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Empirical Performance Evaluation in Collaborative Aircraft Design Tasks

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Abstract The overarching goal at the Integrated Design Laboratory (IDL) is to understand the mechanisms of decision making and exchanges among engineers. In this study a toolbox for the assessment of engineering performance in a realistic aircraft design task is presented. It allows for the assessment of participants in different experimental conditions. The degree of task difficulty and the amount and quality of visualization are systematically varied across conditions. Using a graphical user interface the participants' mouse trajectories can be tracked. This data together with performance evaluation of the generated aircraft design can help uncover details about the underlying decision making process. The design and the evaluation of the experimental toolbox are presented. This includes the number, specificity, and ranges of design variables that can be manipulated by a participant. The major difficulty thereby is to find a "sweet spot" where the task is just difficult enough, such that participants display a progress in their performance. Too easy or too difficult of a task would lead to flooring or ceiling effects, where most participants will always fail or, respectively, perform perfectly. The decisions about the aircraft design parameters are therefore based on a numerical analysis of the design space. With this analysis nonlinearities and interdependencies of design parameters are revealed. The experimental toolbox will be utilized to measure design performance of individuals and groups. The results are expected to reveal ways to support multidisciplinary collaboration.

Keywords. Aircraft design, collaborative engineering, empirical performance evaluation, multidisciplinary collaboration

Introduction

Engineering graduates, when starting their professional careers, will face a challenge they most likely are not yet familiar with. They will need to work in multidisciplinary teams and thereby interact with experts whom they do not share a common understanding and often not even a common technical language with. This is not just an individual challenge, but also a real problem in many engineering projects. Progress is often slow and difficult due to the sheer complexity in many current day projects [9]. For example, aircraft design requires of engineers external exchanges with stakeholders like airlines

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and governments to specify design projects. Projects then typically require that experts from diverse Science, Technology, Engineering, and Mathematics (STEM) fields collaborate on a high technical level.

Researchers at the Institute for Air Transportation Systems work exactly at both these levels of external and internal cooperation. Externally, they cooperate closely with stakeholders like airports, airlines, aircraft and air traffic management to develop holistic understanding of air-transportation. Internally, this knowledge provides significant constraints for aircraft design projects within the the German Aerospace Center (DLR). The holistic understanding provides a framework for integrative aircraft design. In particular it allows to (a) coordinate contributions from different DLR projects and (b) provide unified software tools to serve the multitude of sub-projects. The day-to-day practice of high-level integrative work exposed the need to gain explicit knowledge about the mechanisms of collaborative engineering. This realization is shared with Ilan Kroo and Juan Alonso at Stanford University, who proposed a third generation multidisciplinary aircraft design view, highlighting the need for understanding decision processes in multidisciplinary teams [cite]. We consider the improvement of collaboration among engineers from different subdisciplines and between engineers and stakeholders as a major challenge toward improving engineering education and toward providing conditions for better engineering practice and success. Toward that end, the goal of this paper is to address the question of how engineering performance can be assessed. Note that to limit the scope, the focus will be on methods that measure individual performance, which later should be extended for collaborative engineering. Understanding engineering performance is clearly an empirical question that needs to be addressed with methods from the psychological and sociological sciences.

1. Related Research

Engineering practice is a very complex endeavor that is difficult to study, even more so when it comes to the field of air transportation systems which is complex in its own right [9]. Diverse innovative methods emerge from educational research, for instance, [11] developed a method to introduce multidisciplinary collaboration on project-based teaching such that diverse STEM disciplines can be learned successfully in concert. From an analysis of skill-requirements of newly graduated engineers, [8] deduce guidelines for the graduates' further professional education. By observing engineering students over multiple design sessions, [10] propose how a design tasks sequence can be structured to facilitate creativity.

Creativity is critical to engineering practice because it involves exploration and innovation. Standard approaches, however, have been developed to assess routine work, as [1] argue. Thus, the authors develop novel methods to observe and analyze engineers in their natural work environment. Creativity, on the other hand, has been well studied in laboratory settings (cf. [12] for a review), and there are ideas how standard methods from creativity research can be applied to study professional practice (entrepreneurship in that case) [5,13]. The design process, in contrast, has hardly been studied experimentally. A literature search yielded only two studies [2,7]. Both provide only first insights how to correlate performance measures with other behavioral or biological data; both however are insufficient in that they test a single condition and thus do not identify how external factors may influence behavior.

The picture painted, from the approaches mentioned so far, is that scientists are just begging to develop empirical methods to reveal the process of design. Creating research standards to assess collaborative engineering performance is, in fact, a critical scientific challenge. Researchers at the Institute of Air Transportation Systems are currently embarking on tackling this challenge and seek to introduce methods of cognitive science to investigate the process of engineering. This paper is about the prerequisites and technical challenges and solutions of developing novel experimental studies.

2. Prerequisites for Experimental Research

2.1. Integrated Design Laboratory

The Institute for Air Transportation Systems has established the Integrated Design Laboratory (IDL) in 2012. The IDL is dedicated to investigate aspects of collaboration in the air transport system thus emphasizing the "experimental" or laboratory character within its premises and research staff [4]. Its capacious main room of about 190 m^2 comprises technical equipment such as a large high-resolution display wall, several secondary display sytems for stereo-projection and for touch-sensitive computer interaction, advanced wireless inertia-triggered remote input devices, and diverse presentation support tools.

The IDL is designed and equipped for maximum flexibility in order to support a wide range of work sessions that might require different seating arrangements, number of participants, type and duration of meetings, and moderation styles. Integrated, movable and easily network-enabled working desks and on-site computing facilities support ad-hoc collaborative design tasks to the degree of purely technical feasibility. However, provided this technical environment is only as powerful as the experience and methods which are put to practice. Of course, acceptance and knowledge about the opportunities available need to be communicated and cultivated, which leads directly to future experimental research that will be performed in the Integrated Design Lab.

2.2. Experimental Software Tools

To keep laboratory investigation close to actual work scenarios, experimental studies are based upon VAMPzero [3,6], which is the current software tool used to study preliminary aircraft design configurations at DLR. VAMPzero calculates a mass-breakdown and global performance data by using a mix of statistic (handbook) and low-fidelity physical methods and models. Calculations are initialized with a data set comparable to the Airbus A320 airplane.To create new designs, control parameters in the data set are modified and VAMPzero is re-run.

Participants in the experiments will use VAMPzero through a Graphical User Interface (GUI), as illustrated in Figure 1. The GUI is programmed in MATLAB®, through which parameters are communicated with VAMPzero. The GUI serves several important roles for experimentation. Firstly, and important for the experimental design, only a specified number of control parameters within predefined ranges can be controlled. To avoid confusion, please note that the notions "control parameters" and "control variables" are used in two different but related contexts: (a) the participants define their designs by setting *control parameters* via the GUI; and (b) the specific number, initial

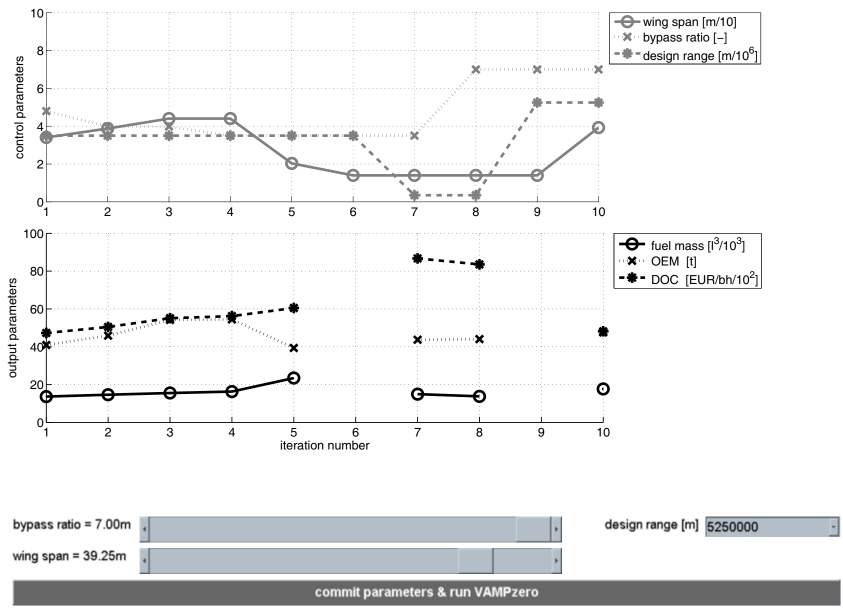

Figure 1. GUI to interact with aircraft design software tool VAMPzero. Control parameters can be changed (pseudo-)continuously or in discrete steps with the sliders and the drop down menu, respectively. When pressing the large red button at the bottom of the screen, these values are passed on as inputs to the a VAMPzero iteration. When the calculation is complete, the control parameters (y-axis, top plot) and resulting output parameters (y-axis, bottom plot) are displayed against the iteration number (x-axis). The results are left empty (here, iterations number six and nine) when the control parameters specify an infeasible aircraft (i.e., VAMPzero does not converge).

setting, and ranges of the control parameters are *control variables* of the experimental design, through variation of which different experimental conditions can be compared.

Secondly, the GUI provides participants with critical feedback about their designs. Like the control parameters, both design goals as well as the amount of visualization are critical factors in the experimental design. All these can be control variables that when manipulated create different experimental conditions.

Thirdly, the GUI is a simple interface that participants can intuitively interact with. An easy access to the design software shifts the focus on design skills in terms of conceptual understanding about relationships between control parameters and objectives derived from the output aircraft design values. This opens up the opportunity for experimental variation in terms of participant groups. For instance, difference of design skills can be tested for novices versus experienced engineers independently of their familiarity with the specific design software or data structures.

3. Experimental Control

The task at hand is to find the right set of experimental control variables, which can be any combination from the in Section 2.2 mentioned (a) control and output parameters of the aircraft design, (b) feedback and information about participants' design solutions, or (c) composition of participant groups.

3.1. Control and Output Parameters

Selecting control and output parameters and the right ranges for the control parameters is critical for the experimental work. Namely, these parameters define a task that participants need to solve by obtaining feasible and as efficient as possible aircraft designs. Whether the experiment can yield meaningful evidence about work performance depends in the first place on the task difficulty. This is because a too easy or a too difficult task will lead to, respectively, flooring or ceiling performances whereby most participants fail or succeed perfectly. The task difficulty needs to be adjusted such that other experimental variables that we are interested in (e.g, type of feedback) may show effects.

3.2. Feedback and Other Information

To narrow down a good task in terms of its parameters is mandatory for the success of the experiment. Once this preliminary work is accomplished, we choose to focus on investigating the level and type of information the participants are provided with. This is because we see the question of how ergonomic factors like visualization and type of information (or the lack thereof) facilitate performance, as most relevant. The results of these experiments are expected to provide insights that will support our efforts to improve the IDL as a work environment.

In the example of Figure 1, the entire history of designs (i.e. choices of control parameters and the resulting outputs) is provided throughout the experiment. If used strategically, this may allow participants to investigate relationships about control and output parameters. Other types of feedback that, depending on experimental conditions, may be available are: (a) mathematical formulas that describe physical relationships; (b) geometry of the aircraft designs produced by the participants; (c) partial derivatives indicating the directions and magnitudes of changes in output parameters with respect to the control parameters—information about the derivatives is ignored by novices [2,7], but we expect experts to use it. At the current stage, the effects of these factors have not been tested.

3.3. Particpant Groups

Although we are considering to extend our research to test experience levels, our initial focus group is students. Whether testing different participant groups is a feasible experimental condition hinges on the selected design task as defined by other experimental variables. For example, a task that is adjusted to work well with students might be too easy for experienced engineers.

4. Systematic Test of Parametric Conditions

The selection of adequate control and output parameters is mandatory for a good experimental design. In several discussion sessions, our team (of engineers and cognitive scientists) deliberately settled for a relatively small number of control and output parameters to setup the systematic testing. As control parameters, the aircraft's *design range*, *wing span*, and the engine's *bypass ratio* were tested. From the output parameters, *fuel mass*, *Take-Off Mass (TOM)*, *Operating Empty Mass (OEM)* and *Direct Operating Costs (DOC)* were investigated in detail. For these output parameters lower values are better, therefore the optimization goal of the task is to adjust the control parameters such that output parameters are minimized. Global dependencies of the control on the output parameters were tested and analyzed.

4.1. Testing Procedure

To evaluate if a given subset of control parameters indeed circumscribes a reasonable design task for engineering students, VAMPzero was repeatedly iterated with different input parameters. Combinations of three control parameters, the values of which were varied in small steps, were tested. Input settings and resulting output values were recorded for each iteration. Tests and the subsequent analysis were performed with MATLAB®.

4.2. Analysis and Results

For analysis, the dependencies of output parameters on a large set of control parameters were visualized. Most indicative were three-dimensional (3D) carpet plots in which the local optima per design variable are highlighted. Examples are shown in Figures 2 and 3. Each subplot in Figure 2 shows how the DOC change for different wing span and bypass ratio settings and a fixed design range; the design range is varied between subplots and increases from the top left to the bottom right subplot. Figure 3 represents the same data, however rearranged such as to vary the engine's bypass ratio from low to high values across the subplots.

Comparison of the subplots in Figure 2 shows a stronger curvature of the DOC surface for increasing design range. Therefore, the DOC shows a larger sensitivity to the remaining two parameters (wing span and design range) for increasing design range settings. The plots also show that overall costs are lower for designs that use engines with a high bypass ratio. For fixed design range and bypass ratio, a clear minimum considering the wing span dimension is observed. Adjusting the latter variable will be trickier for the test persons, since the minimum is not located at the edge of the parameter range under consideration. Furthermore, the value of the absolute minimum to be attained will depend on the settings of the other values. The behaviour of the DOC minimum as function of wing span setting is caused by two conflicting optimization criteria from *aerodynamics* and *structural mechanics*. Introducing a larger wing span will make the aircraft aerodynamically more efficient: a larger amount of air is deflected with a relatively lower velocity over the wing to generate the required lift force. Since the kinetic energy required to deflect the oncoming air is linearly dependent on the mass and quadratically dependent on the velocity, it is energetically more advantageous to have a large wing span. From a structural point of view, having a larger wing span is however disadvantageous: larger bending moments will occur due to increased moment arms of the lift forces, leading to higher material stress and the corresponding heavier structure needed. Conflicts that tap into knowledge from different sub-disciplines involved in aircraft design are necessary for the experimental task.

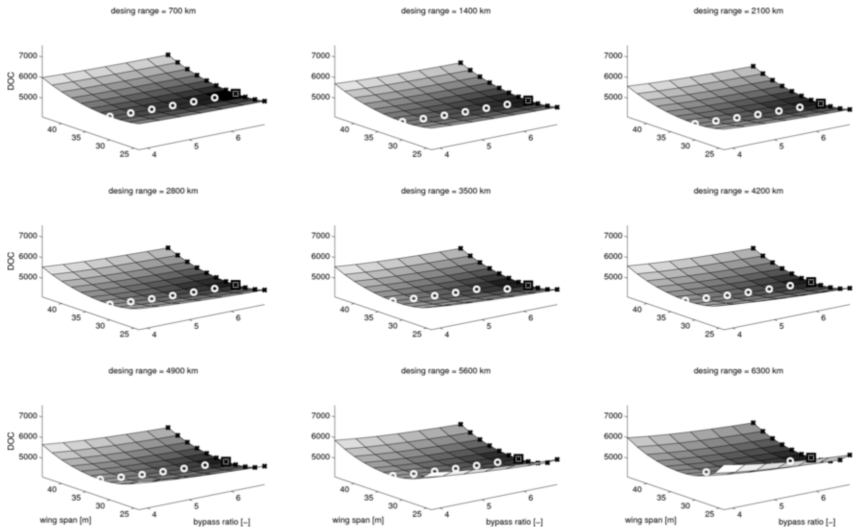

Figure 2. Parametric interdependencies: DOC levels (z-axes) depending on bypass ratio (x-axes), wing span (y-axes), and design range (varied over the subplots). White circles indicate the DOC minima for each tested bypass ratio value, whereas black crosses indicate the DOC minima for each tested wing span value. The global minimum is highlighted using a large black square. Default A320-type setting is for design range = 3 500 km (middle subplot).

Different challenges concerning the design task are evident from Figure 3. For one, it shows that the choice of design range has a non-linear effect on the DOC. This might seem counter-intuitive as one might assume that, the shorter the design range, the cheaper both production and operation are. However, the direct operating costs are reported in Euros (EUR) per business hour with a [EUR / bh] unit. Shorter ranges mean shorter periods in the air and more ground time, which is in fact a cost factor for the operating airline. As an engineering task, this is interesting since it introduces a component from a different discipline—*economics*—which in fact poses relevant constraints for engineering practice. The perspective of Figure 3 also exposes an interaction between wing span and design range, both of which have a non-linear influence on the DOC. The associated vallues in the subplots indicate that the aicraft design can be optimized globally by adjusting wing span and design range for the given engine at hand. All subplots show a similar shape, furthermore it is seen that the engine's bypass ratio does not affect the location of the global minimum largely (with respect to DOC). This can be explained due to the underlying calculation software, in which the relation between the bypass ratio of the engine and the corresponding effect on the engine mass is still to be incorporated. For the experiment, it is interesting to see if participants will exploit this independence—note that they will not have the global relationships among parameters available as displayed here (the task would be trivial otherwise).

Recall that participants will need to optimize for more than just DOC. After similar analyses of the effects of the control parameters on fuel mass, TOM, and OEM, the output parameters fuel mass and OEM were also selected for the experimental task. Traditionally, reducing mass is seen as critical within aircraft design. Optimizing for a combination of both OEM or fuel mass and DOC is then particularly interesting, since counter-intuitive relations might occur. For example, for a set of aircraft requirements

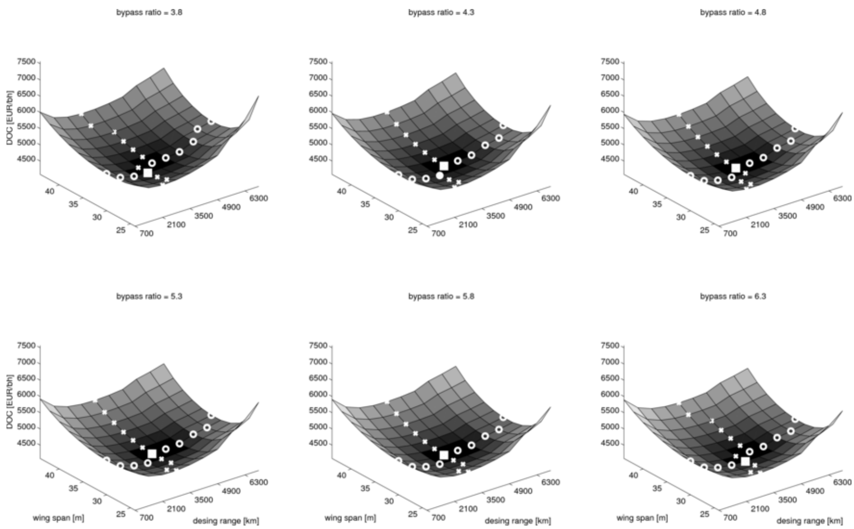

Figure 3. Parametric interdependencies: DOC levels (z-axes) depending on design range (x-axes), wing span (y-axes), and bypass ratio (varied over the subplots). White circles indicate the DOC minima for each tested design range value, and white crosses indicate the DOC minima for each tested wing span value. The global minimum is highlited using a filled white square. Default A320 setting is for bypass ratio = 4.8 (top right subplot).

one could obtain a more DOC efficient aircraft, which is heavier than the configuration at the global mass minimum.

The main result from our analysis is a potentially good set of control and output parameters. In addition, meaningful ranges for the control parameters could be identified. A summary is given in Table 1. These ranges largely depend on the software used to calculate the aircraft properties according to the provided control parameters. Since VAMPzero is an empirical tool, the equations based on statistics limit the values of control parameters at hand. No ranges are reported for the output parameters since these are actual outcomes of the calculations and not predefined like the controls.

description	**control parameters**			**output parameters**		
name	wing span	bypass ratio	design range	fuel mass	OEM	DOC
range	14–44	3.5–7	350–7 000	n/a	n/a	n/a
unit	[m]	[-]	[km]	[l^3]	[t]	[EUR/bh]

Table 1. Details for the *control* and *output* parameters, as selected for the experimental design task.

4.3. Follow-up: Pilot Studies

The next step is to conduct preliminary tests of the experiment with participants. These—so-called *pilot studies*—are required to evaluative whether the current task comprises a proper design exercise. Fine-tuning aside, the pilot studies will also serve to improve the GUI by surveying participants about their experiences in using it. This is particularly relevant in order to find proper variations of feedback levels and potentially additional information that might be displayed, too. Form and amount of feedback are the most relevant experimental variables to be tested, as argued in Section 3.2.

Conclusion

Science is just beginning to unveil the process of collaborative engineering. One missing link is the luck of experimental laboratory testing, which we aim to close by developing rigorous cognitive science methods. Experimental research, which taps into the thought process of engineering, requires innovative techniques. Innovation, in turn, requires preliminary work as it was presented in the current paper. The central result was to identify a design task which we believe to pose the right level of difficulty for undergraduate students. Whether this indeed is the case will be tested with pilot studies, which will also serve to find relevant feedback variables for the experiment. To understand the role of feedback is central to our approach, and we anticipate the experiments to provide insights that will help to improve the IDL as an environment for collaborative engineering. This research is a first step toward finding new ways how to enhance work experiences for individuals and outcomes for their institutions.

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