines in an MDAO workflow to replace with SMs, and train the models consecutively. Despite these recent developments and successful applications, SMs are not yet widely used in the aerospace industry[21].

2.2.3. OFFERING REMOTE ACCESS

A final strategy is to offer the OEM remote access to the design tool. By using a separate, dedicated tool, the OEM can send a design specification as input to the suppliers analysis tool. Then, the input is used by the tool, and the results of interest can be shared with the OEM. This method keeps the analysis tool under control of the supplier, but still provides a method for the OEM to interact with the tool. By facilitating remote access, the analysis tool can be used freely by the OEM, and be included in automated workflows, although the feasibility of this depends largely on the time required to run the design tool. Another aspect to consider, is the way to facilitate the remote access. To enable remote access, a dedicated data stream for the I/O should be enabled, possibly by installing certain software for this purpose. This has to comply with the IT regulations of both the OEM and the supplier.

2.3. INCOMPLETE DATA DEFINITIONS

Another hurdle encountered in collaborative workflows, is the presence of incomplete or unclear data definitions. This can be mitigated by using a common data schema. By agreeing on a common data schema, the parties formally confirm that they understand the parameters involved in the analysis tool. Additionally, by adhering to a common data schema, the number of interfaces between different tools can be drastically reduced. This is useful if multiple analysis tools are used in the same workflow, as the maximum number of interfaces reduces from $N(N-1)$ to $2N$ [27], where N is the number of analysis tools involved. In both AGILE and IDEaliSM, data schema's/interfaces played a central role in streamlining the collaboration, as their presence can be seen in both Figure 2.1 and 2.2.

3

REDUCING DESIGN LEAD TIMES AND COSTS

The second goal of this thesis is to enable the supplier to provide the OEM with high quality data in a reduced lead time. This is after all the motivation to establish such a collaboration in the first place. This goal is partially achieved by setting up a more streamlined collaboration as described in Chapter 2, in which the supplier enables usage of their analysis tool by the OEM. The tool can then be used to perform design space exploration, to analyse designs with a higher level of detail and/or assess novel technologies that could not be explored with the OEMs own methods. If the higher level of detail is already present in the design, this prevents iterations later in the design process, thereby reducing the design lead times and costs. The ability to assess novel technologies allows the technologies to be properly considered, enabling a better design choice.

However, the feasibility to explore the design space is limited if the tools are of higher-fidelity. As stated in Chapter 1, such tools often require more comprehensive input than is available in the conceptual design phase, and they take more time to run. This chapter presents two methodologies to mitigate these issues.

3.1. FRONT-LOADING

Front-loading is defined as "*a strategy that seeks to improve development performance by shifting the identification and solving of (design) problems to earlier phases of a product development process*"[28]. Thomke and Fujimoto, who originally introduced the term, describe two ways of applying front-loading: through project-to-project knowledge transfer, and through rapid problem-solving. In their article, they illustrate these methods by retrospective reports and computer-aided engineering (CAE) tools respectively.

Front-loading principles were a key aspect of the IDEaliSM project[5]. If design processes are automated and MDO studies can be performed, such studies can also be performed preemptively, before a project even starts. The results could then be stored in a front-loaded database of pre-existing solutions, present in the Engineering Library in

Figure 2.2. The effect of front-loading on a project lead time and design maturity is illustrated in Figure 3.1.

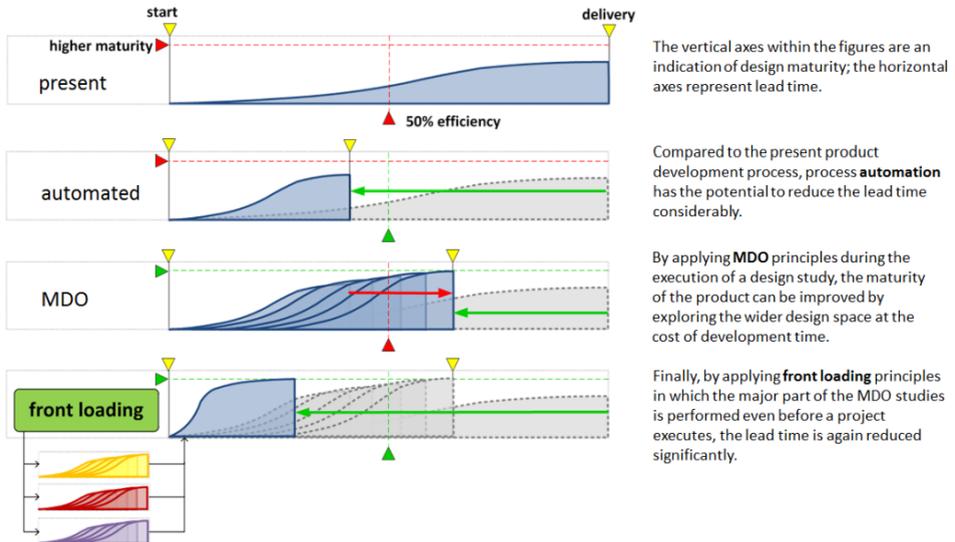


Figure 3.1: Front-loading enables a higher design maturity in shorter lead times[19].

The front-loaded principles successfully accelerated the use cases in the IDEaliSM project. One use case showcased the design of a rudder within a month, where that level of maturity would normally take 2 years[29]. Furthermore, a demonstrator performed in 2017 proved that it was possible to generate detailed designs of a rudder within 30 minutes[19]. Overall, the IDEaliSM framework resulted in a reported potential time savings of 50% overall project time, with time reductions of up to 90% for individual tasks[19]. The reduction in time allowed for a more in depth exploration of the design space, increasing the understanding of design choices, and ultimately lowering risk of the development process.

3.2. SENSITIVITY ANALYSIS

When requesting a design from a supplier, the OEM may realise that the assessment requires more input than they have available. The missing parameters can be estimated, but this introduces a level of uncertainty, and typically obstructs the usage of such tools until the required input is known. The effect of this uncertainty (per input parameter) is determined by two factors: the magnitude of the uncertainty (i.e. how big the range is in which the parameter is expected to be) and the sensitivity of the design to these parameters (i.e. how much a change in the parameter changes the properties of the design). These factors can be assessed using global uncertainty and sensitivity analysis respectively[30]. The scope in this thesis is limited to sensitivity analysis, where it is assumed that the uncertainty analysis has been performed, and the ranges, in which the

uncertain parameters are expected to be, are known.

Sensitivity analysis (SA) can be defined as "*The study of how uncertainty in the output of a model (numerical or otherwise) can be apportioned to different sources of uncertainty in the model input*"[31]. SA thus provides a method to assess which parameters are most sensitive to the design, i.e. which parameter affects the quantities of interest in the design the most. SA can be performed to identify the most influential input parameters and prioritise them, or identify the least influential ones in order to exclude them from the design problem[32]. In a recent master's thesis, sensitivity analysis has been performed to identify the least sensitive design variables in a design problem, and set them constant. The simplified optimisation problem that followed was performed with a time reduction of 40%, while the optimised value was only increased by less than 0.5%[33].

In the context of collaborative DSE, SA can be used to increase understanding of the design space. This understanding can be used by the OEM to prioritise their engineering efforts towards the most sensitive parameters. Moreover, the sensitivity information can be used by both the OEM and the supplier to assess the criticality of their assumptions. If the design turns out to be very sensitive to an assumed parameter, that assumption is very critical to the design and it should a priority to verify this assumption.

4

ENABLING TECHNOLOGIES

During the previously described research projects, a variety of technologies was used to enable the proposed methodologies. This chapter describes the technologies used, to give an impression of the used solutions. Some of the technologies described below are used in the current work as well.

4.1. COLLABORATION PLATFORM

In both AGILE and IDEaliSM, a collaboration platform played a key role in enabling the collaborative workflow, the hosting of engineering services, and data storage. The collaboration platform used in these projects was KE-chain¹, a web-based platform developed by KE-works. With KE-chain, users are able to shape their collaborative work environment by managing user access, creating workflow templates, and configuring the storage of data. These functionalities allow KE-chain to streamline business processes in a variety of ways. For example, in AGILE, KE-chain acted as the central location that integrated the experts and engineering services into a single environment[34]. The different steps in the formulation of an MDAO workflow (such as specifying the available analysis tools, defining design variables and objectives, choosing an MDAO architecture) can be given separate interfaces, that can be linked in a so-called workflow template. Once created, the template can be instantiated any number of times, reducing the setup time for standardised processes significantly. The modules that actually enable these steps (for instance, KADMOS to generate the specified workflow, see below) can be integrated by making use of the Python library *Pykechain*². This way, the users can interact with these modules through KE-chain's front-end, thereby acting as a graphical user interface (GUI). The modules can either be hosted on KE-chain or, if the module is only available on a local machine, be linked to KE-chain through so-called *KE-node* software. The

¹KE-chain engineering platform, KE-works, www.ke-chain.com, [Accessed 30/09/2023].

²KE-chain Python SDK, KE-works, <https://pykechain.readthedocs.io/en/stable/>, [Accessed 30/09/2023].

module then becomes available as a remote service. KE-chain is also used as the collaboration environment in DEFAINE.

4.2. AUTOMATED WORKFLOW FORMULATION

The manual labour involved with formulating and implementing MDAO workflows was traditionally a major barrier in using MDAO. To reduce this labour, several tools were developed to assist in the setup of MDAO systems. The most relevant to this thesis is KADMOS (Knowledge- and graph-based Agile Design for Multidisciplinary Optimization System)[35], a Python library that is able to automatically formulate MDAO workflows, and generate the associated graphs and workflows. It was developed by TU Delft as part of the AGILE project, and is openly available³. The 'agility' in the software's name refers to its ability to rapidly generate new workflows for different purposes. It is not only able to create new optimisation workflows using a different convergence schema, but also to formulate workflows with other goals in mind, such as DOEs and convergence schemes on a single design point. It works in 4 different steps, each step associated with its own graph:

1. The first step is to define all the design and analysis tools. The tools should all conform to the same Central Data Schema (CDS). This results in the Repository Connectivity Graph (RCG) where all tools, including their I/O, are visualised.
2. Then, the MDAO problem can be formulated by specifying the design variables, objective function, constraints and quantities of interest. This results in the Fundamental Problem Graph (FPG) which contains only the tools from the RCG necessary to solve the MDAO problem at hand, and highlights the roles of the relevant functions and variables.
3. The next step is to choose the MDAO architecture. In this step, the FPG is expanded with the necessary convergers, optimisers and consistency constraints. This results in the MDAO Data Graph (MDG).
4. Finally, the MDAO Process Graph can be generated. Here, the variable nodes of the MDG are left out and the process order of execution are added.

Prior to KADMOS, InFoRMA was developed by TU Delft in IDEaliSM[36], a tool capable of automatically formalizing of MDAO workflows. InFoRMA also included capabilities to advise the user on which MDO architecture to use, and included a method to implement the workflow into Optimus (see Section 4.3.1), where the workflow can be executed. The author used the knowledge gained in the development of InFoRMA to assist in the development of KADMOS. Furthermore, the development of InFoRMA revealed the need for a neutral format to describe MDAO workflows, resulting in a prototype. In AGILE, the neutral format was further elaborated by TU Delft into CMDOWS (see Section 4.4.2).

KADMOS is able to generate XDSM (eXtended Design Structure Matrix) diagrams, which can be considered the standard for visualising MDAO systems[37]. To generate more interactive visualisation, the accompanying VISTOMS (VISualization TOol for

³Available at <https://gitlab.tudelft.nl/lr-fpp-mdo/kadmos/>

MDO Systems)[38] tool can be used. VISTOMS is able to read CMDOWS files and visualise them in various forms. The visualisation is done through an HTML page that is accessible by web browsers. This way, the visualisation is interactive, allowing for more detailed investigation of the system than possible through static images generated by KADMOS. This is especially valuable for large, complex MDAO systems with vast amounts of disciplines and potentially hundreds or thousands of parameters. VISTOMS is able to produce three types of diagrams: XDSM diagrams, Edge Bundling diagrams, and Sankey diagrams.

Another tool that enables the automatic formulation of MDAO workflows is MDax (MDAO Workflow Design Accelerator)[39]. It was developed by DLR as a part of AGILE 4.0 (the successor to the AGILE project). Where KADMOS takes a graph-based approach, MDax relies on the XDSM representation to build the MDAO systems. MDax includes a GUI to interact with, whereas KADMOS is only available as a Python library. However, MDax is proprietary to DLR and not openly available.

4.3. WORKFLOW EXECUTION

The realisation of formulated workflows is handled by another set of technologies. The tools described below facilitate the general execution of workflows, the training and validation of surrogate models, and the ability to provide remote access.

4.3.1. PROCESS INTEGRATION AND DESIGN OPTIMISATION

Process Integration and Design Optimisation (PIDO) software enables the execution of multidisciplinary workflows. Within the previously described research projects, two PIDO implementations were used: RCE[40] and Optimus[41]. RCE (Remote Component Environment) was developed by DLR and is open source⁴, while Optimus is developed by Noesis Solutions and is available under a commercial licence. Both applications are capable of linking tools together into workflows, allowing for automated input delivery and output extraction. This makes it possible to execute the MDAO workflows defined in the previous steps. The tools also keep track of data and save it for inspection. While RCE is capable of only executing the workflow, Optimus also has other functionalities to help the user set up workflows for different purposes, implement different optimisation strategies, build surrogate models, etc. The generated workflows can be imported in the CMDOWS format, relieving users from the burden of having to manually configure them. For both RCE and Optimus, extensions have been developed to perform this conversion[42].

4.3.2. SURROGATE MODELLING

The usage of surrogate models played an important role in AGILE, both as a means to shorten the execution time of MDAO workflows and to facilitate cross-organisational usage of analysis tools. To this end, the Surrogate Modelling Repository (SMR)[26] was developed by NLR[24]. It handles the creation, deployment, and sharing of surrogate models. The SMR is proprietary to NLR and not openly available.

Within DEFAINE, the Surrogate Advisory System (SAS)[23] was developed to reduce

⁴Available at <https://rcenvironment.de/pages/download.html> [Accessed 26-10-2023]

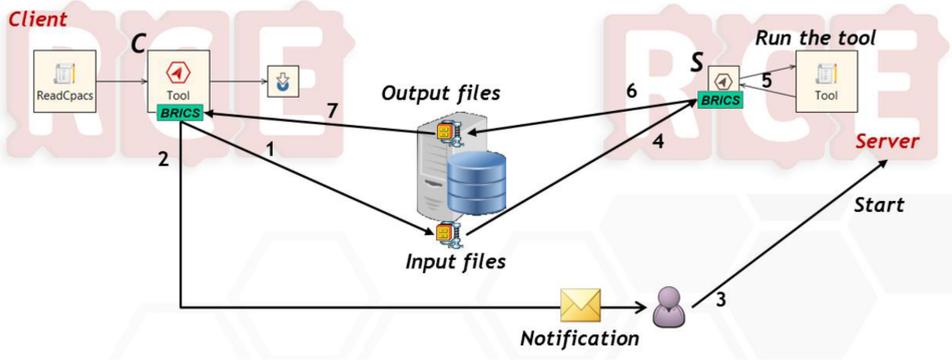


Figure 4.1: Illustration of a remote access workflow using BRICS. The steps taken at the numbered arrows are briefly described in the text below.[10]

the efforts in training and using surrogate models in MDAO workflows. SAS is able to identify disciplines (or groups of disciplines) within a provided workflow suitable for replacement with a surrogate model. SAS also handles the subsequent training, validation, and implementation of the surrogate models. SAS uses KADMOS for the substitution of the surrogate model into the workflow. For the training of the surrogate models, SAS makes use of the open source Surrogate Modelling Toolbox (SMT)[43]. The SMT is available as a Python library and facilitates the training of several types of surrogate models. Since the release of SMT 2.0 in May 2023, the SMT also includes capabilities to handle hierarchical variables and mixed-integer design problems, where both continuous and discrete variables are present.

4.3.3. REMOTE ACCESS

To enable the execution of a cross-organisational distributed workflow, remote access has been used. In remote access, a dedicated tool sends the input to a remote discipline. The analysis tool then reads the input, executes the analysis, and returns the output via the remote access tool as well. In AGILE, BRICS[44] was developed by NLR to fulfill this role. BRICS aims to streamline cross-organisational collaborative engineering work, which is typically prevented by IP and IT security policies. By only sharing the I/O, the tools and their underlying methodologies are not shared between organisations, thereby enabling the cross-organisational workflow. Figure 4.1 illustrates how BRICS can be used to enable remote access. As can be seen, on the client side BRICS sends the input files to a central data server, and notifies the remote specialist. The specialist retrieves the input on the server side, starts the analysis, and uploads the output once the analysis is complete. BRICS can however be configured to automatically execute the tool once input is received, without the specialist manually starting the analysis[10]. This is beneficial in a distributed MDAO workflow, where the tool may be called numerous times. BRICS is proprietary to NLR and not openly available.

4.4. COMMON DATA STANDARDS

To mitigate the issue of incomplete or unclear data definitions, and reduce the number of interfaces between different applications, several common data standards have been proposed.

4.4.1. PRODUCT DEFINITION: CPACS

CPACS (Common Parametric Aircraft Configuration Schema) is an XML-based data schema capable of describing an entire (fleet of) aircraft. It was introduced in 2012 by DLR[45] and is still undergoing recent developments[27]. Using the tree-like structure of XML, CPACS offers an organised way of describing an aircraft at all its levels. For example, in the wing element, which is a child of the aircraft element, the wing parameters such as root chord, tip chord, leading edge sweep and span can be defined. Airfoils can also be defined as a set of x and y coordinates. Other non-physical attributes, like flight conditions, can also be stored in the CPACS format. To support the use of CPACS, several other tools have been developed by DLR, such as TiGL[46] (an application that generates a 3D geometry based on the CPACS file) and CPACS Creator[47], which facilitates the creation and modification of CPACS aircraft representations through a graphical interface.

4.4.2. WORKFLOW DEFINITION: CMDOWS

CMDOWS (Common MDO Workflow Schema)[14] is another XML-based convention, able to describe MDAO workflows. The development of InFoRMA revealed the need for a neutral format to fulfill this function, resulting in a prototype. In AGILE, the neutral format was further elaborated by TU Delft into CMDOWS. The data standard serves purposes: to standardise the definition of MDAO workflows for convenient storage and retrieval, and to facilitate automatic translation to other applications, such as Process Integration and Design Optimisation (PIDO) software. The CMDOWS format is able to store every component of an MDAO workflow, including the analysis tools and their respective input/output (I/O), convergers, optimisers, and the coordinator.

II

METHODOLOGY AND IMPLEMENTATION

5

A METHODOLOGY FOR COLLABORATIVE FRONT-LOADED DESIGN SPACE EXPLORATION

In Part I, the state-of-the-art of collaborative workflows was discussed. Recent research projects such as AGILE and IDEaliSM investigated a collaboration closer than the current industry use. The research projects resulted in novel frameworks facilitating a closer collaboration between aircraft organisations, as well as technologies that enabled the frameworks. The frameworks were successfully applied to industrial R&D use cases and generally regarded as beneficial compared to the status quo of collaboration.

Despite the benefits of these collaborative workflows, the frameworks are not directly applicable to industry use. While effective, the described multi-organisational workflows require all involved partners to collaborate with each other. In the industry, it is more conventional for the OEM to take the role of the central designer and engage in one-on-one collaborations with their suppliers. Furthermore, the workflows were applied in R&D context, where exceptions can be made to IP and IT regulations to enable the specific data streams[19]. This means that the demonstrated workflows are not straightforwardly applicable to regular industry use.

As mentioned in the introduction, the aim of this thesis is to bridge the gap between the previously investigated collaborations encountered in literature, and current industry use. This chapter presents the proposed methodology of this work. To adhere closely to the state-of-the-art in industry, the methodology is aimed at a one-on-one collaboration between an OEM and a supplier. The methodology draws inspiration from the aforementioned research projects to enable and streamline this collaboration, ultimately to achieve the goal of this collaboration (e.g. a proper assessment of a novel technology or a higher detailed design) in a reduced lead time. Key insights gained from literature are applied in the following ways:

- A central data schema has proven to prevent the input/output (I/O) from being

incomplete or unclear. Moreover, a central data schema reduces the number of interfaces between applications, thereby enabling a more scalable exchange of data across multiple stakeholders. Although the methodology is intended for a one-on-one collaboration, the OEM may wish to set up multiple of such collaborations. Finally, data consistency is also an important factor to consider when reusing data from past projects. For these reasons, a central data schema will be used in the methodology.

- Taking inspiration from AGILE and IDEaliSM, the methodology explores a one-on-one collaboration between an OEM and a supplier. In this scenario, the OEM wishes to leverage the suppliers design tools for their DSE purposes. To facilitate this cross-organisational tool usage, three methods, describe in Section 2.2 were identified in the aforementioned research projects: sharing tabular data directly, sharing a surrogate model, and providing remote access. Section 5.1 applies these methods to a collaborative DSE workflow, and discusses their implications on existing workflows of the OEM. To do so, a general DSE workflow is first described, where DSE is performed in the form of one or more DOEs.
- In IDEaliSM, front-loaded principles were successfully applied to reduce the lead times and costs of design studies. The methodology will prescribe how these principles can be used to support the DSE process. To do so, Section 5.2 describes how the collaborative DSE process can be expanded with front-loaded principles.

The chapter ends with Section 5.3, where an overview of the proposed framework for collaborative front-loaded design space exploration is presented.

5.1. COLLABORATIVE DESIGN SPACE EXPLORATION

The design space exploration process is initiated by the OEM during the conceptual design phase, to find a collection of feasible designs, so that an informed design choice can be made. In DSE, designs are generated by systematically varying parameters of interest. In the modern engineering environment, this is done using Computer Aided Engineering (CAE), where the designs are modelled and assessed using computer applications. Efforts are often directed towards a design space of interest using optimising methods, because an exhaustive search of the design space is often not feasible[48]. However, optimising an unknown design problem is not a trivial task either, and can bring great difficulties if done incorrectly. For example, the choice of optimisation algorithm may depend on the behaviour of the model, and if the number of input parameters is great, it can be challenging to choose the right design variables to optimise for. Instead, to initially scout the design space, it is more feasible to use a Design of Experiments (DOE), where a predefined sampling plan is followed to generate the data. Moreover, the supplier may not wish to facilitate an optimisation workflow, where the number of iterations is not known beforehand. Therefore, DOEs are assumed for the remainder of this methodology.

Section 5.1.1 briefly describes the steps taken in a DOE. The workflow presented here will be used as a basis for the rest of this methodology. Section 5.1.2 then discusses how

this workflow is modified when applying the technology sharing methods (TSMs) described in Section 2.2, and how the work is shared between the OEM and the supplier.

5.1.1. A GENERAL DOE WORKFLOW

To understand how a collaborative DSE in the form of DOEs can be enabled, one must first be aware of the steps taken in a DOE in general. Figure 5.1 shows a general workflow for performing DSE using DOEs. The steps can be further described as follows:

- *Define problem*
The first step is to determine what the overall goal of the DSE is, i.e. what knowledge the DSE should deliver. An example is to find the effect of material choices of an aircraft component on its mass and cost. Here, the material choices are the design variables, and the mass and costs the quantities of interests (QOI's).
- *Identify design space of interest*
With the problem defined, the design space of interest can now be specified. The design space to be explored can be defined by the design variables and their bounds or possible values. Bounds are used to limit the design space of numerical variables, whereas the design space of categorical and ordinal variables is defined by their possible values.
- *Create sampling plan*
To populate the design space of interest, a sampling plan can be generated. In a sampling plan, design points are intelligently chosen, such that the gained knowledge is maximised for the number of experiments. The sampling plan depends on the the chosen sampling strategy (such as factorial design, random sampling, or Latin Hypercube Sampling[49]), and the number of samples to be evaluated. The number of samples is typically driven by a time or budget constraint.
- *Execute design study*
The design points in the sampling plan are evaluated using an analysis workflow. The workflow consists of one or more analysis tools. Examples of analysis tools are aerodynamic or structural solvers. To reduce analysis setup times and prevent human errors, such workflows are typically automated as much as possible.
- *Evaluate results*
Finally, the results of the design study are evaluated. If the results are sufficient for the OEM to perform their technology assessment, the goal of the DSE is achieved. Otherwise, an iteration may be necessary. In an iteration, the OEM may wish to explore a new section of the design space, or explore an already investigated section in more depth.

5.1.2. TECHNOLOGY SHARING METHODS

To enable usage the suppliers design tool into the OEMs workflow, a technology sharing method (TSM) must be chosen. The three identified TSMs, namely sharing tabular data

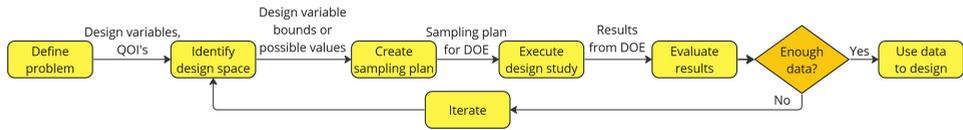


Figure 5.1: The steps taken in design space exploration using DOEs.

directly, sharing a surrogate model, and providing remote access, were described in Section 2.2. These methods (partially) enable a collaboration, but impact the way in which the design tool can be integrated into the OEMs workflow. Following the three identified TSMs, the process can be distributed between the OEM and the supplier in the following manners.

SHARING TABULAR RESULTS OF THE DATA

In the first method, the results of the design study are shared directly with the OEM. In such a case, the OEM specifies the design space they wish to explore to the supplier. Depending on preference of the involved parties, the sampling plan can be provided by the OEM, or generated by the supplier based on the requested design space of interest. Once the sampling plan is made available to the supplier, the DOE can be executed, after which the results are shared with the OEM.

5

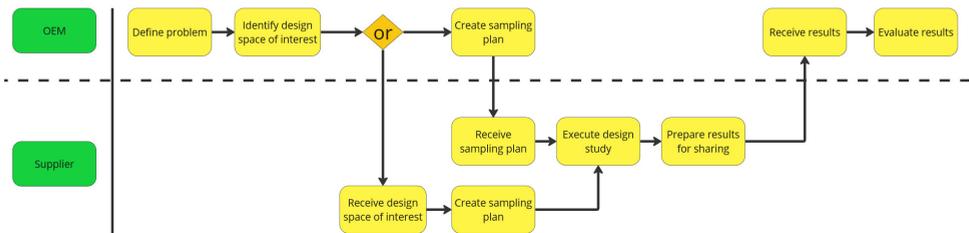


Figure 5.2: A collaborative DSE where the results are shared in tabular form.

SHARING A SURROGATE MODEL

Alternatively, the OEM and supplier could agree upon the creation of a surrogate model, that models a certain subset of the design space with an agreed upon level of accuracy. After completing the design space definition with additional assumptions, the supplier can then perform the DOE (or DOE's) to gather the required training data to build the SM. Once the SM becomes available, it can directly be integrated into the workflow of the OEM. The model then be freely¹ used by the OEM to use in their workflow.

PROVIDING REMOTE ACCESS

Finally, remote access can be used to facilitated cross-organisational tool usage. The OEM and supplier agree on a dedicated method to facilitate remote use of the supplier

¹Depending on the agreement made with the supplier: the model can be offered as a service, where the OEM is charged for the number of times the SM is invoked.

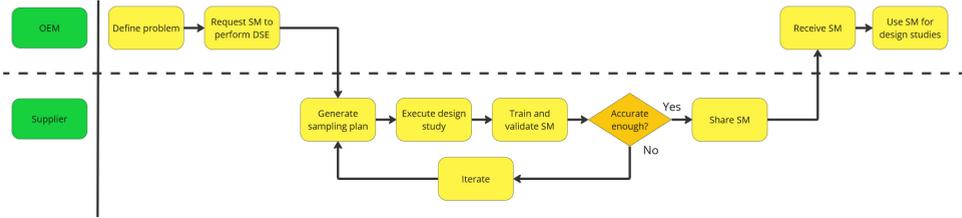


Figure 5.3: A collaborative DSE where a surrogate model is built by the supplier and shared with the OEM.

tool. Once remote access is established, the design tool can be straightforwardly be used for their design studies.

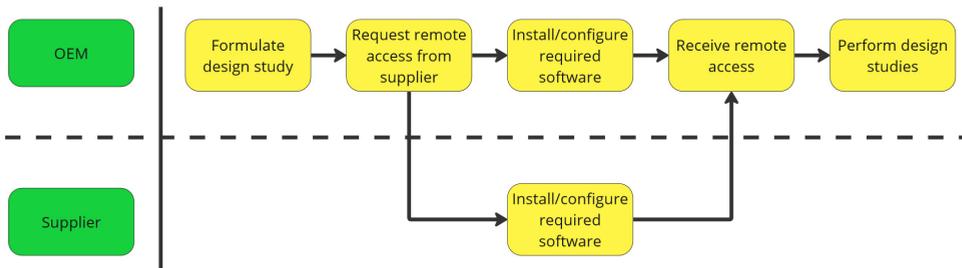


Figure 5.4: A collaborative DSE where remote access enables direct usage of the supplier owned tool by the OEM.

IMPLICATIONS ON EXISTING WORKFLOWS

Given the emergence of MDAO workflows, it is important to consider the effects of the TSMs on an existing workflow.

- In case of sharing tabular data, the supplier is provided with a sampling plan to evaluate. The design tool evaluates the samples, and the numerical results are provided back to the OEM. The singular exchange of data renders the use of a convergence loop, if present, infeasible, due to the required waiting time between the request and availability of the results. The OEM can pre-process the input with their own analysis modules, before submitting the sampling grid to the supplier. Alternatively, the output of the supplier can be post-processed, depending on the order of operations in the workflow. Whichever option is chosen, the omitting of the convergence loop introduces a certain discrepancy in the results, since the data no longer consistent.
- In case of sharing a surrogate model, the supplier provides the OEM with a SM that can be implemented in the OEMs workflow. Once trained, the SM can directly be integrated into the workflow of the OEM. The SM is only valid in the design space of its training data, and is possibly subject to a set of limitations. The OEM should be made aware of these limitations to prevent misuse of the SM. However, even with correct usage, it can be reasonably assumed that for a given sample outside

of the training data, the SM will not result in the same value as the original design tool, thereby resulting a certain error.

- In case of remote access, the workflow is expanded with two actions, namely the sending of input to the supplier and the fetching of the output once ready. However, since these actions are always and only called when the suppliers tool is called, they can simply be integrated into the suppliers discipline. Assuming the sending and fetching of I/O can be automated, remote access has no effect on an existing workflow. This TSM can thus be considered virtually identical to owning the tool itself, in terms of effects on workflows.

As can be seen, the third scenario results in an workflow identical to the scenario where the OEM actually owns the tool, and therefore yields the highest level of accuracy possible. The other use cases might introduce a certain error through their implementation. To assess the magnitude of these errors, a test case was developed, involving an aircraft design scenario. This test case and the corresponding results are presented in Section 7.2.

5.2. APPLYING FRONT-LOADING PRINCIPLES

To enable the reduction of design study lead times and costs, the application of front-loaded principles is proposed. Section 3.1 presented the front-loading aspects used in the IDEalISM project and the benefits it yielded. Front-loading will be applied in a similar way to support design space exploration. Section 5.2.1 describes how front-loaded principles can be enabled by involving a database in the collaborative DSE workflow. Section 5.2.2 proposes several post-processing methods to further assist the DSE process.

5.2.1. INCLUSION OF A DATABASE

To enable the re-use of design study results, the DSE process visualised in Figure 5.1 is expanded with a database. Past results can be stored in the database at the start of a collaborative design study, thereby kick-starting the process. Such a process is visualised by the flowchart in Figure 5.5. The database can then be used to enhance the design space exploration process in several ways. The first way, is to search the database for feasible designs. If an adequate design is already present, it can be directly retrieved, without performing new studies. The database can also be used in the generation of new sampling plans, ensuring that new design studies take existing data into account and shifting efforts towards unexplored sections of the design space. The proposed methods to support the inspection of the database and its use in sampling plan generation are described in Section 5.2.2.

The inclusion of a database, in which results from past design studies can be stored, enables suppliers to perform design studies preemptively, without a specific request at hand. When an OEM requests a design study, the results can then directly be used, thereby lowering their lead times of such studies and shortening the suppliers response time. This way, the supplier front-loads the design study and gains an edge over competitors by being able to help the OEM in a reduced lead time. For the OEM, this results

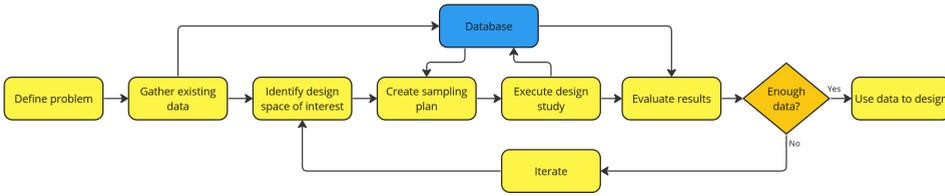
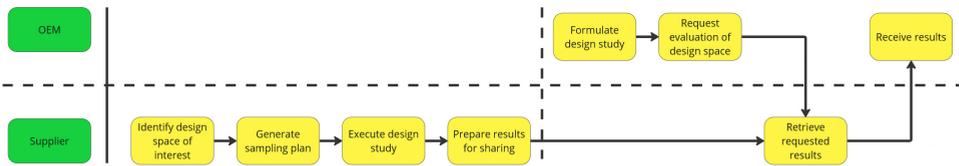
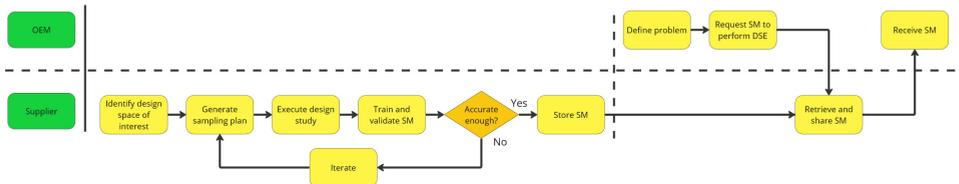


Figure 5.5: The inclusion of a database to the design space exploration process.

in a reduced lead time in their design study as well. Figure 5.6 illustrates how the supplier can perform a preemptive design study, and how this reduces the number of steps taken once the OEM issues a request. This method is only applicable to the sharing of data and surrogate models, since the facilitation of remote access cannot be front-loaded in this way.



(a) A front-loaded DSE process where a supplier shares tabular data with the OEM.



(b) A front-loaded DSE process where a supplier shares a pre-built surrogate model with the OEM.

Figure 5.6: Methods for a supplier to front-load future design studies by performing preemptive design studies.

The scenarios illustrated in Figure 5.6 are idealised, assuming that the supplier has exactly what the OEM is looking for. Nevertheless, if the preemptive design studies result in a subset of the required data, the effort in the design study at hand is reduced.

These preemptive design studies are possible due to the current under-utilisation of existing resources (e.g. computational hardware and software licenses (if any)) involved in the execution of the design tool. If currently the design tool is only used for design studies at hand, there are likely some periods in which the design tool is not used. These periods can be utilised to explore a design space that has a high potential to be interesting for future customers. Considering that such design studies use existing resources, these design studies should be able to be performed at a minimal cost.

5.2.2. EXPLOITING THE DATABASE FOR DESIGN SPACE EXPLORATION

The inclusion of a front-loaded database can reduce the workload of design studies if any relevant data is already present in the database. However, the data can also be used in other ways to support the DSE process. In this thesis, three types of analysis or post-processing are proposed: visualisation, complementary sampling, and sensitivity analysis.

VISUALISATION

An intuitive way to quickly identify trends in data, is through visual representation. Common visualisations such as scatter plots and line graphs are useful methods to do so. However, these methods can only visualise a handful of variables at a time, whereas industrial design problems often contain a much larger number of variables. Moreover, design problems often contain categorical variables, that only take discrete values and are difficult to represent in conventional graphs. In a scatter plot, for instance, categorical values can be represented through the colors and shapes of the data points. If any other variables are present in the data, they cannot be visualised, meaning that the visualisation does not give a complete overview of the data. For these reasons, only certain types of plots were considered for the generic visualisation of data.

The first type is the parallel coordinate plot. In a parallel coordinate plot, several axes are placed parallel next to each other, where each axis represents a dimension. Samples can be represented as lines that cross these axes, where each intersection represents the value of that dimension for that sample. Ticks can be used to indicate the values of the parameters, for both numerical and categorical parameters. This method thus allows for rapid visualisation of higher dimensional, mixed data. A parallel plot generated during AGILE is presented in Figure 6.6.

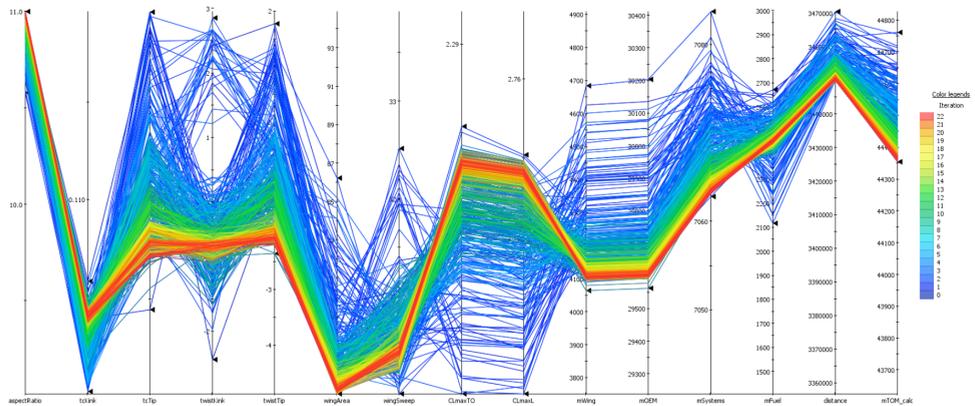


Figure 5.7: A parallel plot generated in AGILE, based on an optimisation study. Here, the colors indicate the iteration number, revealing the progression of the parameters from the initial values to the optimised ones[50].

Another plot type able to visualise multiple dimensions, is the scatterplot matrix. In this plot, the dimensions of the dataset are systematically visualised in scatterplots next to each other in a matrix. The units and the scale of the dimensions are shown

along the edges of the matrix. Furthermore, a categorical variable can be used to classify the data according to that variable. The plots along the diagonal of the matrix show a frequency plot of the different classifications. This plot provides an more intuitive way to identify direct interactions between two variables compared to the parallel coordinates plot. However, only one categorical variable can be visualised at a time, possibly not giving a complete overview of the dataset. A scatterplot matrix generated in this work is shown below in Figure 5.8.

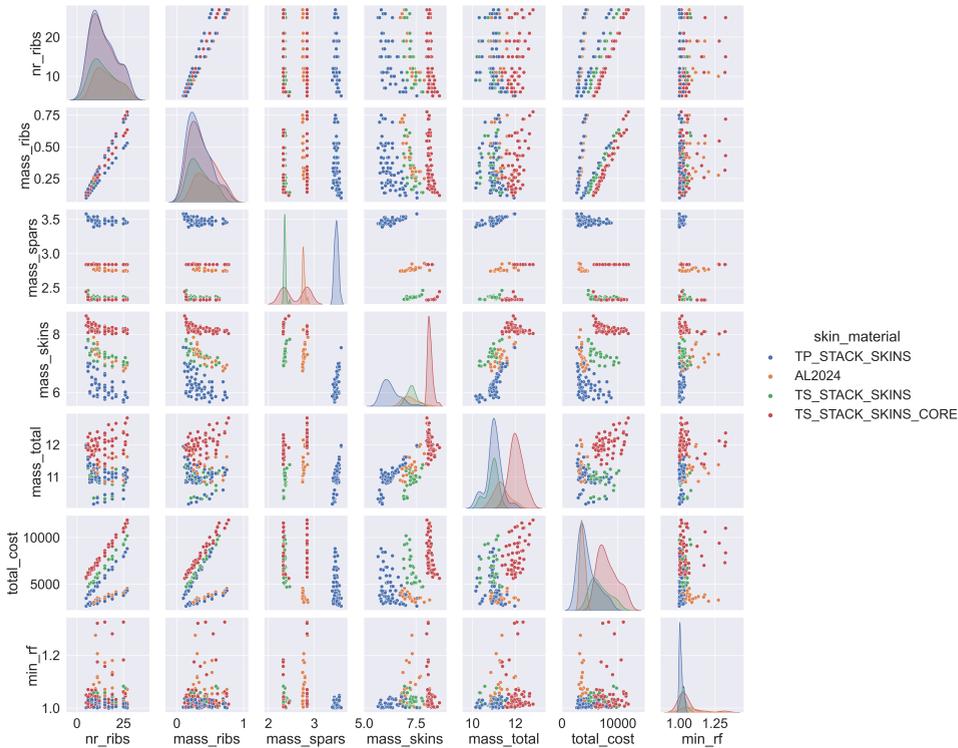


Figure 5.8: A scatterplot matrix based on the movable design case (see Section 6.1).

COMPLEMENTARY SAMPLING

When performing a new design study, the goal is to maximise the knowledge gained from that study. If no data is available in the design space of interest, a DOE can be set up straightforwardly. However, if past results are already present in the design space of interest, these samples should be avoided in future sampling plans, and efforts should instead be directed towards exploring the design space that remains unknown, or towards a subset of the design space that seems particularly promising. In order to assist in this process, a complementary sampling (CS) strategy can be used.

The CS strategies proposed in this work make use of adaptive sampling methods. Adaptive sampling refers to a collection of sampling methods that take already available samples into account[51]. Such methods are typically used in the creation of surrogate

models. In such cases, an initial sampling plan is created using a fraction of the total sampling budget (typically 10% of the total budget). After the initial samples are analysed by the tool to be modelled, a SM is built and used to find the sample with the greatest so-called refinement criterion (RC). The RC is a metric of how valuable that sample is to include in the training data. Different adaptive sampling methods have different definitions for the RC, resulting in different characteristics; for example, some sampling methods have more exploring characteristics, meaning they aim to lower the overall uncertainty of the selected design space, whereas others have more exploiting characteristics, where the new samples are placed near optima in the model output. The adaptive sampling method (and corresponding RC) should thus be chosen to suit the purpose of the SM.

After the sample with the greatest RC is found, the sample is analysed by the tool, and the results are added to the training data. A new SM is then built and the process iterates until the budget is met. This way, the sampling plan adapts to the result of present data, and this typically results in more accurate SMs for the same number of training samples compared to conventional sampling methods.

In the case of a collaborative DSE, where sampling plans are evaluated by another party, it may not be feasible to take this iterative approach due to the frequent back-and-forth communication required. In this case, it is more convenient to create a fixed sampling plan to be evaluated in the new DOE. In this work, the following strategy is proposed:

1. Train a surrogate model based on the existing data.
2. Choose the number of samples in the new sampling plan. Let this number be n .
3. Choose an adaptive sampling method and the corresponding RC.
4. Generate a sampling plan of m samples using an ordinary sampling technique, such as LHS.
5. Evaluate the RC of the m samples using the SM.
6. Select the n samples with the highest RC. This is now the new sampling plan for the new DOE.

Although the strategy makes use of adaptive sampling methods, the sampling plan does not adapt in any way. Instead, it is chosen in such a way that it should complement the existing database the best, and therefore the term complementary sampling was chosen for this strategy.

The adaptive sampling methods considered in this research are:

- *Variance-based sampling*

A simple method to improve the accuracy of a SM, is to identify the regions with the greatest variance. These are, by definition, the regions with the greatest uncertainty. Variances are readily retrieved from Kriging models[51], meaning this method can straightforwardly be implemented. The RC is shown in Equation 5.1

$$RC_{var}(\mathbf{x}) = \sigma_{\hat{y}}^2(\mathbf{x}) \quad (5.1)$$

where $\sigma_{\hat{y}}^2(\mathbf{x})$ is the variance of a sample \mathbf{x} , retrieved from the surrogate model.

- *Expected Improvement for Global Fit*

Another method is the so-called Expected Improvement for Global Fit (EIGF) method. This method is an adaptation of the Expected Improvement (EI) method[52], which determines the expected improvement in finding the minima of the output. EIGF is adapted from EI to have the surrogate model accurately describe the entire domain, rather than only finding the minima. EIGF considers both the variance and the difference in output value with the nearest training sample. This way, the method has both exploring and exploiting characteristics. The RC is shown in Equation 5.2.

$$RC_{EIGF}(\mathbf{x}) = (\hat{\mathcal{M}}(\mathbf{x}) - y(\mathbf{x}^*))^2 + \sigma_{\hat{y}}^2(\mathbf{x}) \quad (5.2)$$

where $\hat{\mathcal{M}}(\mathbf{x})$ is the SM evaluation of a sample \mathbf{x} , and $y(\mathbf{x}^*)$ is the value of the nearest training sample. $\sigma_{\hat{y}}^2(\mathbf{x})$ is again the variance of a sample \mathbf{x} .

The proposed CS strategy can be useful when the OEM and supplier exchange data in the form of tabular data. The OEM can then generate a sampling plan using this strategy, and send it to the supplier to evaluate. If the chosen technology TSM is the sharing of surrogate models, this strategy is less useful. Instead, the supplier can locally use the adaptive sampling methods and iterate whenever a new sample is added to the training data. This updates the surrogate model more frequently, and should thus result in a more accurate surrogate model. In case remote access is chosen as the TSM, the OEM can use adaptive sampling by evaluating individual samples, and using the data to train their own surrogate model.

SENSITIVITY ANALYSIS

As a final analysis method, sensitivity analysis (SA) is proposed. SA can be used for a variety of reasons. For instance, the OEM may wish to simplify the design problem, and exclude the least influential design parameters. Another example, is that either the OEM or supplier (or both) has made certain assumptions to complete a design definition, in order to use the higher-fidelity analysis tool. SA can then be used to assess the impact of these assumptions.

There are a variety of SA methods that can be used to perform SA. However, some methods require a specific sampling plan to be executed. For example, in the Morris method[53], parameters are varied one-at-a-time around a certain starting value. To fit the front-loaded methodology, only SA methods that do not require a specific sampling plan were considered. This way, the SA can be performed regardless of the sampling plan present in the database.

The following methods of sensitivity analysis were considered:

1. *Sobol analysis*

The Sobol method[54] is one of the most widespread methods for global SA. In Sobol analysis, a function is decomposed into its principal components, meaning every contribution to the function is modelled separately. This decomposition allows the variance of the function to be decoupled as well. The relative contributions of these decomposed variances to the overall variance are expressed by the

Sobol indices. The total Sobol indices[55] sum the contributions of one variable and its interactions with other variables.

By considering the analysis tool as a black-box function, the Sobol indices can be determined numerically. To do so, a DOE is performed to sample the function and obtain the data. For the DOE, any random sampling method can be used, although it is recommended to use a pseudo-random sampling method such as the Sobol sampling method[56]. This method makes use of Sobol sequences and result in a sampling plan with a lower discrepancy than if pure random sampling was used[57]. In turn, this results in a faster convergence of the Sobol indices to their true values compared to other random methods[58]. Nevertheless, this means that Sobol analysis can be done on any dataset.

Aside from the Sobol indices, estimators can be used to determine the confidence interval of the sensitivity indices[58]. This can help to determine if the calculated sensitivity index is reliable enough, or if a larger sampling plan is required (the confidence interval reduces with sample size).

2. *High Dimensional Model Representation*

A known limitation of the Sobol method, is the high computational demands required to be accurate[59]. Therefore, a method known as High Dimensional Model Representation (HDMR) was considered[60]. HDMR is a surrogate modelling technique where, like Sobol analysis, a function is decomposed into its principal components. However, this method can also be used to estimate sensitivity indices. The use of the surrogate models promises accurate results even with a relatively low number of samples. Moreover, HDMR can be used on any data set regardless of the sampling plan used.

3. *Statistical power analysis*

The methods presented above are only applicable to continuous, numerical variables. Therefore, these methods are not applicable to categorical variables. To assess the effect of these variables, statistical power analysis can be used[61]. In statistical power analysis, the data set of size n is divided into k subsets based on the chosen categorical variable. For example, if the categorical variable has 5 possible values, 5 subsets are created. A statistical test can then be performed to determine the likelihood that a given categorical level has a different mean than the global mean, and thus significantly affects the design. Because this is a likelihood, this method cannot be used to quantify the influence of variables against one another. Nevertheless, it still provides a way to rank variables.

5.3. [FRAMEWORK OVERVIEW](#)

To implement the methodology described above, a framework was developed. The framework provides a guide on how to enable the collaboration and apply the front-loaded principles, as described above. This section gives a high-level overview of the framework and its components. The usage of the framework can roughly be categorised in three phases: the *Build*, *Operate* and *Analyse* phases. A general overview of the framework is

presented in Figure 5.9. The steps taken throughout the different phases are described in more depth in the sections below.

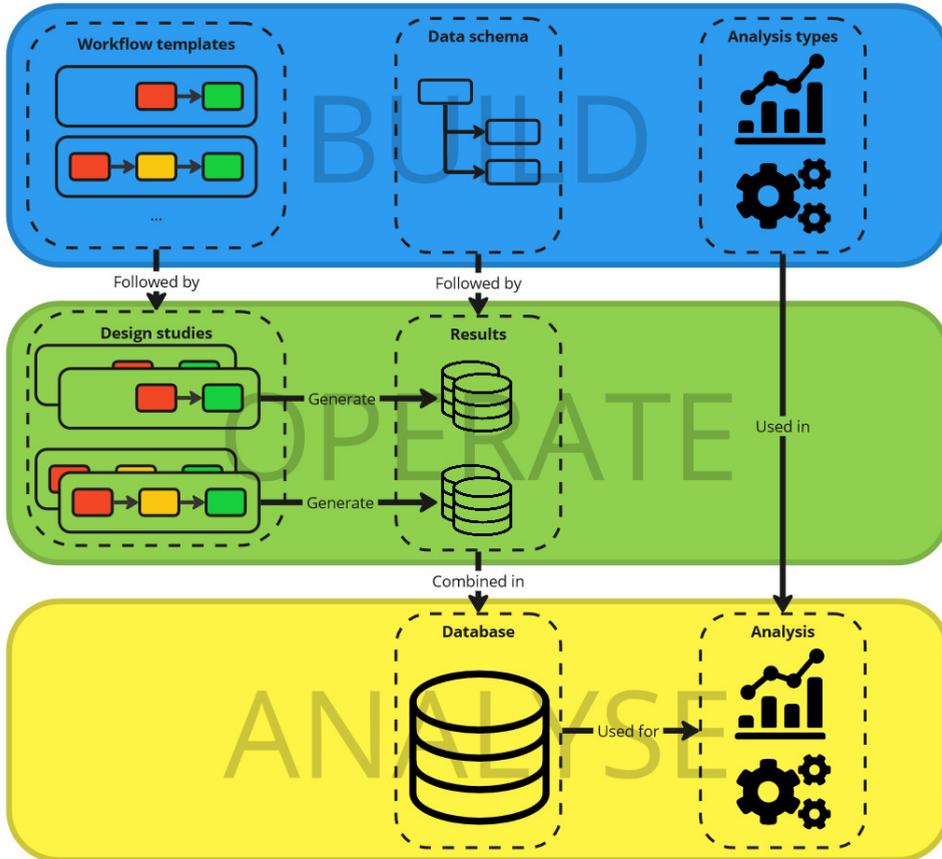


Figure 5.9: An overview of the proposed framework for collaborative front-loaded design space exploration.

5.3.1. BUILD

In the *Build* phase, the OEM and supplier perform the preparatory work to streamline the DSE process. An overview of the steps taken in this phase is shown in Figure 5.10. The steps can be described as follows:

- The OEM and supplier agree upon a central data schema to assure that the OEM and supplier are aware of the complete data definition used in the interaction. Moreover, the common data schema ensures consistency of the data across different design studies, which allows them to be combined in the (front-loaded) database.
- The OEM and supplier agree upon a technology sharing method to enable the col-

laboration. Once decided, the supplier prepares the design tool for usage following the agreed upon TSM. If necessary, integration with the collaborative framework is also configured.

- The OEM and supplier create the design study workflow templates. The templates prescribe the steps taken in a particular type design study and can be instantiated later, thereby minimising setup time of new design studies. For each type of design study, a template can be created. For example, in one template, the OEM can generate the sampling plan themselves, whereas in another template, the OEM only specifies the design space of interest, and leaves the generation of the sampling plan to the supplier. How the workflow templates are specifically designed, depends, among other considerations, on the goals of the design study, the chosen TSM, and the design tool to be used in the collaboration.
- The analysis types to be used on the database should also be configured in this phase. As the analysis of the results could benefit both the OEM and the supplier, both parties can configure the analysis types they deem useful.

5

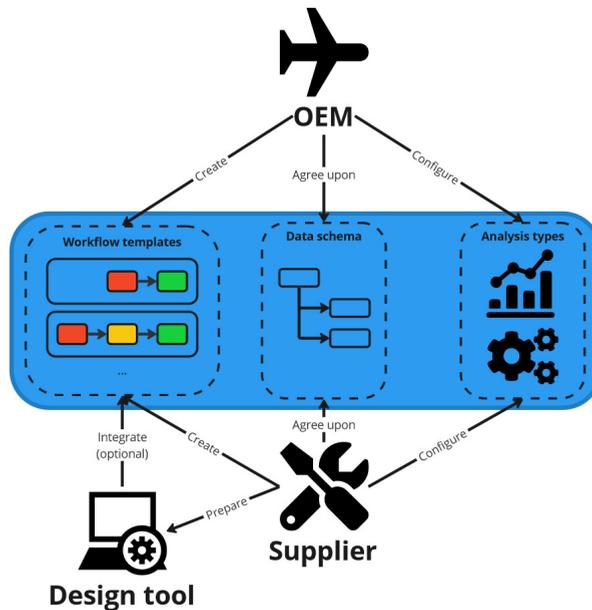


Figure 5.10: An overview of steps taken in the Build phase.

5.3.2. OPERATE

In the *Operate* phase, the design studies are requested by the OEM and executed by the supplier. This is schematically presented in Figure 5.11. By instantiating the existing templates, the OEM can issue a request for a new design study to be executed by the

supplier. The supplier executes the design study using their design tool and prepares the data for sharing. Every template ends with the storage of results, which follow the pre-defined data schema. This ensures that the data is consistent, and enables combination of the data in the front-loaded database.

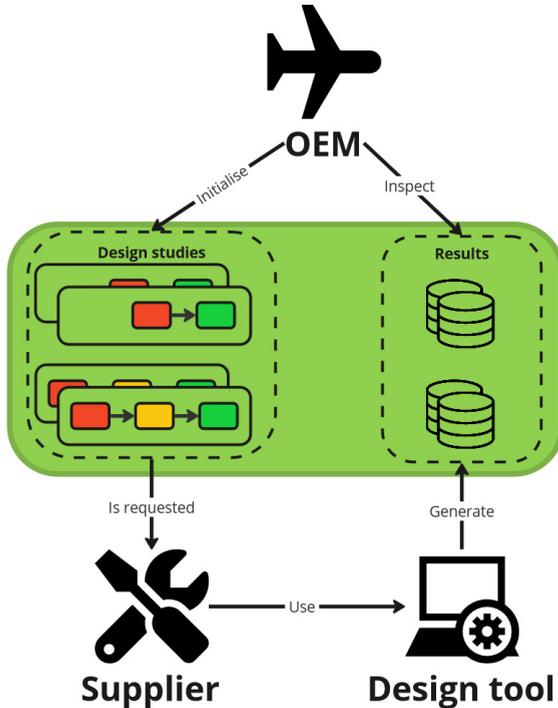


Figure 5.11: An overview of the steps taken in the Operate phase.

5.3.3. ANALYSE

In the *Analyse* phase, the results of the design studies performed so far are collected and can be analysed. An overview of this phase is shown in Figure 5.12 The data can be analysed using the configured analysis types. In this thesis, three analysis types are proposed:

- Visualisation provides a quick overview of the current data present.
- Sensitivity analysis helps determine the most sensitive variables present in the design problem.
- Complementary sampling generates a new sampling plan to maximise the knowledge gained in a new design study.

Both the OEM and the supplier can utilise the analysis methods to support their technology assessment or design studies.

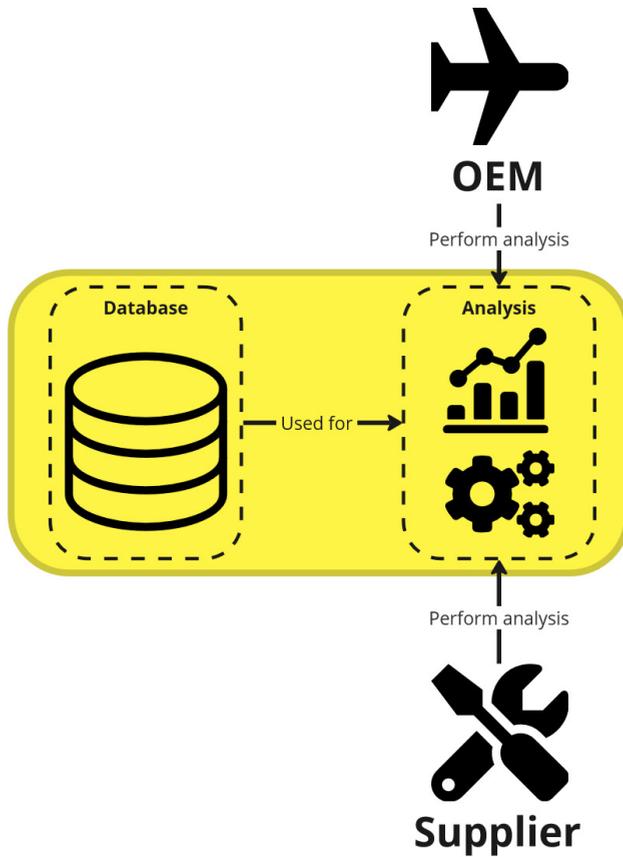


Figure 5.12: An overview of the steps taken in the Analyse phase.

6

IMPLEMENTATION

This chapter presents an implementation of the proposed framework, described in Section 5.3, used in this thesis. The implementation was realised by creating a collaborative environment using KE-chain, the collaboration platform previously described in Section 4.1. The implementation was tailored towards a use case within the ongoing DEFAINE project[7] concerning the structural design of an aileron. A description of this use case is given in Section 6.1. Then, the implementation of the framework for collaborative front-loaded design space exploration is presented. The environment was built using the direct sharing of data in tabular form as the chosen technology sharing method. This TSM was chosen due to the preferences of the involved parties, as well as the straightforward ability to reuse available data, thereby front-loading the DSE process.

The Build, Operate and Analyse phases are discussed in Section 6.2, 6.3, and 6.3. How the other TSMs can be realised in a KE-chain environment, is described in Section 6.5.

6.1. CASE DESCRIPTION

The implementation revolves around the design of an aircraft movable, where SAAB acts as the OEM designing a UAV and GKN Fokker Aerostructures as the Tier 1 supplier of movables. The OEM reaches out to the supplier because they wish to consider novel materials such as composites, which they cannot evaluate using their own in-house design tools. The supplier is thus asked to design a set of movables for some outer dimensions and aerodynamic loading. The quantities of interest the OEM wishes to know are the mass, total cost and structural integrity of the movable.

The design variables in this problem are high-level structural variables, such as number of ribs and choice of material. These parameters drive certain lower-level parameters: the number of ribs, for instance, divides the skin surface into different zones, where every zone can have a different material thickness. Since these variables all concern the structural layout of the movable, the supplier specifies the design variables in this case, with the goal of delivering a set of feasible designs to the OEM. The OEM can then perform a trade-off by identifying the Pareto front of the lowest mass and cost.

The movables are designed using the MDM[62] as the design tool. The MDM is a Knowledge Based Engineering (KBE) application, developed by GKN Fokker Aerostructures using ParaPy¹, able to model aircraft components, and provides an interface for analysis tools to interact with. This way, an automated workflow can be created to design and assess structural components of aircraft, based on a given parametrisation. Furthermore, to handle the hierarchy in the design variables, a novel dynamic workflow generation algorithm was used[63]. The hierarchy in design variables can be specified in a Design Study Configuration (DSC) file.

An overview of the design process in this use case is presented in Figure 6.1. The steps can be described as follows:

1. The OEM initialises the design study by specifying the outer dimensions and the aerodynamic load cases the movable should withstand. These parameters stem from the OEMs internal design studies and are driven by e.g. manoeuvrability requirements. The OEM also specifies the desired QOIs: mass, cost and structural integrity. In this case, the structural integrity is expressed as the critical reserve factor, i.e. smallest reserve factor present in the design. The reserve factor, defined as the ratio between the resistible load and required load, is determined on every component in the movable. A reserve factor greater than 1 indicates that all components satisfy the structural requirements.
2. The supplier receives the design study specification, and prepares the model and analysis tools for the design study. Examples of steps taken here are the importing of the OEMs specifications into the model, and loading the libraries with properties of the relevant materials.
3. Then, the design study configuration is initialised. As mentioned before, the high-level design variables drive certain lower-level parameters. In this step, the supplier defines the design variables and this underlying hierarchy.
4. The supplier executes the design study locally and prepares the results for sharing. Here, the results are shared in the form of tabular data, so the supplier prepares a spreadsheet of the results to upload to the KE-chain environment.
5. The OEM is notified that the results are available, and uses the results for their technology assessment.

6.2. BUILD PHASE

The collaborative environment presented here is created in KE-chain. This means that a third party is now involved in the collaboration between the OEM and the supplier, to provide the collaborative environment as a service. This can be realised in a variety of ways. For example, it could be the supplier who hosts the collaborative environment, as a means to rapidly respond to potential customers (OEMs). Alternatively, the OEM could host the collaborative environment, and create different projects to interact with

¹“Parapy Software Development Kit”, Parapy B.V., <https://parapy.nl/> [Accessed 25/11/2023]

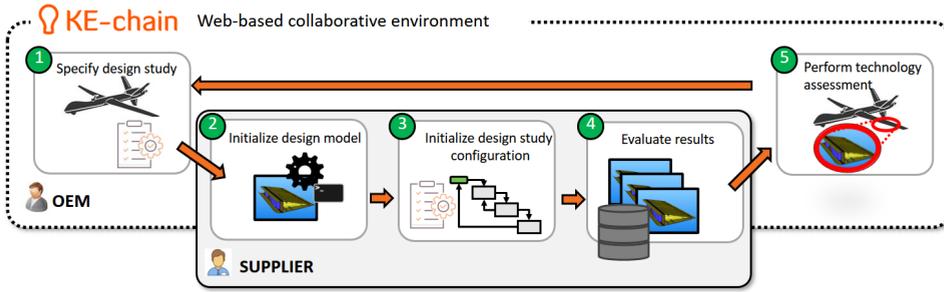


Figure 6.1: Overview of the steps taken in a design study in the movable use case.

different suppliers of different types of components, to accelerate their technology assessment. The latter corresponds with the overall scenario of this thesis, and will thus be used for the rest of this work. Regardless who hosts the collaborative environment, every project is based on a single OEM-supplier interaction, as this was the focus of the methodology.

To setup a new project in the collaborative environment, first the hosts invites the users to the environment and sets the permissions. The users in such cases are the engineers of the OEM and the supplier that will work on the design studies. The experts can have different roles, such as architect (OEM), integrator (supplier), or discipline experts (both OEM and supplier), each with their own set of permissions. This streamlines the division of labour and can be done through KE-chains native accessibility options. An example of a division in roles and permissions is shown in Table 6.1.

Role	Permissions
Architect	Invite users and manage permissions
	Set data schema
	Create and manage workflow templates
	Instantiate new design studies
	Work on design studies
Integrator	Perform analysis on database
	Set data schema
	Upload results directly to database
	Adapt workflow templates
	Work on design studies
Discipline expert	Perform analysis on database
	Work on assigned design studies
	Access analysis on database (read-only)

Table 6.1: Example of role division within a collaborative environment.

The suppliers tool should also be prepared for the chosen technology sharing method. In the case of sharing tabular data, the results can be uploaded to KE-chain as an Excel sheet. A post-processing script to gather the results and store them in an Excel sheet

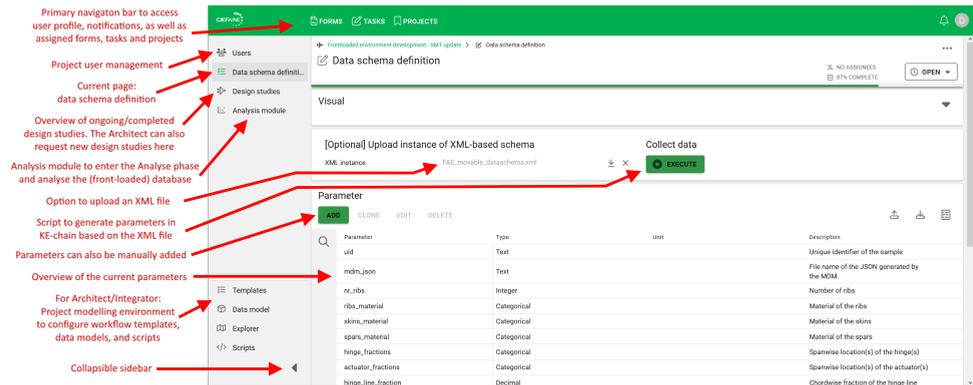


Figure 6.2: Interface for the specification of a data schema in the collaborative environment. The sidebar in the left is used to navigate to the different phases.

should thus be created, if the analysis tool does not store the results as such by default.

6.2.1. DATA SCHEMA SPECIFICATION

When a new project is created, the data schema should be specified. In the role division described above, this is done by the architect and the integrator. The schema describes the parameters used in the interaction, to ensure that the design definition is complete and can be straightforwardly used by the analysis tool. Parameters are defined with a name, type (text, integer, decimal, categorical or ordinal), unit and description. Parameters can be manually created or altered using the KE-chain interface or by uploading an Excel spreadsheet. However, as common data schema's are often XML-based, the option was implemented to upload an XML-file, and have the parameters created from the leaf nodes in the file. To enable this functionality, a Python script making use of the Pykechain library was developed by the author. The script assigns a default parameter type based on the value the XML-element holds (e.g. 3.14 will be recognised as a decimal). For categorical, ordinal, and textual values, the correct type cannot be determined based on a single XML-instance, and should thus be adjusted by the architect and/or integrator. Nevertheless, this method still reduces the manual efforts in creating the data schema in KE-chain, and reduces risk of human error.

6.2.2. WORKFLOW TEMPLATE CREATION

With the data schema configured, the workflow templates can be created. The templates are shaped by KE-chains standard widgets and supported by custom Python scripts where necessary. In the current implementation, this was done by the author, but in a real scenario, this would be done by the architect and integrator. The Python scripts described in the rest of this chapter were thus developed by the author, and make use of the Pykechain library to interact with the collaborative environment. Some functionalities make use of additional libraries, these are specified where relevant.

Every template describes a certain workflow, with one or more steps to be taken in that workflow. User access can be tailored by the architect and integrator, so that the

The screenshot shows the 'Design Step' configuration interface. At the top, there are navigation tabs for 'FORMS', 'TASKS', and 'PROJECTS'. Below this is a table of design steps:

Design Step	Design Step uid	Parent step	mdaoArchitecture	Allocated parameters	Architecture settings
step 1	1		unconverged-ODE	cost, target_rlb_pitch	Full factorial - 3 levels
step 2	2	step 1	unconverged-OPT	mass, skin_zones_material_allocation, spar_zones_material_allocation	

Below the table, there are sections for 'Configure DSC file settings' and 'Generate DSC file'. The 'Generate DSC file' section has an 'EXECUTE' button. Below that, there is a section for 'DSC and CMDOWS files' with a list of generated files and download icons.

Red arrows and text annotations highlight key features:

- Arrows point to 'step 1' and 'step 2' in the table, with text: "The previously configured data schema parameters are allocated to the design steps".
- An arrow points to the 'Parent step' column for 'step 2', with text: "Nested design steps are indicated by allocating a parent".
- An arrow points to the 'Generate DSC file' section, with text: "Additional settings".
- An arrow points to the 'EXECUTE' button, with text: "The DSC and CMDOWS files are generated by executing the scripts".
- An arrow points to the download icons for the generated files, with text: "The files can be downloaded here".

Figure 6.3: Interface for the generation of Design Study Configuration files. Parameters are allocated to the design steps, indicating hierarchy. The file is generated using a Python script, which is activated upon clicking the button, after which it can be downloaded from the window at the bottom of the page. CMDOWS files can also be generated.

discipline experts of the OEM and supplier only have access the relevant interfaces. Notifications can also be configured, so that the supplier can be notified if the OEM issued a design study request or the OEM can be notified if the supplier completed the study and shared the results.

For every type of workflow, a custom template can be created. For instance, in a DOE study only the design variables and QOI's are specified by the OEM, whereas in an optimisation study the objective variables and constraints would also be defined. Which parameters are to be specified by the OEM and which ones are left to the supplier, is dependent on the specific OEM-supplier interaction and the parties preferences. Specific interfaces can also be included to configure additional settings required to execute the design study. An example of such an interface is the DSC file generation interface, shown in Figure 6.3. Here, the supplier discipline experts can specify the hierarchy in the design variables mentioned in the case description above. Several design steps can be defined, each step containing a set of allocated parameters. The XML-based DSC file can then be generated based on this definition, again using a Python script. The DSC file can then be downloaded and used in the offline workflow of the supplier.

Every template ends with the ability to store the results of the design study. One workflow template was created with only the results section, thereby providing the supplier the option to upload any preexisting results without a specific request from the OEM. This rapidly makes the data available for inspection by the OEM, and for the analysis methods described in Section 6.4.

6.3. OPERATE PHASE

After the build phase, the project is configured, and the operate phase commences. In the operate phase, the OEM (architect) can request design studies by instantiating the

configured workflow templates. The interface for this is shown in Figure 6.4. As can be seen, the configured workflow templates are presented to the user in a drop-down menu. The templates minimise setup time of new design studies, and the respective partners are automatically notified if action is required of them.

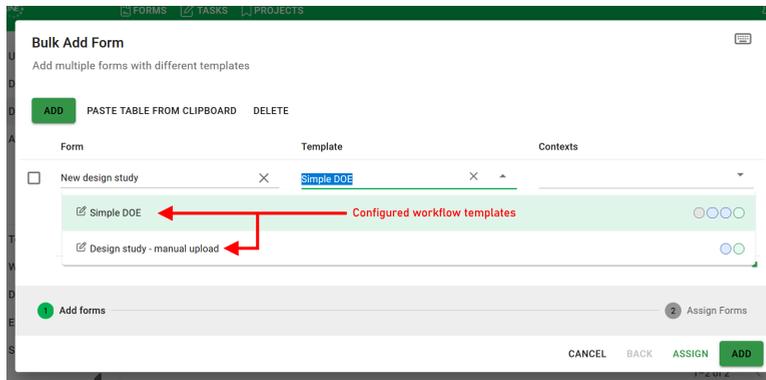


Figure 6.4: Interface for creating a new design study instance. The user is presented with an overview of the created workflow templates.

6

6.4. ANALYSE PHASE

At any point, the users can collect the data by executing the 'Collect data' script. This script collects the results of the completed design studies performed within KE-chain, and stores them separately (in KE-chain) for the analysis scripts to use. This prevents the need to rerun the data collection script every time an analysis module is executed. After the script is completed, the user is presented with the overview shown in Figure 6.5. A brief overview of the dataset is shown: which parameters stayed constant and with what value, and which varied throughout the design studies. The analyse module does not make a distinction in what is considered as input or output of the design tool, so it is important for the users to remain aware of this distinction.

6.4.1. VISUALISATION

After data collection, plots can be generated to visualise the collected data. The plot types mentioned in Section 5.2.2 can be generated through the interface shown in Figure 6.6. The plot creation script was developed by the author, and makes use of certain libraries (described below) to facilitate the visualisation.

To generate a plot, user can specify which parameters should be included in the plot. Additionally, the user can specify a "Variable of interest", which is used in a different way depending on the plot type. The plots are generated in the following ways:

- The parallel plot is generated using the Plotly[64] library. The script includes a function to automatically relabel the axes ticks if a categorical variable is represented, which not offered by Plotly by default. A particularly useful aspect of this library, is that the plots can be generated as interactive HTML files, which can be

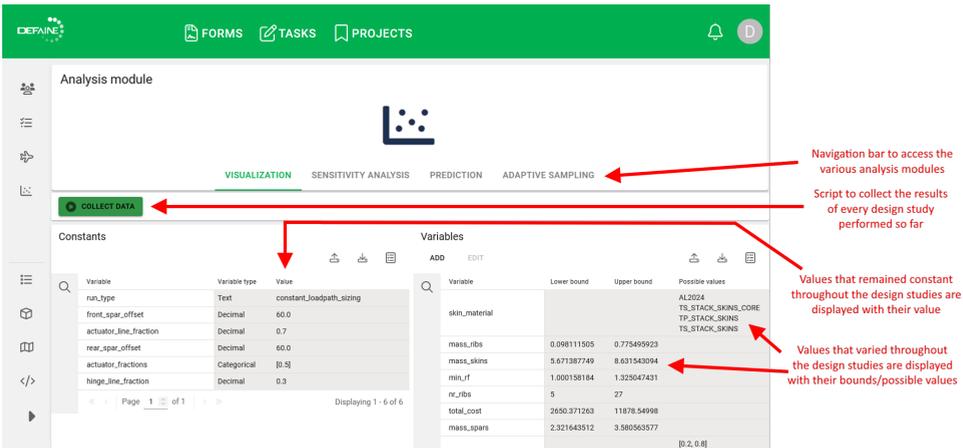


Figure 6.5: Overview of the parameters after the collection of results. Parameters that stayed constant over the design studies are displayed left with their respective values. Varying parameters are displayed on the right with their respective bounds or possible values.

hosted in a KE-chain attachment viewer. This makes the plot interactive in the KE-chain environment, allowing the user to reorder the axes and filter the data in one or more dimensions. For the parallel plot, the variable of interest determines the color of the lines. This way, the effects of the variable of interest can be more easily traced.

- The scatterplot matrix can be generated with the seaborn[65] library, which generates static images. The image can be enlarged in the KE-chain window to better inspect the graph. For this plot, the variable of interest is treated as the categorising variable. This is the categorical value that determines how the data is labeled in the plots. A scatterplot of the results from this design study was shown in Figure 5.8. Here, the skin material was chosen as the categorical variable to group the data.

Overall, the plots can be generated in a matter of seconds, thereby enabling the architect to quickly assess the results of numerous design studies, which contain hundreds of possible designs. Through visualisation, the OEM can quickly identify which designs are the most interesting and identify trends, which supports the technology assessment process.

6.4.2. SENSITIVITY ANALYSIS

In the sensitivity analysis window, the input/output variables to be considered can be selected, as well as the desired methods for analysis. Numerical and categorical variables are evaluated separately, as the methods are not applicable to one another. The numerical analysis methods used in this work, Sobol analysis and HDMR, make use of the SALib[66] Python library for SA. The method for categorical variables, statistical power analysis as described in [61], was implemented by the author.

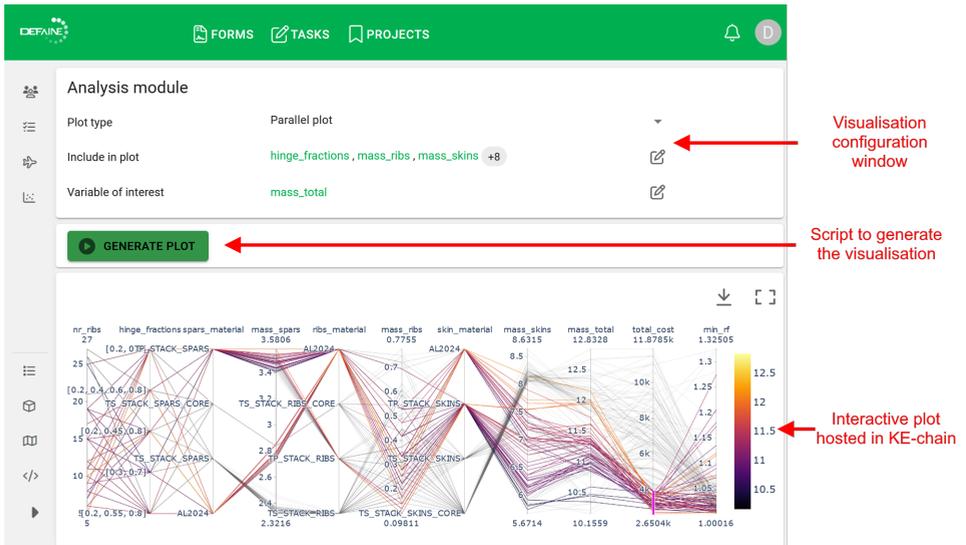


Figure 6.6: Visualisation window in the front-loaded environment. A parallel plot has been generated, where the *mass_total* variable determines the color of the lines. A filter has been placed to highlight the designs with the lowest cost.

6

After the analysis settings are configured and the script is executed, the results are updated in the tables at the bottom of the window. Here, the numerical variables are presented with their sensitivity indices and the corresponding 95% confidence intervals. Categorical variables are shown with their P-values, representing their likelihood to significantly affect the design.

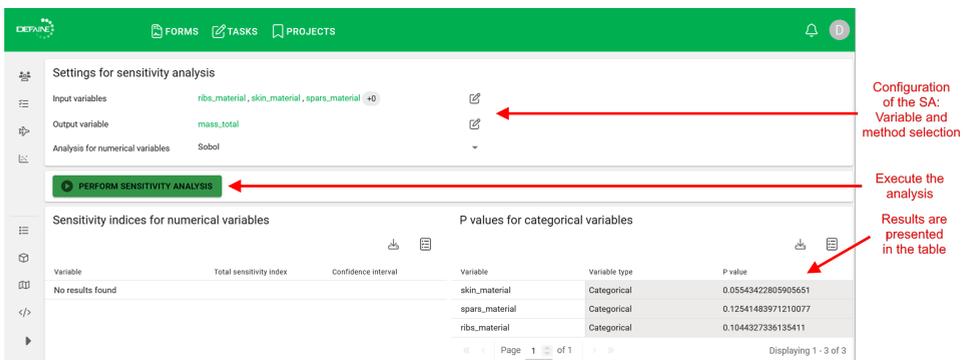


Figure 6.7: Sensitivity analysis window in the front-loaded environment. The sensitivity of the total mass with respect to the component material choices has been calculated.

6.4.3. SURROGATE MODELLING AND COMPLEMENTARY SAMPLING

To implement the complementary sampling strategies as described in Section 5.2.2, a surrogate model must first be trained on the collected data. The adaptive sampling methods can then be used to propose a new sampling grid for future design studies. To separate the two processes, a separate environment was created for each process.

SURROGATE MODELLING

In the surrogate model window, a SM can be trained based on the collected data. To do so, first the input and output variables should be specified in the interface show in Figure 6.8. Then, the SM can be automatically trained by clicking the *Generate surrogate model* script. The training of SMs is enabled with the Surrogate Modelling Toolbox (SMT)[43]. The SMT was recently updated to, among other additions, use kernels that can effectively model mixed-variable design spaces. As not only predicted values, but also variances are required for the proposed adaptive sampling methods, it was chosen to set the SM type to Kriging.

Because the SMT module relies on certain libraries that could not be hosted in KE-chain, a KE-node was used as an interface between the hosted KE-chain environment and the authors machine, where the surrogate modelling functionalities were locally executed. When the KE-node is running, users can seamlessly train SMs and interact with them. To store the SM after training, it is serialised as a *.pickle* file and stored in KE-chain². This prevents the model from having to be trained every time a script using the SM is executed.

With the SM trained, it is possible to use it to make predictions. To interact with the SM, the table at the bottom of the page can be filled in with the desired samples. The columns of this table are automatically updated when the surrogate model is trained. This way, the table always represents the specified I/O of the SM. When the *Predict* script is executed, the predicted values and variances are updated in the table, thus providing a way to interact with the model. This allows the OEM to quickly scout the design space based on the available data, without requesting a new design study from the supplier. If the OEM finds a particularly interesting prediction, but the variance is too great, the OEM can issue a request for a new design study, to verify the prediction.

COMPLEMENTARY SAMPLING

Finally, to support future design studies, the complementary sampling window can be used. This window is shown in Figure 6.9. To make use of adaptive sampling, a surrogate model has to be trained. To configure the new sampling plan, then number of samples to be evaluated and desired number of samples in the sampling plan should be configured (the aforementioned parameters m and n in Section 5.2.2). Furthermore, the sampling strategy, i.e. the refinement criterion, should be selected. When the script is run, m random samples are evaluated, and the n samples with the highest criterion are returned. These are presented in a table, which can be downloaded and straightforwardly be used as the sampling plan for a new design study.

²As recommended by the SMT documentation, see https://smt.readthedocs.io/en/latest/_src_docs/surrogate_models.html#for-models-written-in-pure-python

Choose which variables to include in the SM

Train the SM

Execute prediction script after entering input variables in the table

Table columns with input variables can be filled in by the user

Output variable columns are automatically filled in by executing the script

Sample	ribs_material	skin_material	spars_material	mass_total	mass_total_variance
Sample	TS_STACK_RIBS_CORE	TS_STACK_SKINS	AL2024	11.179516551169908	1069332.017752488
Sample	TS_STACK_RIBS	TS_STACK_SKINS_CORE	TS_STACK_SPARS_CORE	12.386172096456905	336724.3983698066
Sample	AL2024	AL2024	AL2024	11.472360280545901	0.005530738587065596

Figure 6.8: Surrogate modelling window in the front-loaded environment. A surrogate model has been trained on a set of input parameters, with the total mass again chosen as the QOI. The table below provides an interface to interact with the surrogate model. An arbitrarily chosen set of samples has been provided and evaluated by the surrogate model.

Displays the parameters upon which the SM is trained

Panel to configure settings for CS plan generation

Script to generate the CS plan

Overview of the generated sampling plan, can be downloaded

Sample ID	hinge_fractions	nr_ribs	ribs_material	spars_material	skin_material
Sample 0001	[0.2, 0.55, 0.8]	7	TS_STACK_RIBS	TS_STACK_SPARS_CORE	AL2024
Sample 0002	[0.2, 0.8]	6	TS_STACK_RIBS	TS_STACK_SPARS_CORE	AL2024
Sample 0003	[0.2, 0.8]	18	TS_STACK_RIBS	AL2024	TP_STACK_SKINS
Sample 0004	[0.2, 0.55, 0.8]	23	TS_STACK_RIBS	AL2024	TP_STACK_SKINS
Sample 0005	[0.2, 0.45, 0.8]	13	TS_STACK_RIBS	AL2024	TP_STACK_SKINS

Figure 6.9: Complementary sampling window in the front-loaded environment. Based on the trained surrogate model and the chosen settings, a grid with proposed samples is generated. The grid can easily be exported to an Excel spreadsheet.

6.5. ALTERNATIVE SCENARIOS

As mentioned in the introduction, the current implementation is tailored towards the sharing of results in the form of tabular data. The framework can however be tailored to suit different needs. To use the other technology sharing methods, the framework can be adapted as follows:

- In case the technology is made available through surrogate models, the workflow templates follow a different logic. First, the OEM specifies the design space they are interested in, as well as the desired accuracy. Once defined, the supplier performs the necessary steps to gather the required training data, trains and validates

the model, and makes it available for usage. Every requested design study thus results in a SM that predicts the design space of interest in that study. The OEM can then interact with the SMs as described in Section 6.4.3. In this case, the analysis module can be adapted to not collect the results of design studies, but instead list the trained SMs, and thus subsets of the design space that can be explored. Moreover, a script could be developed to interface with the SMs from the analysis window. When an evaluation of a design is requested, the script searches the available SMs for the one that predicts the relevant design space. The visualisation and SA modules can be then applied to the *predictions* of the SMs. However, the training of SMs and CS strategies are not applicable in this case.

- If the technology is made available through remote access, the supplier is much less involved with the design studies once the connection is setup. The design study templates then contain an interface to interact with the tool, similar to the interface for surrogate models described above. In KE-chain, remote access could be provided by using KE-nodes that locally interact with the suppliers tool. The OEM can then use different design study workflows to use the suppliers tool for their purposes, and separate the different results. The analysis module can be used in its entirety to further inspect the results generated by the different design studies.

Finally, a scenario can be hypothesised where none of the technology sharing methods are considered an option by either the OEM or the supplier. Instead, the supplier can still facilitate the OEM by evaluating a single design, as is the current state-of-the-art, while also sharing sensitivity indices on certain parameters. This way, if the OEM has to assume certain parameters to complete the design definition, the OEM can be informed on the consequences of those assumptions. The supplier then performs a DOE to gather the required data for the SA, without sharing this data with the OEM. After the supplier performs SA, they only share the results of the evaluated design (the values of the requested QOIs) with the sensitivity indices of the uncertain parameters. This way, the OEM can simplify the design problem if some parameters turn out to have a negligible effect on the QOIs, or prioritise their efforts on the most sensitive parameters.

III

VERIFICATION AND VALIDATION

7

TEST CASE: SUPERSONIC BUSINESS JET

To verify the proposed methodology, a test case was developed by the author. This chapter describes the application of the framework to the developed test case. The test case simulates a scenario in which an OEM has a workflow with lower-fidelity design tools, and wishes to incorporate a supplier-owned higher-fidelity tool into the workflow. The scenario is described in Section 7.1, and will be used to assess three aspects of the methodology:

- To enable the usage of the supplier-owned tool in the OEMs workflow, a technology sharing method must be chosen. Section 5.1.2 described how two TSMs, sharing of tabular data and sharing a surrogate model, alter an existing MDAO workflow and introduce a certain error. To quantify this error in the test case, three separate MDAO workflows were created. The created workflows and the effect of the TSMs are described in Section 7.2.
- If the OEM wishes to explore a certain explored subset of the design space in more depth, existing data should be used to avoid similar samples and direct efforts towards interesting regions in the design space. To do so, Section 5.2.2 proposed a complementary sampling strategy. This allows the OEM to generate more effective sampling plans for sequential design studies. To verify this CS strategy, described in Section 7.3.
- To gain insight in the behaviour the design in response to its design variables, sensitivity analysis was proposed in Section 5.2.2. The application of SA can assist the OEM in identifying the most critical design variables, that should be prioritised in their design efforts. Furthermore, the impact of assumptions made to complete the design definition can be assessed. This can assist both the OEM and the supplier, as both may have to make certain assumptions. This test case was used to verify the proposed SA methods for numerical variables, namely Sobol analysis and HDMR. This is described in Section 7.4.

In this chapter, a number of data sets will be generated, compared, and combined. To assist the reader in keeping an oversight on which data set is used in which cases, Table 7.1 can be used.

Data set	Description	Used to
1	DOE simulating the sharing of tabular data. Shares the same sampling plan as Data set 2 and 3.	Compare TSMs
2	DOE simulating the sharing of a surrogate model. Shares the same sampling plan as Data set 1 and 3.	Compare TSMs
3	DOE simulating remote access/ownership of the tool. Shares the same sampling plan as Data set 1 and 2.	Compare TSMs Verify CS Perform SA
4	DOE using a sampling plan generated the proposed complementary sampling strategy.	Verify CS Perform SA
5	DOE using a sampling plan generated using LHS.	Verify CS
6	DOE using a trained surrogate model based on Data set 3 and 4	Perform SA

Table 7.1: Overview of the data sets used in this chapter

7.1. CASE DESCRIPTION

The test case describes the scenario in which an OEM is designing a supersonic business jet. To design the wing, the OEM has set up a workflow using low-fidelity analysis tools, that describe the wing only in high-level parameters. At some point, the OEM wishes to verify their results using a higher-fidelity analysis tool, and reach out to a supplier in possession of such a tool. However, the higher-fidelity tool requires the wing to be modelled in greater detail than the OEM currently has available. For example, the suppliers design tool requires the position of a kink in the wing to be specified. The test case presented here revolves around the expansion of the design problem with the parametrisation of the kink in the wing. In this test case, the author takes on the role of both the OEM and the supplier.

The test case was based on the supersonic business jet (SSBJ) case, first described by Sobieszczanski-Sobieski, Agte, and Sandusky to test their decomposition algorithm[67]. The SSBJ case has since been used as a test in other MDAO implementations[68, 69]. In the SSBJ case, the wing of a supersonic business jet is parametrised and optimised for maximum cruise range, while adhering to constraints. The wing is defined by high-level parameters shown in Table 7.2. Within the SSBJ case, four analysis disciplines are present: propulsion, structures, aerodynamics and performance. The disciplines are

represented using analyses of relatively low fidelity, as typically used in the early conceptual design stage. The implementation of these disciplines, as well as the baseline values of the parameters in the design problem, was retrieved from the SSBJKADAMOS repository¹. A DOE workflow of the SSBJ problem is presented in Figure 7.1.

Symbol	Definition	Value	Unit
λ	Taper ratio	0.25	-
Λ	Wing sweep angle	55	deg
S_{ref}	Reference area	1000	ft ²
AR	Aspect ratio	5.5	-

Table 7.2: The wing parametrisation originally present in the SSBJ problem.

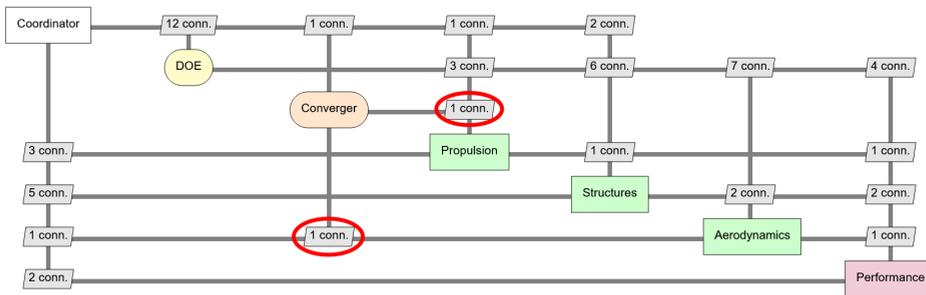


Figure 7.1: XDSM of a DOE workflow in the SSBJ problem. The red circles indicate the drag, and show how the propulsion and aerodynamics disciplines are coupled. The full XDSM showing all variables can be found in Appendix B.

The parameters described in Table 7.2 are extracted from the standard SSBJ problem, and were used to create a top-down wing planform. To enable the usage of the higher fidelity tool, the wing parametrisation must be expanded to model the kink in the wing. This was done using the three parameters shown in Table 7.3. The baseline values of the new parameters were chosen such that the baseline design does not include a kink.

Symbol	Definition	Value	Unit
λ_{kink}	Kink taper ratio	0.625	-
$\Lambda_{outboard}$	Outboard sweep angle	55	deg
$b_{kink,nd}$	Spanwise kink location (non-dimensionalised)	0.5	-

Table 7.3: The new design variables of the expanded SSBJ problem.

The higher-fidelity tool implemented in this use case was Panair, an openly available panel solver capable of describing supersonic flow about arbitrary three-dimensional geometries. Panair was thus used to replace the low-fidelity aerodynamics discipline originally present in the SSBJ problem. Choi et al.[70] described Panair as a mid-to-high

¹Available at <https://bitbucket.org/imcovagent/ssbjkados/src/master/> [Accessed 16-10-2023]

fidelity aerodynamic solver, but Chan[71] validated that the results for cruise conditions (small disturbance, not transonic, irrotational flow and negligible viscous effect) are very comparable with higher fidelity solvers, such as Euler CFD simulations.

The implementation of Panair as an aerodynamic solver that can replace the original aerodynamics discipline was a lengthy process, described in Appendix A. Once the higher-fidelity aerodynamic solver was configured, it could substitute the originally present aerodynamic discipline. This resulted in the workflow visualised in Figure 7.2. The original XDSM, as well as the expanded XDSM listing all parameters, are presented in Appendix B.

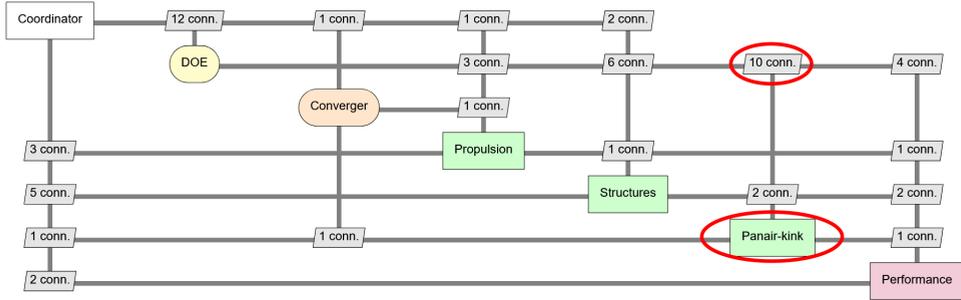


Figure 7.2: XDSM of the SSBJ DOE workflow with the higher-fidelity solver (*Panair_kink*) implemented. Note how the number of connections between *Panair_kink* and the DOE is increased. The full XDSM showing all variables can be found in Appendix B.

7

With the expanded design problem defined, the OEM is now able to formulate design studies, and request them from the supplier. An interface for requesting such design studies in the KE-chain implementation is visualised in Figure 7.3. The window shown here is an *instantiation* of a workflow template, which the OEM and supplier have configured in the past. As the author takes on both roles in this test case, this workflow template was developed solely by the author. The tables shown for design variables, constants and QOIs, are part of the workflow template, whereas the contents of those tables are only part of this specific instantiation. This allows the OEM to rapidly set up separate design studies for different purposes (e.g. different design variables, different bounds for those variables). Furthermore, the *DOE configuration* window shown at the bottom of the figure, allows the OEM to quickly generate a sampling plan based on the design study specification. In this case, the sampling plan contains 256 samples, uses Sobol sampling, and only varies the kink related parameters, while keeping the other parameters constant. The sampling plan (not shown) can be generated by executing the *Generate sampling plan* script developed by the author.

7.2. COMPARISON OF TECHNOLOGY SHARING METHODS

With the case prepared, the first test was to identify the effect of the technology sharing methods. Section 5.1.2 described the effect of these technology sharing methods on existing workflows, and stated that by modifying the workflow, a level of error could be introduced. To investigate the magnitude of this error, three scenarios were developed

The screenshot shows the KE-chain environment interface for a design study. It features a green header with navigation icons for FORMS, TASKS, and PROJECTS. The main content area is divided into four panels:

- Design variable - Integer:** A table with columns for Design variable, Parameter, and Lower bound. It shows "No results found".
- Design variable - Decimal:** A table with columns for Design variable, Parameter, Lower bound, and Upper bound. It lists:

Design variable	Parameter	Lower bound	Upper bound
Kink taper ratio		0.5	0.75
Outboard sweep angle		44	66
Spanwise kink dimension		0.4	0.6
- Constant:** A table with columns for Constant, Parameter, and Value. It lists:

Constant	Parameter	Value
Aspect ratio	AR	5.5
Reference area	S_ref	1000
Wing sweep angle	Lambda	55
Thickness over chord ratio	tc	0.5
Taper ratio	lambda	0.25
- QoI:** A table with columns for QoI and Parameter. It lists:

QoI	Parameter
Range	R

At the bottom, there is a 'DOE configuration' section with 'Number of samples' set to 256 and 'Sampling method' set to Sobol. A 'Generate sampling plan' button with an 'EXECUTE' button is also present.

Red arrows and text annotations provide additional context:

- An arrow points from the text "To define the design space to explore in this study, bounds are specified" to the 'Design variable - Decimal' table.
- An arrow points from the text "Variables, constants and QOIs are linked to the previously configured data schema (not shown for decimal design variables)" to the 'Design variable - Integer' and 'Design variable - Decimal' tables.
- An arrow points from the text "If a parameter remains constant, the constant value is given" to the 'Constant' table.
- An arrow points from the text "Sampling plan generation settings" to the 'DOE configuration' section.
- An arrow points from the text "The sampling plan (not shown) is generated using this script" to the 'EXECUTE' button.

Figure 7.3: Interface for the requested design study in the KE-chain environment. The OEM specifies the design space of interest and which QOI's to investigate. The parameters are linked to the specified data schema. This template also provides the option to generate a sampling plan in the KE-chain environment based on the design study specification.

based on the test case:

- Scenario 1 simulates the usage of design tools through the sharing of tabular data. As mentioned in Section 5.1.2, this renders the usage of convergence loops unfeasible. The workflow shown in Figure 7.2 was thus converted to a non-converging workflow. The propulsion discipline now uses the initial value for drag,
- In Scenario 2, a surrogate model was trained to replace the *Panair_kink* tool. To train the surrogate model, a separate DOE was performed to gather the required training data. The sampling plan used in this DOE was generated with Latin Hypercube Sampling. In addition to the kink parameters, the design space here also included the total weight of the aircraft with the baseline value $\pm 50\%$, since the total weight can vary over the iterations. The surrogate model was trained using the automatic training functionality provided by the SAS[23]. In this module, several types of surrogate model are trained and validated, and the most accurate is returned and stored. After the surrogate model was trained, it was saved as a *.pickle* so that it can quickly be retrieved.
- Scenario 3 simulates remote access to the design tool. The workflow thus remains unaltered.

The XDSM's of the scenario's can be found in Appendix B. The same sampling plan was used for all three scenarios, and was generated with the goal to assess the kink parameters. The sampling plan thus kept the baseline values shown in Table 7.2 constant,

and varied the kink parameters presented in Table 7.3 with $\pm 20\%$. The chosen sampling strategy was the pseudo-random Sobol sampling method, mentioned in Section 5.2.2, because of its low discrepancy.

The different scenario's were executed and resulted in Data sets 1, 2 and 3 respectively. Data sets 1 and 2 were compared with Data set 3, since Scenario 3 should provide the highest level of accuracy. The surrogate model in Scenario 2 was built using a different sampling plan than previously described, but with the same number of samples. The results were compared using the root mean square error (RMSE) and the mean average error (MAE). The MAE is also expressed as a percentage of the mean range found in the data. The workflows were executed using RCE as the PIDO software.

Scenario	RMSE	MAE	MAE (%)
1 vs. 3	1.704	0.976	0.664
2 vs. 3	1.563	0.995	0.676

Table 7.4: Accuracy comparison of the technology sharing use cases based on the SSBJ test case (N=256).

The results of the comparison are shown in Table 7.4. As can be seen, Scenario 2 is more accurate in terms of the RMSE than Scenario 1. However, when comparing the MAE, the use of the surrogate model seems to result in slightly greater errors.

To investigate the errors in more depth, the histogram of the relative errors was generated. The histogram is shown in Figure 7.4. The histogram reveals that in Scenario 1, more samples have an error near 0. On the other hand, the error distribution in Scenario 2 shows a more smooth behaviour, similar to a normal distribution.

Furthermore, the execution logs generated by RCE revealed that in the Scenario 3, Panair was called 377 times, over the course of 256 samples. This means that at least for 121 samples, the calculated drag by Panair was within the margin of error, and an iteration was not necessary to reach convergence. The histogram comparing the relative error between Scenario 1 and 3 confirms this.

In other words, for almost half of the samples, the workflow in Scenario 1 and 3 was identical, resulting in no error. Thus, in this scenario, usage of the surrogate model almost always resulted in a small error, whereas sharing tabular data sometimes resulted in no error at all, and in larger errors otherwise.

Overall, with both scenarios resulting in errors below 4%, both technology sharing methods can be considered feasible for design space exploration in the conceptual design stage. As such, the OEM and supplier would likely agree on the sharing of tabular data as the TSM for this use case, as this method is closest to the current state-of-the-art. However, as roughly half of the samples did not require additional iterations to reach convergence, the main drawback of sharing tabular data was not relevant for those samples. If the OEM knows the convergence loop will be necessary due to strong coupling between the disciplines, the sharing of a surrogate model may be preferable.

7.3. COMPLEMENTARY SAMPLING

With an initial DOE performed, the complementary sampling strategy proposed in Section 5.2.2 can now be used to generate a sampling plan, that avoids already available data

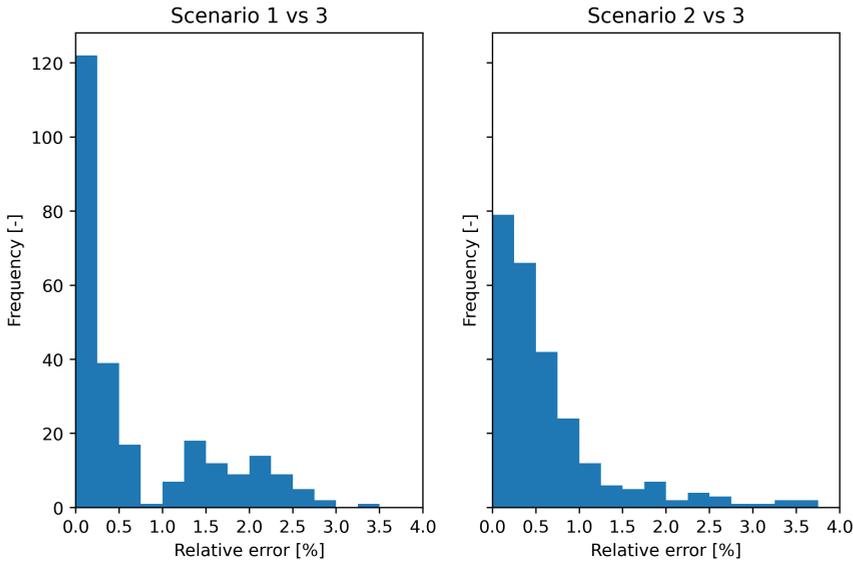


Figure 7.4: Histogram showing the relative error of Scenario 1 and 2.

and shifts efforts towards unexplored regions in the design space. In this section, an experiment is conducted to verify the usage of such a CS plan. To do so, two new sampling plans were generated in the same design space as the initial DOEs (Scenario's 1, 2 and 3). One sampling plan was generated using the proposed CS strategy, whereas the other sampling plan uses an ordinary sampling plan, not taking into account the samples from the initial DOE. These scenario's will henceforth be known as Scenario 4 and 5 respectively. Both sampling plans were evaluated using the DOE workflow from Scenario 3, after which the results were combined with the results from the initial Scenario 3 DOE, Data set 3. To compare the two sampling plans, two surrogate models will be trained based on the respective combined data sets. It is assumed here that the accuracy of a surrogate model represents the quality of the sampling plans, i.e. how well the sampling plans describe the design space.

To generate the sampling plan for Scenario 4 using the CS strategy, the steps described in Section 5.2.2 were taken in the following way:

1. A surrogate model was trained based on the 256 available samples (from Data set 3).
2. It was chosen to have 250 samples in the new sampling plan
3. The chosen adaptive sampling method was EIGF, as this method is regarded as an easy to implement, but reliable method for adaptive sampling[51].
4. A sampling plan of 2000 samples was created using LHS. For every sample, the refinement criterion was evaluated using the trained surrogate model.

- The 250 samples with the greatest RC were selected. This is the new sampling plan to be used in the upcoming DOE.

The CS plan is visualised over Data set 3 in Figure 7.5a. The ordinary sampling plan for Scenario 5 was generated using Latin Hypercube Sampling, and also contains 250 samples. The ordinary sampling plan is shown in Figure 7.5b.

To compare the effectiveness of the two sampling plans, the sampling plans were used in two follow-up DOEs. The DOEs used the same workflow as Scenario 3, and resulted in Data sets 4 and 5. Two surrogate models were trained based these data sets in combination with Data set 3. The models were validated using k-fold validation, and the RMSE values of the models were measured to compare the accuracy of the models. The training and validating of the surrogate models was done using SAS functionalities[23].

Data set	RMSE of trained surrogate model
Data set 3 + 4 (complementary sampling)	1.52
Data set 3 + 5 (ordinary sampling)	2.33

Table 7.5: Comparison of complementary sampling versus ordinary sampling.

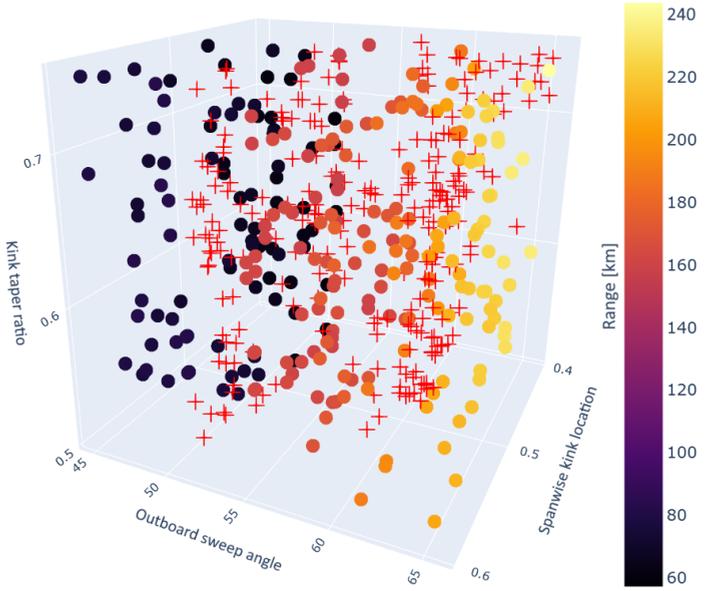
The results are shown in Table 7.5. As can be seen, the model trained using the CS strategy has a lower RMSE and can thus be considered more accurate. This verifies that the CS strategy correctly shifts efforts towards critical or unexplored regions of the design space, and results in a higher quality data set. However, caution must be taken when choosing the number of samples to include in the new sampling plan, n , and the number of samples to evaluate using the surrogate model, m . If the ratio of m to n is too great, the samples in the new sampling plan will only cluster around the area with the greatest RC. This is visualised in Figure 7.6, where m was chosen to be 20000, instead of 2000 as before. The ratio of m to n should thus be chosen such that a meaningful selection can be made out of the m samples, but small enough to avoid clustering. However, an in-depth investigation to determine the ideal ratio has not been performed.

7.4. SENSITIVITY ANALYSIS

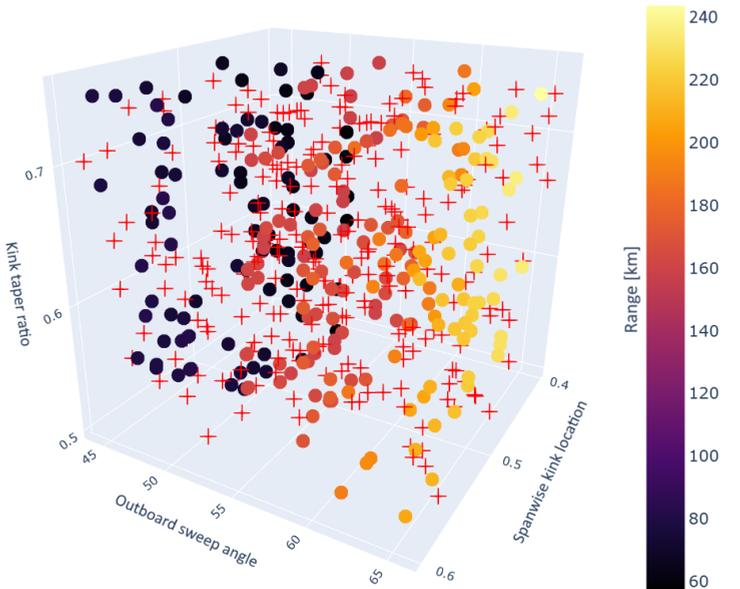
Finally, to gain insight in the behaviour of the newly introduced kink parameters, sensitivity analysis was proposed. When visually inspecting the results of Scenario 3 in Figure 7.5a, it seems that the outboard sweep angle is the most sensitive parameter to the range of the design. The expectation is thus that sensitivity analysis will reflect this.

The first SA is based on Scenario 3 using Sobol analysis. The results are presented in Table 7.6. Contrary to the expectation, the outboard sweep is ranked as the variable least sensitive to the objective. However, it can also be observed that the resulting confidence interval is quite large. This indicates that a larger data set should be used to obtain more certainty about the sensitivity indices.

Table 7.7 shows the results of Sobol analysis on combined Data sets 3 and 4, i.e. the initial DOE and the sequential DOE using CS. The analysis now correctly ranks the outboard sweep as the most sensitive variables, but only by a small margin. In fact, the sensitivity index assigned to the variables is roughly equal. This should mean that the



(a) Complementary sampling grid generated using the EIGF method.



(b) Ordinary sampling grid generated using LHS.

Figure 7.5: Comparison of the sampling grids evaluated in the sequential DOE. The dots represent the results from the initial DOE, with their colors depending on the QOI value (range) corresponding to that design. The values associated with the colors are indicated by the legend on the right. The crosses represent the sampling points in the proposed sampling plan.

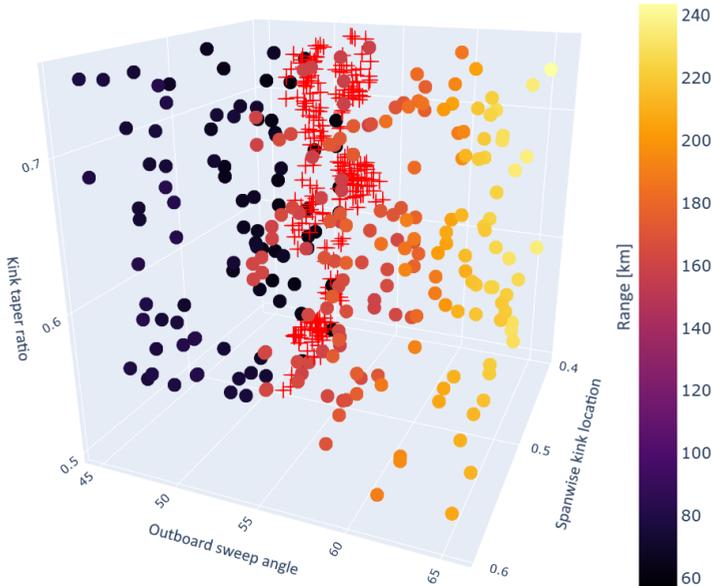


Figure 7.6: The effect of the ratio of evaluated samples to samples in the new grid. If this ratio is too great, the samples tend to cluster around the regions with the greatest refinement criterion.

Variable	Total sensitivity index	Confidence interval
b_{kink}	0.88998	0.34909
$\Lambda_{outboard}$	0.67829	0.3243
λ_{kink}	1.10916	0.2141

Table 7.6: Sobol analysis on the SSBJ test case based on Data set 3.

variables should affect the output of the model equally, which does not appear to be the case.

Variable	Total sensitivity index	Confidence interval
b_{kink}	0.8364	0.2286
$\Lambda_{outboard}$	0.8459	0.291
λ_{kink}	0.7905	0.2141

Table 7.7: Sobol analysis on the SSBJ test case based on Data sets 3 and 4.

Table 7.8 shows the results of HDMR analysis on the combined Data sets 3 and 4. Using this method, the results of this analysis seem to correspond well with the observations made before. HDMR analysis was also tried on Data set 3 alone but this was not possible in the used implementation due to the minimum of 300 required samples².

²See https://salib.readthedocs.io/en/latest/_modules/SALib/analyze/hdmr.html [Accessed 19-10-2023]

Variable	Total sensitivity index	Confidence interval
b_{kink}	0.051	0.021
$\Lambda_{outboard}$	0.880	0.023
λ_{kink}	0.017	0.016

Table 7.8: HDMR analysis on the SSBJ test case based on Data sets 3 and 4.

Finally, since HDMR analysis is based on the use of surrogate models, Sobol analysis was performed using a surrogate model trained on the combined Data sets 3 and 4. The sampling plan used in the sensitivity analysis was generated using Sobol sampling, and since the surrogate model can quickly be evaluated, a large number of samples could be used. The DOE resulted in Data set 6 and contained 8196 samples. The results are shown in Table 7.9. This time, Sobol analysis correctly indicates the outboard sweep angle as the most sensitive variable. However, the same conclusion could already be drawn using HDMR analysis. Considering that an HDMR implementation is readily available, this can straightforwardly be used, and there is no need for the OEM or supplier to manually train a surrogate model, and then use it for Sobol analysis.

Variable	Total sensitivity index	Confidence interval
b_{kink}	0.038	0.005
$\Lambda_{outboard}$	1.00	0.071
λ_{kink}	0.001	0.0001

Table 7.9: Sobol analysis on the SSBJ test case based on Data set 6.

If done correctly, the conclusions drawn from the sensitivity analysis can assist the OEM or the supplier in their design problem. In this case, the OEM explored the introduction of a kink to the wing planform, which was not possible with their low-fidelity analysis tools. Sensitivity analysis revealed that the outboard sweep angle was the most sensitive parameter, and the positioning of the kink was not as critical. This information can be useful when the positioning of the kink is important to other design requirements, for instance the positioning of the landing gear. However, the test case has also shown the sensitivity indices can give the wrong impression, especially when the data set is small. In order to validate the results of the sensitivity analysis, visual inspection of the data is still required.

7.5. A CRITICAL REFLECTION ON THE TEST CASE

The test case described in this chapter was developed to verify certain aspects of the methodology proposed in this thesis. Although these aspects have successfully been assessed,

First of all, in this test case, only the aerodynamics solver was substituted with a higher-fidelity analysis tool. The introduction of a kink to the wing planform was used as the goal of the design studies described above: to explore the effects of adding this kink to the planform. However, it is likely that the introduction of a kink to the planform would affect the internal structure as well. In a real scenario, the structures discipline

should thus also be adapted to account for this.

Furthermore, when comparing the TSMs, it was revealed that 121 samples did not need an iteration to converge the drag. This is odd, given the usually strong coupling between aerodynamics and propulsion. After careful inspection of the results, it was noted that certain combinations of spanwise kink position and kink taper ratio resulted in a wing with no kink at all. As a matter of fact, one can derive that following the wing parametrisation used in this chapter, the wing will not have a kink if

$$\lambda_k = 1 - (1 - \lambda)b_{kink}$$

This means that in the chosen design space, there is a region that describes a very similar, nearly kinkless, wing. This would explain the relatively low influence of the kink positioning in the explored design space, and why almost half of the samples in Scenario 3 did not require at least one iteration to converge.

Despite these limitations, the purpose of this test case was not to perform a valid design study, but to explore a one-on-one collaboration between an OEM and a supplier, and how CS and SA can support this process. It was therefore chosen to present the test case as it is. If anything, the flaws should serve as a reminder to carefully consider the implications of choosing a certain parametrisation, or which disciplines are affected if a design problem is expanded.

8

DEFAINE USE CASE: UAV MOVABLE DESIGN

To validate the proposed methodology and its feasibility in industry use, the framework was also applied to a use case in the DEFAINE project. This case was introduced in Section 6.1, and has been used to showcase the methodology and the implementation thereof to industry partners within the DEFAINE consortium. The use case mainly contained categorical variables, and was thus used to verify statistical power analysis as a sensitivity analysis method for non-numerical variables. The results of this analysis are presented in Section 8.1. Finally, to qualitatively assess the methodology, a questionnaire was created to gather the feedback of the DEFAINE consortium. The outcome of this questionnaire is discussed in Section 8.2.

8.1. SENSITIVITY ANALYSIS

In this case, sensitivity analysis was used to identify which choice of material, per component type, had the greatest impact on the mass of the movable. It was expected that the skin material is the most sensitive, considering that the majority of the movable mass originates from the skin. Since the material choices are categorical variables, statistical power analysis was used to perform the sensitivity analysis. The results are presented in Table 8.1. As can be seen, the P-value is lowest for the skin material choice. This means that, indeed, the skin material has the greatest likelihood of significantly affecting the mass of the movable. Performing sensitivity analysis in this manner can thus be a way to quickly identify the most sensitive design variables.

Variable	P-value
Skins material	0.055
Ribs material	0.104
Spars material	0.125

Table 8.1: Statistical power analysis on the DEFAINE movable use case.

8.2. QUALITATIVE ASSESSMENT

As the goal of this thesis was bridge the gap between collaborative workflows encountered in literature and current state-of-the-art in industry, the feasibility of the proposed methodology is an important aspect of the solution. To assess this aspect, a questionnaire was prepared by the author and answered by industry partners within the DEFAINE consortium. The questionnaire contained three parts: the first part inquired about the usage of the technology sharing methods, whereas the second part investigated the front-loaded methodology and the currently implemented features. The last part provided the partners the option to express what challenges they felt were not yet addressed by the methodology and its current implementation.

Table 8.2 represents the opinions of industry partners on the technology sharing methods considered in this thesis. The partners were asked how much they agreed with the presented statement, where strong agreement corresponds to a 5 and strong disagreement with a 1. An option to provide qualitative feedback was also provided.

Statement	Tabular data	Surrogate model	Remote access
This method is (or can be made) compliant with IP our regulations.	4.3	3.3	1.7
Using this method, the other party's tool can easily be integrated into my own workflow.	3.33	3.7	1.3
This method can reliably generate accurate data.	4	4.3	4.7
This method is feasible to implement in industry use cases, outside of research projects such as DEFAINE.	4	4.3	2.7

Table 8.2: Industry partner opinions on the technology sharing methods. Strong agreement corresponds to a 5 and strong disagreement with a 1.

Overall, the OEM and suppliers in the DEFAINE consortium largely shared the same opinions on these statements. As can be seen, the sharing of tabular data is considered the most compliant with current IP regulations. One argument against the use of SMs, was that SMs enable near infinite evaluation of designs, whereas currently, the number of designs to be evaluated by a supplier is strictly determined when agreeing on such a collaboration. On the other hand, it was said that SMs could be preferred to be shared over a table of results, due to the inherent uncertainty of the SM. There was thus no

unanimous preference in technology sharing method.

Ease of integration of the other partners design tool was ranked fairly low overall, indicating that closer collaborative workflows are still considered challenging to set up. All TSMs were considered able to generate accurate data, with remote access ranking as the most accurate option. However, IT related issues are considered the main objection against the use of remote access. The opening of data streams and installation of dedicated software to do so were mentioned as obstructions that render this method unfeasible for standard industry use.

Overall, the sharing of tabular data and sharing of surrogate models were considered a feasible way to facilitate collaboration. However, it was noted that "reliability of generated data can be related more to the correct use of models than to which of solutions is implemented".

Table 8.3 shows the results of the second part of the questionnaire. Here, the partners were asked to rank the usefulness of the modules in the presented methodology on scale from 1 to 10.

The results indicate that the module considered to be the most useful, is the workflow template capabilities. The creation of templates that can be instantiated to reduce the setup time of new design studies, is thus the most appreciated module. Ranked second are the data collection and visualisation capabilities. The data collection capability includes the ability to upload already available data to the collaborative environment, thereby front-loading the design process. Then, sensitivity analysis and CS were ranked equally, with the surrogate modelling capability ranked as the least appreciated. The surrogate modelling capability here refers to the ability to train a SM based on the data present in the collaborative environment, and not to the use of surrogate models as a TSM. Despite the lower ranking, it is important to consider that in order to execute an CS strategy, a SM must be trained.

Feature	Average score
Workflow template creation and instantiation	7.7
Automatic collection of results	7.3
(Interactive) visualisations of the results	7.3
Sensitivity analysis	6.7
Surrogate model training	6
Complementary sampling strategy	6.7

Table 8.3: Industry partner opinions on the collaborative front-loaded methodology. The aspects are rated in terms of usefulness on a scale from 1 to 10.

The last part of the questionnaire provided the possibility to list remaining challenges not addressed by the current methodology. The named issues were primarily related to IT infrastructure, but IP regulations were still mentioned as a challenge. This relates to the comments listed before regarding the technology sharing methods: despite these methods reducing the compromised IP, the contemporary IP protocols still prove a major obstacle in implementation. Whether the sharing of tabular data or sharing of surrogate models is the preferred method in terms of IP regulations, can be argued from both sides, and as such, no universal conclusion can be drawn. Moreover, the state-of-

the-art of collaboration does not consider workflows such as presented in this thesis, or even explored in recent literature. However, such workflows are considered beneficial in terms of project lead times/costs and market competitiveness, and so to employ them, changes in IP policies may be required.

Overall, feedback was positive and it is believed that the methodology can streamline the collaboration between OEMs and Tier-1 suppliers. Even if usage of SMs or RA as a way to facilitate cross-organisational tool utilisation is infeasible, the sharing of tabular data (which can be considered the current state-of-the-art) can also be used. Usage of a collaborative environment provides a way for OEMs and supplier to structure their collaborative designs studies, and streamline the request of design studies through the creation of workflow templates. Furthermore, the methodology presented a way for suppliers to front-load the design process by performing preemptive design studies. Available data could then straightforwardly be reused, improving the response time of the supplier and reducing the lead time of the OEMs design studies. Moreover, it was noted that "front-loading is an accelerator for higher-fidelity technologies, thereby enabling their usage in the conceptual design phase.". Applying front-loading principles thus enable usage of higher-fidelity design tools, which in turn enable a proper assessment of novel technologies, that can only be analysed with such tools. A final comment made about the framework noted "that outside of a collaborative environment, similar frameworks and engineering flows could be envisioned inside an organisation.". The front-loaded methodology was thus also considered useful outside of a collaborative environment.

9

CONCLUSIONS AND RECOMMENDATIONS

The goal of this thesis was to explore a closer collaboration between an OEM and their Tier-1 supplier, with the goal to accelerate the conceptual design phase. To do so, a methodology for collaborative front-loaded design space exploration was proposed. The goal of this methodology is to enable a closer collaboration between an OEM and their suppliers and exploit the collaboration to reduce design lead times and costs. The methodology was implemented in a collaborative environment and applied to a test case, as well as an use case within the DEFAINE research project.

To answer the research question of this thesis, the subquestions can be answered as follows:

- *How can a workflow where an OEM and a Tier-1 supplier collaboratively perform design space exploration be enabled?*

To facilitate the collaboration, several collaborative frameworks developed in recent research projects were investigated. Certain elements, such as the usage of a common data schema and workflow templates, were reused in this work. To enable the usage of design tools across organisations, technology sharing methods were investigated. The implications of these methods on existing workflows as well as their applicability in industry use have been researched in this work. It was found that both the sharing of tabular results and the sharing of a surrogate model result in a very small error compared to remote access, which is considered equivalent to having actual ownership of the tool. The margin of error was considered small enough to render all methods technically feasible for design space exploration in the conceptual design phase. However, the implications of the technology sharing methods should still be considered: if a strong coupling is known to be present among certain disciplines, the sharing of tabular data should be avoided as this renders usage of a convergence loop unfeasible. Furthermore, a survey among the DEFAINE consortium revealed that remote access is considered infeasible due

to the IT regulations present in the organisations. IP regulations are still considered the limiting factor in enabling a cross-organisational collaboration, and both the sharing of tabular data and a surrogate model can be argued as the preferred method.

- *How can the supplier provide the OEM with high quality data in a reduced lead time?*

To reduce the response time of suppliers, a methodology for design space exploration using front-loaded principles was developed. A front-loaded database allows the supplier to optimally reuse past results in future design studies. Visualisation of the database enables an intuitive method to inspect the database, and browse through the available designs. In particular, the parallel plot was considered useful due to its interactive implementation, allowing the users to dynamically filter through the data. Aside from the ability to identify trends and find designs through visualisation, the database presents the opportunity to analyse the results to support the design exploration process. The analysis methods proposed in this work were sensitivity analysis and a complementary sampling strategy. Sensitivity analysis proved a useful metric to quickly determine the most sensitive parameters, although manual inspection is still required to validate the results of the analysis. For numerical variables, HDMR analysis performed better than Sobol analysis with a small number of samples, and is thus considered the preferred choice for such use cases. The complementary sampling strategy proposed aims to take existing samples into account when generating a new sampling plan, avoiding the evaluation of similar samples and shifting efforts towards unexplored or critical regions of the design space. The complementary sampling plan generated in this work resulted in a higher quality data set compared to ordinary sampling methods, measured by comparing the accuracy of trained surrogate models. The methodology was well received among the DEFAINE consortium and could also be envisioned outside of a collaborative environment to streamline engineering workflows within an organisation. It was deemed that the front-loading principles accelerate the usage of higher-fidelity tools, thereby enabling them in the conceptual design phase. In turn, this enables the supplier to perform preemptive design studies, that reduce the required work when an OEM issues a request, thereby improving their response time.

Overall, the proposed methodology provides a practical guide to implementing a collaborative design space exploration in industry use cases. The implementation was set up in a general way, such that it can be tailored towards the specific interactions, particularly through the ability to create custom workflow templates.

However, the current IP regulations still remain as a challenge to overcome in such collaborations. Nevertheless, the methodology for front-loaded design space exploration could also be envisioned within an organisation to accelerate internal design studies. This could still improve the collaboration between OEMs and their suppliers if collaborative design space exploration is considered infeasible. To give an example, the supplier has the option to not only evaluate a single design for the OEM (as is the current state of the art), but also provide the sensitivities on uncertain parameters, thereby helping

the OEM in their design problem. Furthermore, the framework enables the supplier to perform preemptive DOE's in regions of interest and generate surrogate models, thereby reducing the response time when the OEM requests a design.

9.1. RECOMMENDATIONS

Based on the work performed in this thesis, several recommendations for future work can be made.

- *Expand the front-loaded methodology for optimisation workflows*

The methodology presented here was centred around design space exploration in the form of DOEs. The methodology can be expanded to include optimisation workflows as well, storing the results of such design studies in the front-loaded database. Moreover, the methodology can be expanded to exploit the front-loaded database when performing optimisation. For instance, the database could be searched (automatically) for an informed initial guess, potentially reducing computational time required for the optimisation. Alternatively, a surrogate model can be trained based on the database and used in the optimisation. Then, during the optimisation, the surrogate model can first be used to evaluate the sample at hand. If the variance of the evaluation is within a (configurable) margin of error, that output value is used and the (expensive) design tool is not called. This could further reduce the computational time required for optimisation.

- *Improve the complementary sampling strategy*

In this work, a complementary sampling strategy was proposed to exploit the database to generate more effective sampling plans for follow-up DOEs. The strategy proved more effective than ordinary sampling in such DOEs, but can still be refined to reduce clustering in the new sampling plan. Furthermore, the strategy currently relies on a certain ratio between the number of samples to include in the new sampling plan, and the number of samples to evaluate using the surrogate model trained for this strategy. A more in-depth investigation could be performed to find the ideal ratio for which this strategy works best, but a more effective approach would be to use a more sophisticated strategy, such that the user is no longer required to provide these values.

- *Find sensitivity analysis methods for mixed-variable design problems*

Finally, the sensitivity analysis methods presented here were only capable of assessing either numerical or non-numerical variables. As these methods resulted in different metrics (sensitivity indices for numerical variables, P-values for non-numerical variables), the results of these analyses could not be compared with each other. A method that could compare both types of variables could greatly increase the applicability of sensitivity analysis in mixed-variable design problems.

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A

IMPLEMENTATION OF PANAIR IN THE SSBJ TEST CASE

As mentioned, Panair was chosen as the higher-fidelity aerodynamics solver for this test case. Panair is openly available as Fortran 90 code¹. Panair can solve flows about arbitrary geometries and as such, the parametrisation of the design problem, shown in Table 7.2, must be transformed to a 3D geometry. To do so, first some parameters related to the top-down wing planform were derived, assuming the wing planform to take the shape of a trapezoid:

$$b = \sqrt{AR \cdot S_{ref}} \quad (\text{A.1})$$

$$c_r = \frac{2S_{ref}}{b(1 + \lambda)} \quad (\text{A.2})$$

$$c_t = \lambda c_r \quad (\text{A.3})$$

Note that the span of one wing is half of the total wing span b . To create a 3D geometry based on this planform, an airfoil must be selected. It was chosen to implement the NACA 64-206 airfoil², because of its usage on supersonic aircraft such as the General Dynamics F16 Fighting Falcon[72]. The airfoil was scaled to match the thickness to chord ratio as specified in the design problem.

Panair uses geometry that follows the Langley Wireframe Geometry Standard[73]. For this purpose, the pyPanair module, developed by GitHub user SaTa999, was used³. An example of a generated wing is visualised in Figure A.2a. Note that only one wing has to be generated, since symmetry can be imposed in the solver.

¹Available at <https://www.pdas.com/Panairdownload.html>

²Retrieved from <http://airfoiltools.com/airfoil/details?airfoil=naca64206-il> [Accessed 19-10-2023]

³Available at <https://github.com/SaTa999/pyPanair> [Accessed 19-10-2023].

With the original geometry able to be mapped into Panair, the design problem was expanded with the kink parameters, shown in Table 7.3. The variables were implemented in the following way:

$$b_{kink} = \frac{b}{2} \cdot b_{kink,nd} \quad (\text{A.4})$$

$$\Lambda_i = \Lambda \quad (\text{A.5})$$

$$c_k = \lambda_k c_r \quad (\text{A.6})$$

$$c_t = \lambda c_r \Rightarrow c_r = \frac{S_{ref}}{b_{kink}(1 + \lambda_k) + (\frac{b}{2} - b_{kink})(\lambda_k + \lambda)} \quad (\text{A.7})$$

The wing planform and its parameters are visualised in Figure A.1. The implementation of these new variables was chosen to minimise influence on the existing variables. A 3D geometry based on the expanded design problem is shown in Figure A.2b.

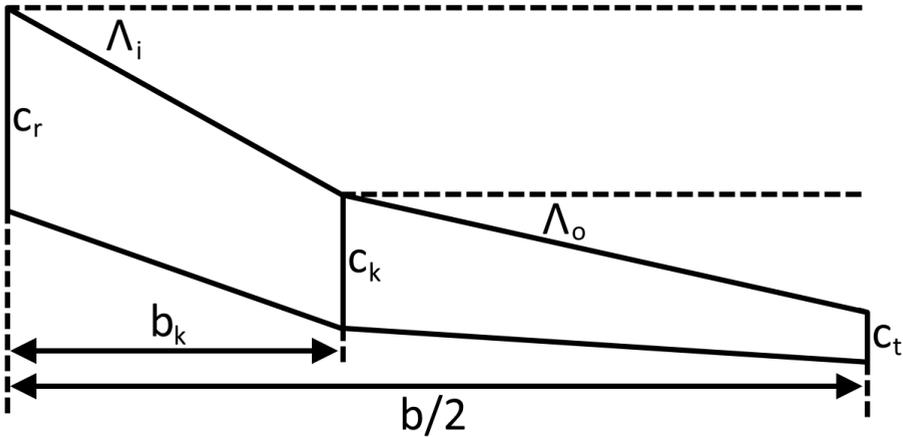
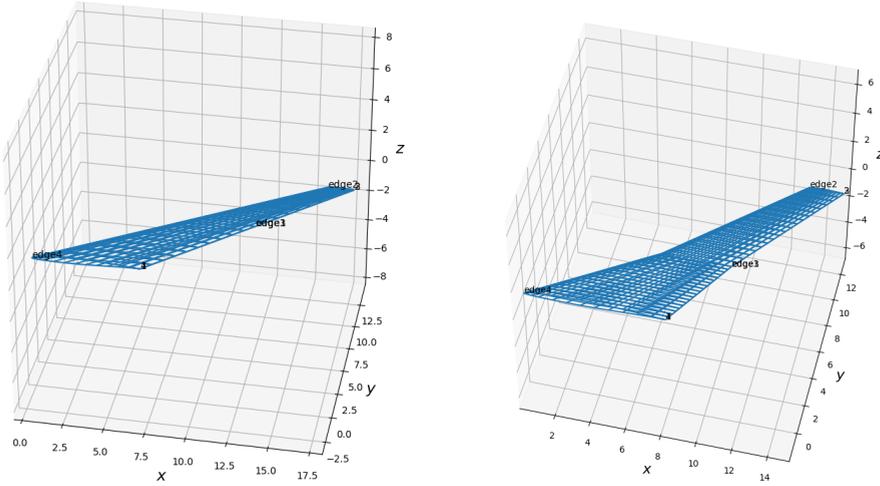


Figure A.1: Overview of the wing planform used in the SSBJ test case.

To analyse the geometry, an auxiliary file has to be generated, which describes the flow conditions. This is also handled by the pyPanair module. After the geometry and auxiliary file are generated, the files can be pre-processed by Panin⁴ and subsequently be analysed by Panair. Both of these programs are available as Fortran 90 code, and thus have to be compiled before they can be executed. This was done using Cygwin⁵ with the *gcc-core* and *gcc-fortran* packages installed. Once compiled, the programs can then be executed through the Cygwin terminal as well. To automate this process and call it from Python, a bash script was written. When Panair is executed, the results are dumped in a text file. The file can straightforwardly be read to retrieve the results. The generation of geometry, execution of Panin and Panair, and extraction of results were implemented

⁴Available at <https://www.pdas.com/panindownload.html> [Accessed 19-10-2023].

⁵Available at <https://www.cygwin.com/> [Accessed 19-10-2023].



(a) Geometry of the original design problem.

(b) Geometry of the expanded design problem.

Figure A.2: Examples of generated 3D geometries to be analysed by Panair.

in a Python module. This module thus enables a fully automated way to analyse a given wing under certain conditions.

However, to replace the aerodynamics solver in the SSBJ problem, additional functionality was required. The lower-fidelity solver sets the lift equal to the total weight of the aircraft, and then finds the drag corresponding to that lift using a drag polar. To add this capability to the new aerodynamics discipline, the angle of attack was systematically varied using a root finding algorithm on the function:

$$f(\alpha) = C_L(\alpha) - \frac{W_T}{0.5\rho V^2 S_{ref}} \quad (\text{A.8})$$

where $C_L(\alpha)$ was found using Panair and the other variables were derived from the input parameters. S_{ref} is directly used as an input variable, V was determined with the Mach number and speed of sound. The Mach number is part of the input parameters, and the flight altitude, also part of the input parameters, was used to derive the speed of sound and air density ρ based on ISA conditions[74].

After convergence, the drag can be extracted and returned to the user. This means that for a single evaluation of the new aerodynamic discipline, Panair had to be called multiple times sequentially. Nevertheless, the evaluation time of the discipline was roughly 15 seconds⁶, depending on the number of evaluations before convergence of Equation A.8 is reached. This evaluation time was significantly higher than those of the other disciplines, but it was still deemed usable for the purposes of this test case.

Considering that the optimisation problem concerns only the design of a wing, it was chosen to only have the wing modelled in Panair. However, the drag determined by the

⁶On a machine with an Intel i7 Quad core 2.8GHz processor and 16GB DDR4-2400MHz memory.

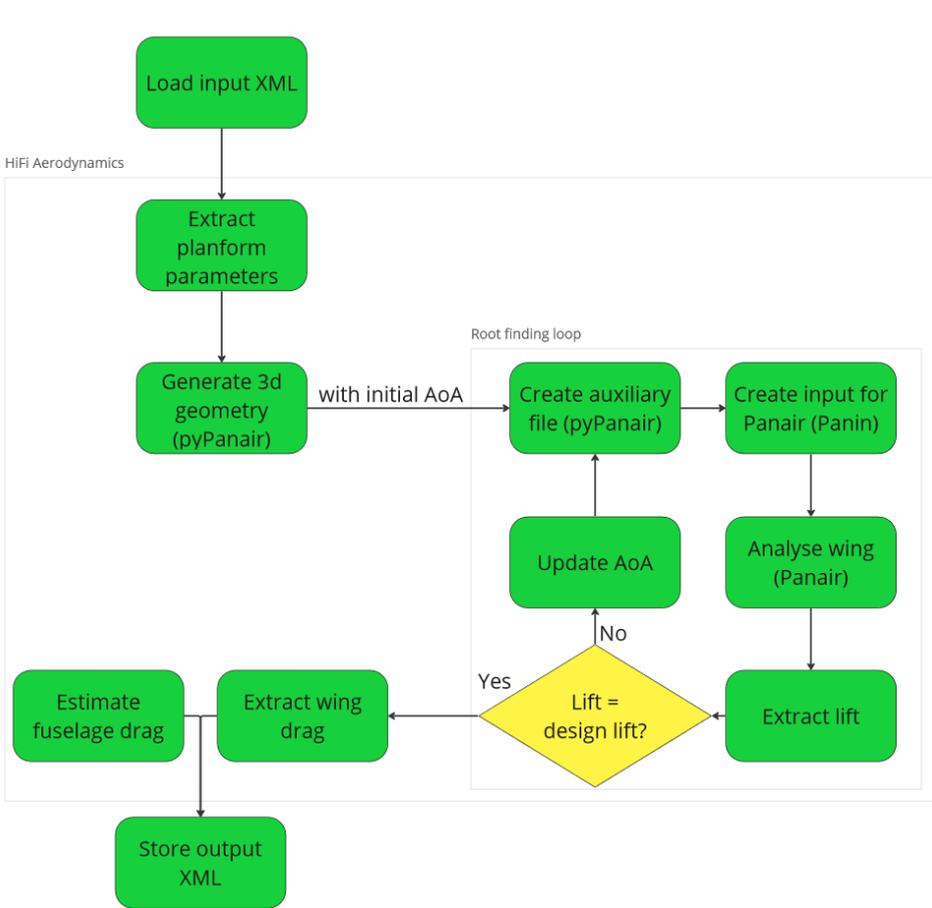


Figure A.3: Flow chart of the higher fidelity aerodynamic solver implemented in the SSBJ test case.

original aerodynamics discipline is the drag of the total aircraft, since the thrust in the propulsion module is set equal to this drag. For the validity of this test case, the fuselage drag should thus be modelled. To do so, empirical methods as described in [75] were used. Interference drag between the fuselage and the wing was assumed to be minimal and is neglected.

These functionalities were all implemented in a Python script, such that the higher-fidelity aerodynamics solver fulfills the same role as the lower-fidelity one, and can therefore directly replace the lower fidelity module. To fit the existing implementation, where every discipline in the test case extracts input from and writes output to XML files, wrapper functions were written. The tool is now ready, and an overview of all steps taken is presented in Figure A.3.

B

TEST CASE DIAGRAMS

The following pages contain the full XDSMs of the original SSBJ design problem and the DOE workflow with the higher-fidelity aerodynamics solver substituting the *Aerodynamics* module.

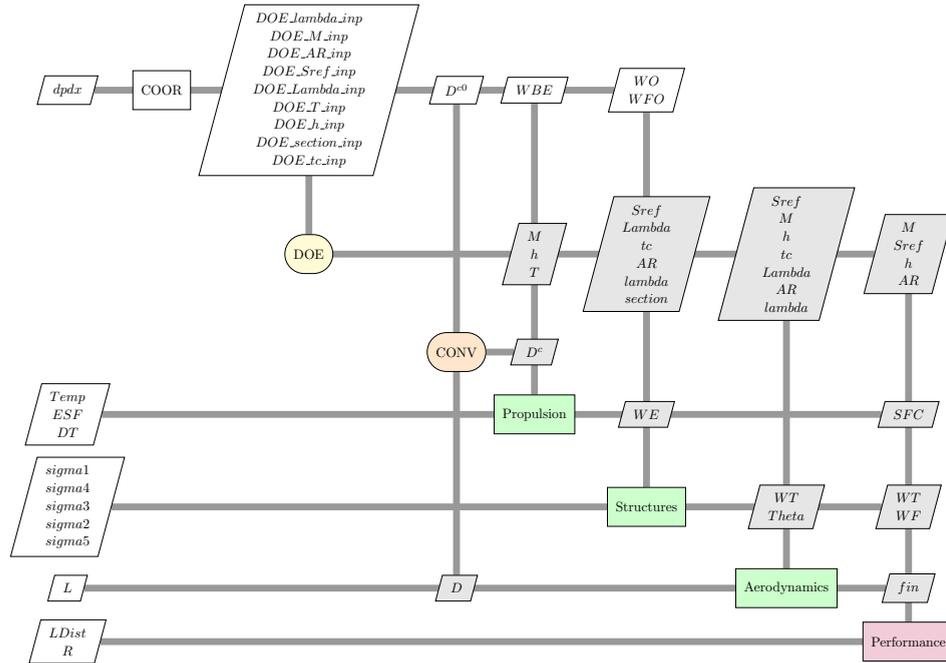


Figure B.1: XDSM of the original SBJ problem.

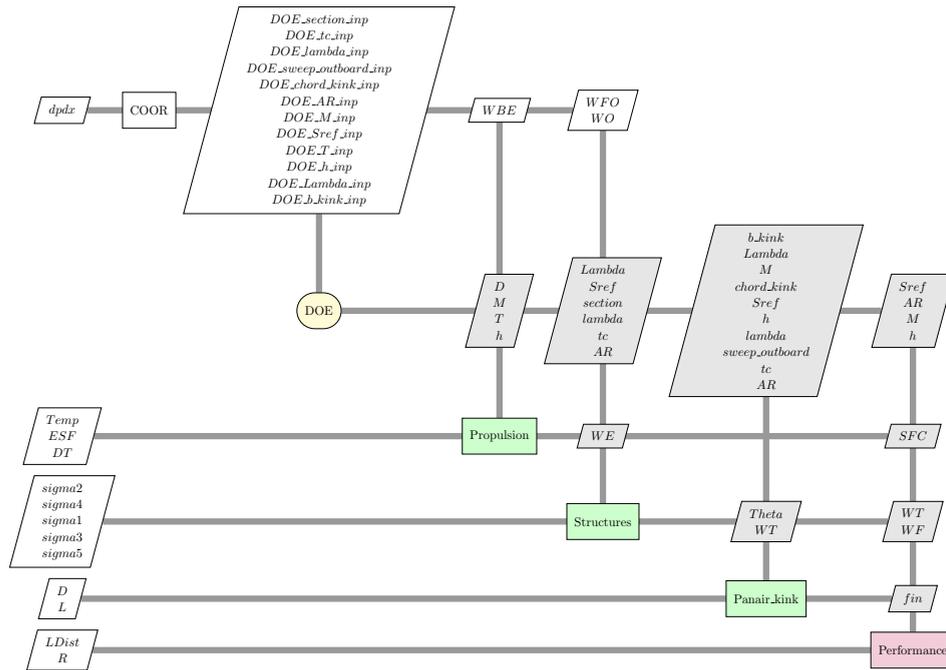


Figure B.2: XDSM of Scenario 1, with *Panair_kink* replacing the aerodynamics module. The workflow has been converted to an unconverged DOE, because a converged workflow is unfeasible when data is shared in batches.

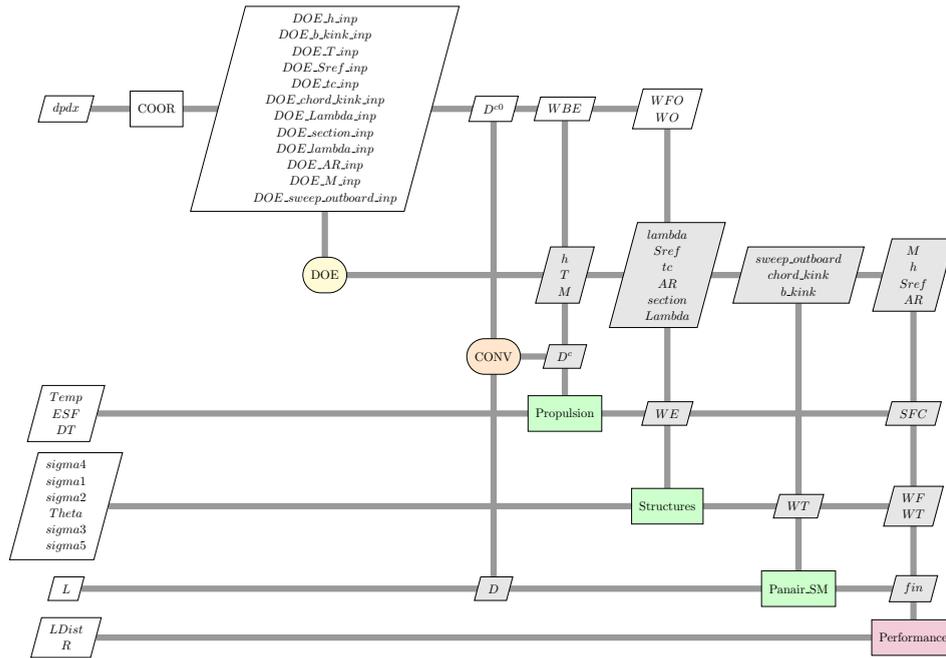


Figure B.3: XDSM of Scenario 2, with *Panair_SM* replacing the aerodynamics module. The surrogate model has been trained a dataset with varying kink parameters and total aircraft weight.

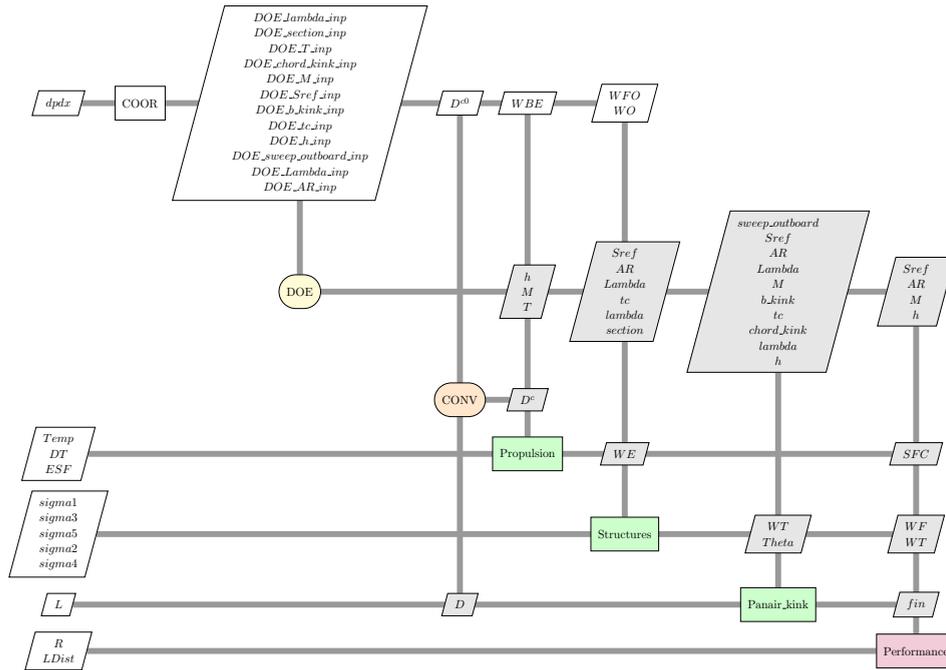


Figure B.4: XDSM of Scenario 3, with *Panair_kink* replacing the aerodynamics module. Remote access enables usage of the tool as if it was in the OEMs possession.