

Multi-fidelity Multi-disciplinary Optimisation of Propeller Design by Visual Analytics

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Abstract

This paper introduces a comprehensive framework for multi-fidelity, multi-disciplinary optimization of propeller design using visual analytics. The proposed methodology integrates advanced data visualization techniques, surrogate modelling and optimisation methodologies to handle high-dimensional data across various disciplines, including aerodynamics, aeroacoustics, and structures. By leveraging multi-fidelity simulations, the framework balances accuracy with computational efficiency, enabling detailed exploration and optimization of propeller designs. Interactive visualization tools in the framework facilitate the identification of optimal design parameters and trade-offs, highlighting its potential to improve decision-making in engineering design processes in terms of confidence and knowledge creation.

CCS Concepts

• **Human-centered computing** → Visual analytics; • **Computing methodologies** → Modeling and simulation; • **Mathematics of computing** → Mathematical optimisation;

1. Introduction

The design and optimization of engineering systems, encompassing propellers and other aircraft components, involve complex, multi-disciplinary interactions. Traditional approaches to managing these high-dimensional design challenges often lead to information overload and hinder the extraction of meaningful insights. By integrating Visual Analytics with Multi-Disciplinary Optimization (MDO), a powerful framework for multi-criteria, multi-objective decision-making can be established. A web-based visual analytics tool can further enhance this process, enabling clients and decision-makers to explore and compare design choices interactively, without requiring expertise in the backend code or the complexities of the optimization process.

Keim et al. [KMS*08] highlight the growing importance of visual analytics in managing the massive and heterogeneous data volumes that are increasingly common in various domains. They emphasize that visual analytics combines visualization, data mining, human factors and statistical techniques. Siddiqui et al. [SKL*16] showed a visual data platform called zenvisage for easily finding desired visual patterns from large datasets.

A study by Piotrowski et al. [PKC19] addresses the issues of overplotting and data clutter in static displays. They introduced an interactive toolkit combining parallel coordinates and scatter plots, enhanced with machine learning methods to manage multidimensional engineering design data. In another work, Kipouros et al. [KIPS13] applied these principles to aerodynamic turbomachinery design, showcasing how parallel coordinates can manage

high-dimensional design spaces effectively. This study highlighted the ability of parallel coordinates to identify crucial relationships between design parameters and objectives, facilitating intelligent decision-making and design space exploration. Sacha [Sac18] presented a knowledge generation model for visual analytics, consisting of a computer and a human part. The computer part deals with analysing and visualising existing data generated using different models used within the system. The human part is a reasoning process composed of exploration, verification and knowledge generation loops.

Even though multiple visual analytics tools are present for engineering design, there is a lack of tools that incorporate the features of multi-fidelity, multi-disciplinary optimisation, and a multi-objective decision-making environment. A lot of companies like Airbus use similar in-house tools and therefore, it is necessary to create an open-source framework using visual analytics. The current study applies it to a propeller design and optimisation. We integrate data from various simulation fidelities and disciplines, aerodynamics, aeroacoustics, and structures, into a cohesive visual analytics software environment allowing for a comprehensive exploration of the design space, combining the strengths of high-fidelity simulations for accuracy with the computational efficiency of lower-fidelity models.

2. Methodology

This section describes various methodologies used in this study. Figure 1 shows a schematic view of the methodologies used for the

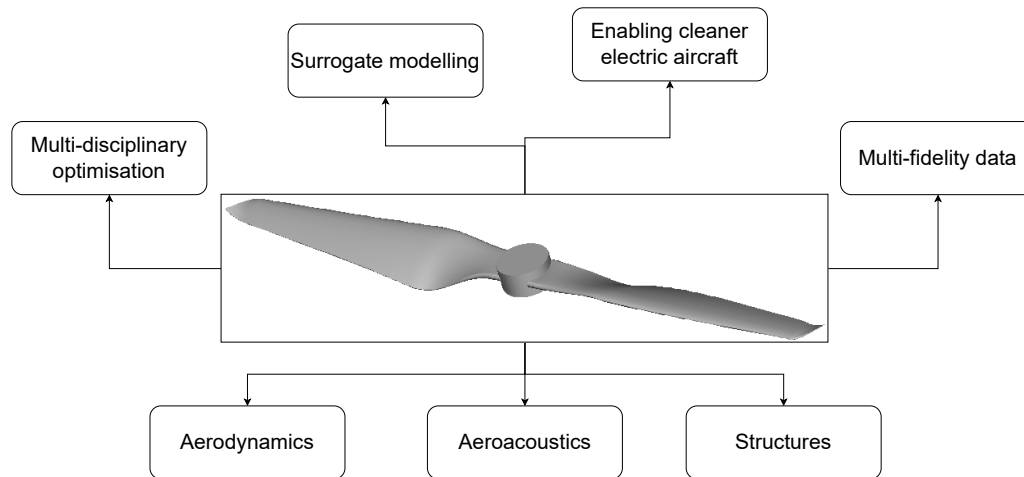


Figure 1: Methodologies used in the optimisation framework for a propeller for visual analytics and key enabling technologies.

propeller design study and the different disciplines being studied in this framework.

2.1. Multi-fidelity data

This section describes the data available in three different disciplines for a propeller - Aerodynamics, Aeroacoustics and Structures. For the mid-fidelity aerodynamic data, the lifting line theory coupled to a free vortex wake model is used to calculate the VAWT 3D unsteady flow and force field past the rotor and the interaction between blade and fluid flow [MBP*17, BMB*18]. The LLFVW algorithm is based on nonlinear lifting line formulation by Garrel [VG03] and is mentioned in detail by Balduzzi [BMB*18]. For the high-fidelity aerodynamic data, the Lattice Boltzmann Method (LBM) is used to compute the flow field because it was shown to be accurate and efficient for similar low Reynolds number rotor applications [GSA*24, SWAI23, GJS*18, Shu24, TASI24, SAB*24, SWI22]. High-fidelity far-field noise is computed using the Ffowcs Williams and Hawkins [FWH69] (FW-H) acoustic analogy implemented in PowerFLOW. In particular, the formulation 1A of Farassat and Succi [FS80] extended to a convective wave equation is used in this study [BPF09]. The mid-fidelity structural analysis within QBlade uses the finite element analysis (FEA) capabilities of the open-source multi-physics engine, Project Chrono [TSM*16, Pro19]. The structural model for propellers in the QBlade-Chrono coupling interface is composed of Euler-Bernoulli beams, which are articulated within a co-rotational framework [RN16].

2.2. Surrogate modelling

The surrogate modelling approach, Kriging, assumes that points close to each other in a design domain have similar functional values [Toa23]. Ordinary Kriging involves constructing a correlation matrix among the data points and optimizing hyperparameters to minimize the prediction error [FKB06]. However, this process can be computationally intensive, especially with large datasets, due to

the need to invert the correlation matrix. To address this, efficient computation techniques, such as adjoint-based methods, are employed to reduce the computational load.

Multi-Fidelity Kriging (MFK) extends Ordinary Kriging by integrating simulations of varying fidelity levels. It combines low-fidelity (inexpensive) simulations with high-fidelity (expensive) ones using a linear autoregressive model [KO00]. By optimizing the scaling factor and other hyperparameters, MFK provides a robust framework for making accurate predictions across different simulation fidelities. Kriging, particularly in its multi-fidelity form, is useful for understanding the behaviour of a propeller over a range of operational and design parameters. This enables a more comprehensive exploration of the design space, leading to better-informed decisions and optimized propeller designs.

2.3. Optimisation methodologies

After the unsampled data points are generated using the Kriging approach, single and multi-objective optimisation is carried out for the selected parameters. For a propeller, the parameters can range from number of blades, RPM, freestream velocity, diameter, chord and twist distribution. Some of the parameters can be kept constant and some of them can be given as constraints. For single-objective optimisation, a Genetic Algorithm (GA), which is an evolutionary algorithm, is used utilising the open-source pymoo optimisation toolbox. For multi-objective optimisation, the Unified Non-dominated Sorting Genetic Algorithm (U-NSGA-III), based on [DPAM02], is used which extends the general framework of a genetic algorithm with specific modifications for mating and survival selection to handle multi-objective optimisation problems effectively.

3. Knowledge Generation Model & Decision Making environment

Figure 2 shows the Knowledge Generation Model applied in this study, which has been extended based on the work done by Sacha

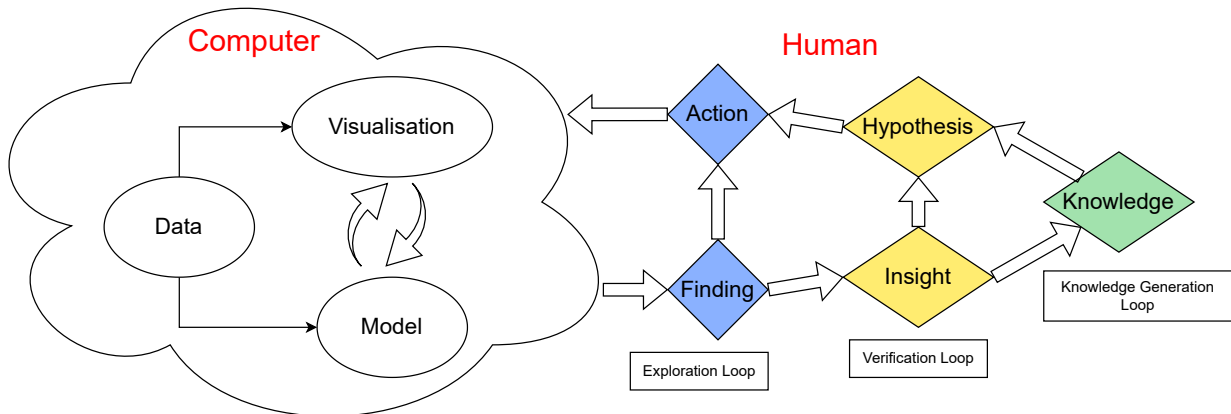


Figure 2: Knowledge generation model for visual analytics.

[Sac18]. This model in visual analytics integrates human reasoning and computational processes to facilitate data exploration and knowledge extraction. This model emphasizes the interactive collaboration between humans and machines, where data is processed and visualized by the system, enabling analysts to explore, generate, and verify hypotheses, creating an iterative loop of analysis and refinement.

For the current study, the model begins with collecting and integrating **data** from various disciplines, such as aerodynamics, aeroacoustics, and structures. High-fidelity simulations and low-fidelity models (multi-fidelity) provide a range of data that informs the optimization process. The U-NSGA-III multi-objective optimization **model** is used to explore the design space, providing Pareto-optimal solutions that balance trade-offs between competing objectives like efficiency, noise, and structural performance. The surrogate models serve to reduce the computational cost of evaluating the design options. The results from the optimization process are transformed into visual formats, such as Pareto fronts. **Visualization** tools enable users to identify optimal solutions and understand the relationships between various design parameters.

In the **exploration** loop, engineers and designers can interact with the visualized data to explore different propeller design possibilities. They can manipulate input design and operational parameters and observe how those changes affect propeller performance, helping them to generate hypotheses about the best design strategies. In the **verification** loop, as potential solutions are identified, they are tested against the design criteria through further simulation and analysis. This loop ensures that the proposed designs meet the necessary performance standards and constraints. Finally, in the **knowledge generation** loop, insights gained from the exploration and verification loops are consolidated into actionable knowledge. This might involve selecting the best propeller or airfoil design for further development or identifying new design spaces for improvement.

An example of interactive framework has been developed by the

authors for Project FutPrint50 [KSK23] in the form of an open-source web tool, which was also used to support the development of a technology roadmap [SKK23].

4. Results

Figure 3 shows what the web-based user interface looks like. This new framework extends the previous development by introducing multi-fidelity components, alongside a user interface to run analysis and optimisation. The user must upload an input CSV file containing the multi-fidelity data for different disciplines such as aerodynamics, aeroacoustics and structures. The first line in the interface shows the name of the propeller (in this case which is APC 18x5.5). There are two options: High-Fidelity and Mid-Fidelity. Depending on which options are selected, the two plots below show the data points and the Kriging surrogate model fitted into the data. The data represents the variation of propeller thrust and torque against the blade sweep. If only single fidelity is selected, the simple Kriging model is used; whereas, if both fidelities are selected, the multi-fidelity Kriging model (labelled as "Multi-fidelity Prediction" in the graph) is used. If more than one variable parameter is present, then the Kriging model is used for both parameters to give a contour plot for each thrust and torque.

Next, based on the parameters given by the user in the CSV file and predictions made by the Kriging model at data points, multi-objective optimisation is carried out. In the case of the present study, it is the thrust and torque of the propeller. For each parameter, both maximisation and minimisation options are given. Based on the options selected, Pareto front plots are shown below the two graphs shown in Figure 3 after clicking the "Optimize" button. The user has an option to choose either high-fidelity or mid-fidelity or both data when optimising the parameters. This helps in analysing whether gathering expensive high-fidelity data brings any improvement in the design and optimisation process.

Multi-Fidelity Multi-Disciplinary Multi-Objective Optimisation Framework

Propeller: APC 18x5.5

Choose file | input_csv.csv

- High-Fidelity
- Mid-Fidelity

Optimize Thrust: Maximize ▾

Optimize Torque: Minimize ▾

Optimize

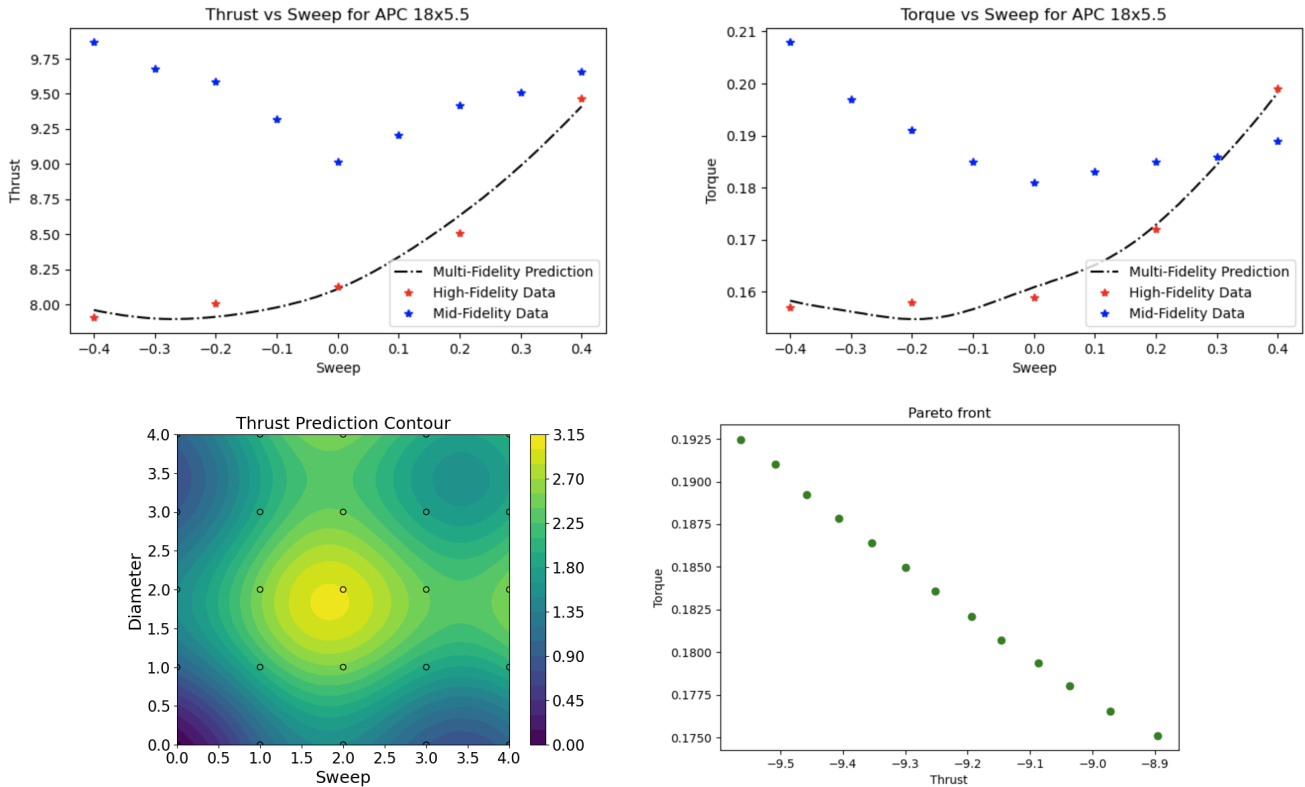


Figure 3: Multi-fidelity Multi-disciplinary Multi-objective Optimisation web-based user interface.

5. Conclusions and Recommendations

Integrating visual analytics within a multi-fidelity, multi-disciplinary optimization framework for propeller design significantly enhances the understanding and decision-making process. By bringing together diverse methodologies, such as aerodynamics, aeroacoustics, and structural analysis, into a unified platform, this approach allows for a comprehensive exploration of the design space. The use of interactive visualization tools empowers engineers to identify critical design parameters, analyze trade-offs, and optimize performance across various criteria in real-time. This not only simplifies the complexity of handling high-dimensional datasets but also facilitates a more informed and efficient design process, making it a valuable tool for both research and industrial applications in aerospace engineering.

Various developments can be taken up in the future for this web-

based framework. Many more parameters can be taken as input from the user, which will allow even higher flexibility to study parameters from all disciplines together. Instead of using surrogate models like Kriging, analytical models can be implemented in the backend to generate performance values at all data points in the range of interest. Such analytical models are mostly cheap low-fidelity models such as Blade Element Momentum Theory for propellers. For flow visualization, detailed mid-fidelity and high-fidelity data can be taken as input and flow parameters can be visualized in the 2D and 3D domains to better understand the propeller performance in the web-based interface.

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