

D2.5 Front-loaded engineering process methodology

Author, company:

- Robin Augustinus, Fokker Elmo
- Max Baan, ParaPy,
- Gianfranco La Rocca, TU Delft,
- Bastiaan Beijer, KE-works
- Bas van Manen, Fokker Aerostructures

Version:

1.0

Date: February 7, 2024

Status:

Final

Confidentiality:

Public





Change log

Revision	Date	Prepared by	Checked by	Description
1.0	February 7, 2024	Robin Augustinus Bastiaan Beijer Bas van Manen Gianfranco La Rocca Max Baan	Bastiaan Beijer Max Baan	First version





Contents

Change	e log	2
Acronyr	ns	4
Acknow	/ledgements	4
1.	Introduction	5
1.1.	The need for front-loading	5
1.2.	State-of-the-art design processes	6
1.3.	Challenges	7
2.	Methodology Description	7
3.	Implementation example – aileron use case	11
3.1.	Front-loaded database	11
3.2.	Workflow generation	13
3.3.	Methodology evaluation	14
4.	Conclusion	15





Acronyms

Acronym	Definition
OEM	Original Equipment Manufacturer
DEFAINE	Design Exploration Framework based on AI for froNt-loaded Engineering
MDAO	Multi-disciplinary Design Analysis and Optimization

Acknowledgements

This research is partly funded by the ITEA 3 Call 6 project DEFAINE of the European Union.





1. Introduction

This document will describe the front-loading methodology created within the DEFAINE project. Chapter 2 will go through the steps needed to be able to prepare and perform front-loading for any use case. In addition, Chapter 3 will present an implementation example and go through the steps of the methodology and how they have been applied on the use case example. Finally, Chapter 4 will present some final conclusions.

1.1. The need for front-loading

The demand for air transportation has been increasing dramatically and is forecasted to grow further by 50% in the next 15 years¹. How to satisfy such demand, while dealing with the current (almost) saturated infrastructure and the increasingly stringent environmental constraints is the ultimate challenge. The European goals to reduce the emission levels of noise, CO2 and NOX by 65, 75 and 90%, respectively by 2050 are extremely ambitious and hardly realistic when considering the high technological level already achieved within existing aircraft programs, combined with the often-conservative approach of aircraft manufacturers. Whether and to what extent it is possible to improve the performance of existing aeronautical systems and how to assess the actual value of novel solutions and lower their development risk are key questions for industry, research institutes and academia.

A radically different product development process is necessary to address the increasing complexity of aeronautical products and processes, enhance designer's productivity and integrate knowledge and capabilities that are distributed within the company and across the supply chain. In the effort to maintain and extend industrial leadership, modern organizations have already started to significantly alter the nature of their engineering processes, moving, for example, from the old sequential development process to concurrent engineering processes.

The digital transformation has led to a steep increase in the adoption of automation tools. Software development platforms have become available, such as Knowledge Based Engineering (KBE) systems, that allow engineers to develop custom-purpose automation solutions for design activities not suitable for general purpose of-the-shelf tools. These tools offer engineers signification reductions in effort and lead-time of specific design tasks, albeit for a limited scope and limited conditions. Besides, the development of such automation solutions requires investments in terms of time and needed expertise. Multidisciplinary Design Analysis and Optimization (MDAO) is another methodology that is increasingly being adopted in industry to support designers in the exploration of the design space and effective search of optimal solutions, by means of numerical methods and coordination strategies to account and exploit the interactions of multiple disciplines. However, these methods, which rely on the availability of the aforementioned design automation solutions to generate the design options proposed by the optimizer, require major work in the formulation and integration of the computational workflows and computation time.

To fully exploit the novel engineering tools, automation efforts and the potential of MDAO, a new methodology is needed where engineering efforts are *front-loaded*, i.e. shifted towards the start of

¹ www.icao.int/, Long-Term Traffic Forecasts, 2018; www.airbus.com/aircraft/market/global-market-forecast.html, 2019





the design process, or even before the actual request for a new design from the customer. The aim of this methodology would be not only to reduce product development time, but also to lower the risk related to the adoption of new technologies and improve the collaboration between OEMs and suppliers.

1.2. State-of-the-art design processes

In the current design process, efforts are made to move from a sequential to a more concurrent design process. This product development approach still comes with inefficiencies, as parallel activities are started on the basis of assumptions, which eventually need to be adjusted and call for design re-iterations. By automating interfaces to analysis modules and by implementing a model-based approach to system design, it is possible to reduce the time to perform design iterations and even perform some limited optimization, as long as the architecture of the product to be designed is fixed and the goal is to size the components of such architecture. Figure 1 shows an example of how GKN Fokker Aerostructures applies model-based approach to movable design, including some of the corresponding analysis interfaces.

When multiple architectures need to be explored, which is the case when different combinations of product configurations, material and manufacturing processes are considered, the process complexity increases dramatically. A lot of manual work is required to adjust the various computational frameworks and the time to evaluate all possible architectures may become untenable. Having these manual actions in the process makes it inefficient as these steps can only be performed during office hours. Software licenses and computational resources are therefore not used for a large part of the day.

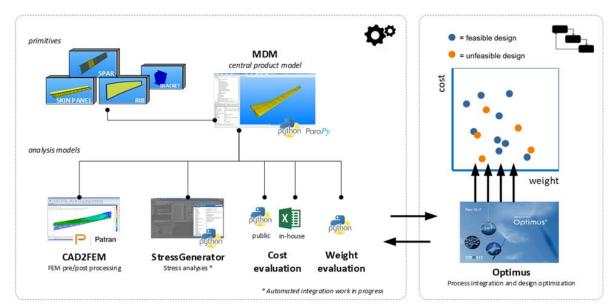


Figure 1 State-of-the-Art design process example from GKN Fokker Aerostructures





1.3. Challenges

Automation of engineering tasks is becoming more and more available. Although nowadays different development phases run concurrently and parts of the process have been digitized, the possibilities to perform large design space explorations and in-depth analysis of multiple product architectures within the available lead time are still very limited. This is due to the following challenges:

- The development of new products requires the involvement of multiple actors in the supply chain, however technical collaboration is hampered, among others, by inefficient approaches to share data and models, which are mostly based on manual exchange. For an OEM, limited accessibility to data and expertise from supplier can affect the capability to make well substantiated design decisions in the early stages of the process, while these decisions often have the largest impact on product performance. On top of that, it is very difficult to completely grasp the effect of design decisions since multiple teams and disciplines are involved in the process.
- The current setup lacks a framework to efficiently reuse readily available data and exploit them to the full extent. This means that previously created designs are rarely reused as a basis for new designs, thereby designs are always created on-demand, rather than anticipated.
- The lack of a fully automated design process results in inefficient use of licenses and computational resources, meaning the front-loading methodology cannot be used to its full extent. The inability to formulate multidisciplinary computational workflows (MDAO systems) that can quickly adapt to different design requirements and architectures further limit the scope and applicability of front-loading.

2. Methodology Description

DEFAINE delivers a novel design exploration framework that enables large-scale exploration of designs and data analysis to analyse the designs and mine new knowledge and flexible modelling tools to infuse the engineering applications and processes with the new knowledge. This framework enables design and manufacturing companies in high-tech industries to adopt a product development process based on front-loaded principles. Such framework enables the efficient generation of a large number of designs, including multiple architecture options, in the early stages, or even before the start, of a new project. The achieved front-loaded process not only significantly reduces the inefficiencies of the concurrent engineering approach generally applied in industry, but goes beyond the front-loaded development process prototyped in the seminal project IDEaliSM. The methodology developed in IDEaliSM² was based on constant workflows and engineering services, thus suitable for single product architecture studies and limited in its capability to automatically generate new designs based on a set of previously generated (front loaded) designs. The ability to efficiently involve multiple stakeholders in the development process was also limited, although sufficient for a proof of concept.

The novel design space exploration developed in DEFAINE can be fed with a multitude of possible requirement sets, on the base of which computationally efficient multidisciplinary

² https://idealism.ifb.uni-stuttgart.de/





engineering workflows are automatically formulated and executed, generating and storing a large set of design solutions. These design solutions are then used to train efficient surrogate models that can capture the trends in the design space, self-evaluate their accuracy and automatically improve it accordingly, and generate, on demand and with little computation time, new design solutions not included in the initial set of designs.

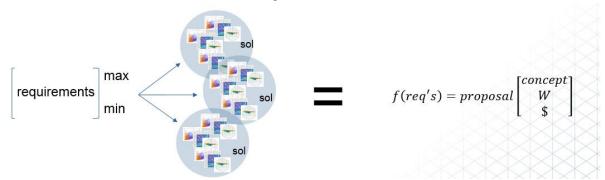


Figure 2: Abstract view of the major goal of the frontloaded design process: expressing the characteristics of a dataset of front-loaded solutions in a functional relation³

With the help of techniques from the field of Artificial Intelligence, DEFAINE extends the IDEaliSM front-loaded process further, by analysing the resulting design data to discover trends and relations as function of the varied requirement sets. The general principle of this novel, "AI-enriched" front-loaded development process is depicted in Figure 3.

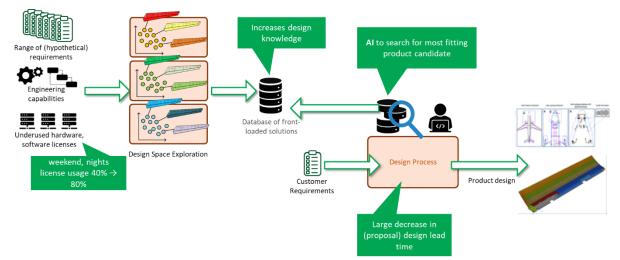


Figure 3: Principle of AI-enriched front-loading development process.

In the "AI-enriched" front-loaded development process simulation workflows are deployed to explore by sampling specified portions of the design space. This process can be performed by a company in a proactive manner, i.e. before the actual start of a design project. In this way, hundreds of design points can already be generated and stored in a database of front-loaded solutions. The automatic generation of these design points can be performed without any designer involvement, any time, any day, thereby maximizing the utilization of licences and hardware. Data analytics and surrogated model techniques, based on AI approaches, are used to identify design

³ GKN Fokker Aerostructures - Mission to the moon whitepaper





space trends, sensitivities and predict new design points, including an estimation of their accuracy. If necessary, a predicted design point can be analysed in more detail, by triggering a new analysis and optimization workflow, whose outcome can be used also to improve the existing surrogate model.

As all the designs stored in the database include multiple performance indicators, such as mass, cost, risk, etc.., once a new design is required, it is possible not only to quickly produce one solution, but a set of solutions, arranged on a Pareto front. Besides, for each design solution it is possible to estimate the sensitivity to the design requirements. These two options in particular, would enable a Tier 1 supplier to respond to a design request from an OEM in a much more proactive and comprehensive manner, thereby strengthening her position in the supply chain.

As all the designs stored in the database include multiple performance indicators, such as mass, cost, risk, etc.., once a new design is required, it is possible not only to quickly produce one solution, but a set of solutions, arranged on a Pareto front. Besides, for each design solution it is possible to estimate the sensitivity to the design requirements. These two options in particular, would enable a Tier 1 supplier to respond to a design request from an OEM in a much more proactive and comprehensive manner, thereby strengthening her position in the supply chain.

A number of methodological and technological solutions are at the base of the DEFAINE framework to enable front loading, including the following:

- **Design of Experiments (DoE)** methods, including adaptive versions, to efficiently and effectively sample the design space.
- **Surrogate models** to 1) create efficient models of the design space, both for visualization scope, as well as for fast estimation of new designs not included in the DoE; 2) replace computational expensive (set of) tools. **Advisory capabilities** solutions have been developed to help users identifying the most convenient surrogate modelling strategy for a given multidisciplinary analysis and optimization workflow, and automatically implement them [D4.1.2]
- **Diagnostic and assessment methods** to evaluate the accuracy of the generated surrogate models, the reliability of design points extracted from the surrogate, as well as the **sensitivity of the generated designs** w.r.t. the set requirement and design parameters.
- Infill techniques to improve the global and local accuracy of generated surrogate models
- Advanced **data visualization techniques** to help designers making sense of the large amount of data generated for each design and help them selecting relevant design and design sets.
- **Dynamic workflow** formulation and execution methodologies, to enable architecture design explorations and design studies where the number and type of design variables, analysis tools and constraints is allowed to change within the same workflow execution process [D4.1.3]
- Various **data standard** to enable storage, communication and exchange of design study set up's, workflow formulations [D4.2.1] and product configurations
- **MBSE approach to model requirements** and verification methods and map them on the components of the MDAO workflow, to enable requirement traceability, automated verification, as well as requirement-driven product optimization

The following KPIs are directly impacted by the enabled front loading approach:





- KPI 6.1 & 6.2: Improved quality of generated design solutions
- KPI 4: improved exploration of the design space
- KPI 7: improved ability of OEM and supplier to quickly perform substantiated trade-off decisions, shortening lead times





3. Implementation example – aileron use case

GKN Fokker Aerostructures is a specialist in the design of metallic and composite aeronautical structural components such as wings, fuselages and empennages. In one of the DEFAINE use cases, the conceptual design of an aileron is covered. The conceptual design process includes architectures and material trade-offs and sensitivity studies. The objective of the use case is to apply the DEFAINE front-loading methodology to the design process of an aileron, where the initial design request originates from SAAB for the design of an aileron for a new UAV.

The aileron considered for this use case consists of skin panels, ribs, spars and brackets. Several requirements are imposed on the aileron design, such as stress, cost and mass requirements. The design and sizing will be performed using the Multidisciplinary Modelers (MDM) application of Fokker Aerostructures.

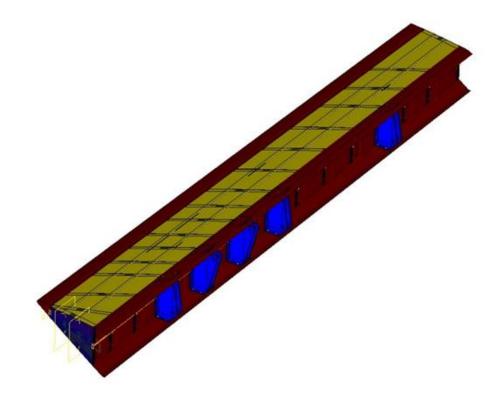


Figure 3: Aileron design as generated by the MDM application

The methodology described in Chapter 2 is applied to the aileron design of Fokker Aerostructures (as illustrated in Figure 3). The methodology implementation consists of two parts: Using AI to predict an aileron design and using the automatic multi-architecture workflow to populate the database.

3.1. Front-loaded database

Once the design request from SAAB arrives and the initial wing design is shared, GKN Fokker Aerostructures can start by using previously generated front-loading results as well as creating new Design Space Exploration workflows to further populate the database with aileron design variants. On top of the initial movable design, the database is populated with other variants to investigate the





impact of different technologies on the movable design. Since this process is automated, very limited human interaction is required. In this step, the previously underused hardware can now be used to almost non-stop size and analyse different variants of the aileron. By enabling design space exploration early in the conceptual design phase (when conceptual decisions are not yet made), the front-loaded data can be used to fully explore different design options when time is crucial.

This can be done by directly selecting a design point from the database, or by using the implemented AI-algorithms within commercial off the shelf tools to predict a cost and mass based on the data from the database.

	untituded environment develo	privertl - Development GKN Fokker	Ampthattans							
		study - including sp								
	senerate design a	study - including ap	int alleron						2 NO ASSIGNEES	EVALUATE RESULTS
-									El marcona tere	
Evo	eriments			3 ccu						
cxp	ennents									a 1
	Experiment	case_id	timit_toor	tip_lenit	hings_fractione	hinge_moment (Nm)	number_of_ribs	mass (kg)	cost (\$)	configuration
Q		case_id defaine_saab	root,Javit 0.65	tip_lenit 0.75	hings_fractions [0.2, 0.75]	hinge_stoment (Nm) 300	number_of_nbs 24	mass (kg) 7.81	cost (5) 3,497.78	
	Experiment									
	Experiment Experiment 0051	defaine_saab	0.65	0.75	[0.2, 0.75]	300	24	7.81	3,497.78	
	Experiment Experiment 0051 Experiment 0052	defaine_saab defaine_saab	0.65	0.75	[0.2, 0.75] [0.2, 0.75]	300 300	24 24	7.81	3,407.78 7,487.22	
	Experiment Experiment 0051 Experiment 0052 Experiment 0053	defaine_saab defaine_saab defaine_saab	0.65 0.65 0.65	0.75 0.75 0.75	[0.2, 0.75] [0.2, 0.75] [0.2, 0.75]	300 300 300	24 24 24	7.81 6.74 7.68	3,407.78 7,487.22 8,581.46	
	Experiment Experiment 0051 Experiment 0052 Experiment 0053 Experiment 0054	defaine_saab defaine_saab defaine_saab defaine_saab	0.65 0.65 0.65 0.7	0.75 0.75 0.75 0.8	[0.2, 0.75] [0.2, 0.75] [0.2, 0.75] [0.2, 0.75]	300 300 300 300	24 24 24 24 24	7.81 6.74 7.68 7.31	2,497.78 7,487.22 8,581.46 3,404.17	
	Experiment Experiment 0051 Experiment 0052 Experiment 0053 Experiment 0054	defaine_saab defaine_saab defaine_saab defaine_saab defaine_saab	0.65 0.65 0.7 0.7	0.75 0.75 0.75 0.8 0.8	[0.2, 0.75] [0.2, 0.75] [0.2, 0.75] [0.2, 0.75] [0.2, 0.75]	300 300 300 300 300	24 24 24 24 24 24	7.81 6.74 7.68 7.31 6.39	3,407.78 7,487.22 8,581.46 3,404.17 7,443.49	
	Experiment Experiment 0051 Experiment 0052 Experiment 0054 Experiment 0055 Experiment 0056	defaine_saab defaine_saab defaine_saab defaine_saab defaine_saab defaine_saab	0.65 0.65 0.7 0.7 0.7	0.75 0.75 0.8 0.8 0.8 0.8	[0.2, 0.75] [0.2, 0.75] [0.2, 0.75] [0.2, 0.75] [0.2, 0.75] [0.2, 0.75]	300 300 300 300 300 300	24 24 24 24 24 24 24	7.81 6.74 7.68 7.31 6.39 7.18	3,497.78 7,487.22 8,581.46 3,404.17 7,443.49 8,507.67	
	Experiment Experiment 0051 Experiment 0052 Experiment 0053 Experiment 0055 Experiment 0056 Experiment 0057	defaine_saab defaine_saab defaine_saab defaine_saab defaine_saab defaine_saab defaine_saab	0.65 0.65 0.7 0.7 0.7 0.35	0.75 0.75 0.8 0.8 0.8 0.8 0.8	(0.2, 0.75) (0.2, 0.75) (0.2, 0.75) (0.2, 0.75) (0.2, 0.75) (0.2, 0.75) (0.2, 0.75) (0.2, 0.5, 0.76)	300 300 300 300 300 300 300	24 24 24 24 24 24 24 25	7.81 6.74 7.68 7.31 6.39 7.18 11.38	2,497.78 7,487.22 8,581.46 3,404.17 7,443.49 8,507.67 4,324.19	
	Experiment Experiment 0051 Experiment 0052 Experiment 0054 Experiment 0055 Experiment 0056 Experiment 0056	defaine_saab defaine_saab defaine_saab defaine_saab defaine_saab defaine_saab defaine_saab defaine_saab	0.65 0.65 0.7 0.7 0.7 0.35 0.35	0.75 0.75 0.8 0.8 0.8 0.45 0.45	[0 2, 0.75] [0 2, 0.5, 0.75] [0 2, 0.5, 0.75]	300 300 300 300 300 300 300 300	24 24 24 24 24 24 25 25	7.81 6.74 7.66 7.31 6.39 7.18 11.38 9.53	2,497.78 7,487.22 8,581.46 3,404.17 7,443.49 8,507.67 4,324.19 8,183.28	
	Experiment Experiment 0051 Experiment 0052 Experiment 0054 Experiment 0055 Experiment 0056 Experiment 0058 Experiment 0059	defaine_saab defaine_saab defaine_saab defaine_saab defaine_saab defaine_saab defaine_saab defaine_saab defaine_saab defaine_saab	0.65 0.65 0.7 0.7 0.7 0.35 0.35 0.35	0.75 0.75 0.8 0.8 0.8 0.8 0.8 0.8 0.45 0.45 0.45	[0 2, 0, 75] [0 2, 0, 5, 0, 75] [0 2, 0, 5, 0, 75] [0 2, 0, 5, 0, 75]	300 300 300 300 300 300 300 300 300	24 24 24 24 24 25 25 25 25	7.81 6.74 7.66 7.31 6.39 7.18 11.38 9.53 11.19	3,447,78 7,487,22 8,581,46 3,464,17 7,443,49 8,567,47 4,324,19 8,182,28 9,475,39	
	Experiment Experiment 0051 Experiment 0052 Experiment 0054 Experiment 0055 Experiment 0056 Experiment 0056 Experiment 0059 Experiment 0059	defaine_saab defaine_saab defaine_saab defaine_saab defaine_saab defaine_saab defaine_saab defaine_saab defaine_saab defaine_saab defaine_saab	0.65 0.65 0.7 0.7 0.35 0.35 0.35 0.35 0.35	0.75 0.75 0.8 0.8 0.8 0.8 0.8 0.45 0.45 0.45 0.5	(0.2, 0.75) (0.2, 0.75) (0.2, 0.75) (0.2, 0.75) (0.2, 0.75) (0.2, 0.5, 0.75) (0.2, 0.5, 0.75) (0.2, 0.5, 0.75) (0.2, 0.5, 0.75)	300 300 300 300 300 300 300 300 300	24 24 24 24 24 25 25 25 34	7.81 6.74 7.66 7.31 6.39 7.18 11.38 9.53 11.10 15.80	3,447,78 7,447,22 8,581,46 3,464,17 7,443,49 8,507,67 4,324,19 8,507,67 4,324,19 8,475,59 5,641,00	

Figure 4: Front-loaded database with aileron designs

~	Forms	©TASKS ∏PROJECTS							
			VISUALIZATIO	N SENSITIVITY ANALYSIS	PREDICTION	ADAPTIVE SAMPLING			
Variab	ble								
Select	t variables for surrog	ate model							
Input vari	riables	hinge_moment , root_limit , tip_limit +							
Output va	ariable	mass	Ċ						
Conparti									
Genera	rate surrogate mode	- SMT update			Predict with s	urrogate model - SMT update			
Otx	Terminated a	fay ago.			OEXECUTE	Terminated a day ago.			
	dicting for sample (1/7): :	Sample							
ADD	CLONE EDIT	DELETE						4	4 1
		Sample 2	hinge_moment	root_limit		tip_limit	mass	mass_variance	
	RFILTERS	Sample	300	0.55		0.65	8.190159068739025	0.05040512064901981	
CLEAR		Sample		0.55					
		Sample	1000	0.55		0.85	10.30383755697987	0.4636156818759925	
CLEAR						0.85	10.30383755697987 7.9838105092010005	0.4636156818759925 0.06553989909010102	
CLEAR Sample		Sample	1000 500 300	0.7 0.55 0.35		0.65 0.45	7.9838105092010005 10.398646354605448		
CLEAR	oment Max	Sample Sample Sample Sample	1000 500 300 1000	0.7 0.55 0.35 0.55		0.65 0.45 0.8	7.9838105092010005 10.398646354605448 19.686190529848425	0.06553989909010102 0.0655116180996125 0.08062917127168448	
CLEAR Sample hinge_mor Min root_limit	t Max	Sample Sample Sample Sample Sample	1000 500 300 1000 300	0.7 0.55 0.35 0.55 0.65		0.65 0.45 0.8 0.8	7.9838105092010005 10.398646354605448 19.686190529848425 9.943192326796296	0.06553989909010102 0.0655116180996125 0.08062917127168448 0.05545545305815826	
CLEAR Sample hinge_mor Min	Max	Sample Sample Sample Sample	1000 500 300 1000	0.7 0.55 0.35 0.55		0.65 0.45 0.8	7.9838105092010005 10.398646354605448 19.686190529848425	0.06553989909010102 0.0655116180996125 0.08062917127168448	

Figure 5: Running algorithms to predict design points and inspecting the results





3.2. Workflow generation

Based on desired ranges of design variables, new data points can be automatically generated and added to the existing database. A design study can be initiated from KE-chain, where the key parameters are defined. The design variables are chosen, and their range is defined, as well as the objectives and constraints for the design study. Finally, the type of workflow is configured, which can be a Design of Experiment or an optimization. The workflow is automatically generated and started by a Fokker Aerostructures engineer. The process of automatically generating the workflow using KADMOS is visualized in Figure 6. While the workflow is running, calculated design points are uploaded live to the database. With this new information, SAAB can either select a point from the database or predict a new point with the AI algorithms explained in the previous section.

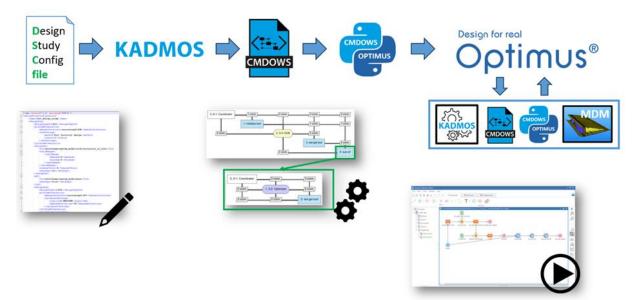


Figure 6: Process of automatically generating a workflow using KADMOS

an vit	BFORMS CTASKS DPROJECTS							4 🛛			
4년 Users 덴 Data schema defini	Parameter definition										
t∲- Design studies	Design variables (continuous)										
🗵 Analysis module	ADD EDIT DELETE						≙ ∂	¥ 🗄			
	Q. Design variable (continuous) Data schema refe No results found	rence Upper bound	Lower bound	Nominal value	Selection variable?	Data type	internal data mode	el			
	Design variables (list based)						£ d	•			
	Q Design variable (list based) No results found	Data schema reference	List options	Nominal value	Selection variable?	Data type	internal data mode				
	Constraint variables										
	ADD EDIT DELETE							4 🗉			
E Templates	Q Constraint No results found		Data schema reference	Constraint operator	Reference value	Selection constraint?	Internal data mode	el.			
Explorer Scripts	Objective variables										
Scripts	ADD EDIT DELETE						æ 8				







14

3.3. Methodology evaluation

A significant factor in the design process is the little time available before design choices need to be made. This often limits the number of designs variants that can be explored, potentially leading to a sub-optimal design. The front-loaded methodology proposed in this document enables a significantly higher usage of computational resources and enables the front-loading of design points before all design requirements are established. Using response surface modeling techniques and AI algorithms, the entire design space can be mapped with high accuracy. The resulting RSMs are used to quickly evaluate design variants in the design process, while only the final solution is analyzed natively. Not only does this result in a more optimal design in terms of mass and weight, the sensitivity and robustness of the design is much more known, meaning impact of design changes can be anticipated. Shifting computational efforts to before the start of the design process, when there is more time, results in a more extensive analysis of design variants in the actual design process.





4. Conclusion

This document has presented a front-loaded product development methodology which started development within the ITEA IDEaliSM project and has been expanded on within the DEFAINE project.

Using this front-loaded methodology should enable any owner of a complex Engineering design problem to pick their set of suitable tools with which to execute the front-loaded methodology. Within this methodology, different technologies are combined such as response surface methods, design space exploration, as well as smart use of data, predictive generation of hypothetical designs and re-use of data.

Using these technologies enables acquisition of additional design knowledge through analysis of front-loaded design results, as well as the sensitivity of design parameters within different parts of the design space. In addition, having the front-loaded design results ready will drastically increase the speed at which OEMs can be supported with conceptual design decisions, through data or RSMs already being present beforehand.

Finally, this document has shown an implementation of this front-loading methodology on a use case presented by GKN Fokker Aerostructures, showing the real-life potential of this methodology and how the benefits within this use case came to life. This use case showed a significant decrease in lead time and increase in the amount of design variants that can be evaluated, through use of the DEFAINE front-loading methodology.

