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Application of Probabilistic principles to Set-Based Design for the optimisation of a hybrid-electric propulsion system

Andrea Spinelli, Luchien Anderson, Hossein Balaghi Enalou, Bahareh Zaghari, Timoleon Kipouros, Panagiotis Laskaridis

School of Aerospace, Transport and Manufacturing, Cranfield University, College Road, Cranfield, MK43 0AL, United Kingdom

E-mail: andrea.spinelli@cranfield.ac.uk

Abstract. Current research in hybrid-electric aircraft propulsion has outlined the increased complexity in design when compared with traditional propulsion. However, current design methodologies rely on aircraft-level analysis and do not include the consideration of the impact of new technologies and their uncertainty. This can be a key factor for the development of future hybrid-electric propulsion systems. In this paper, we present a methodology for exploring the design space using the principles of Set-Based Design, which incorporates probabilistic assessment of requirements and multidisciplinary optimisation with uncertainty. The framework can explore every design parameter combination using a provided performance model of the system under design and evaluate the probability of satisfying a minimum required figure of merit. This process allows to quickly discard configurations incapable of meeting the goals of the optimiser. A multidisciplinary optimiser then is used to obtain the best points in each surviving configuration, together with their uncertainty. This information is used to discard undesirable configurations and build a set of Pareto optimal solutions. We demonstrate an early implementation of the framework for the design of a parallel hybrid-electric propulsion system for a regional aircraft of 50 seats. We achieve a considerable reduction to the required function evaluations and optimisation run time by avoiding the ineffective areas of the design space but at the same time maintaining the optimality potential of the selected sets of design solutions.

1. Introduction

Hybrid-Electric aircraft has been an important research topic in the last 10 years. While research has been able to outline the technological gap required to enable this class of aircraft, the complexity of the propulsion system requires more detailed design and optimisation methods which also accounts for the uncertainty of the technology [1]. Major challenges are in the energy density of batteries, the thermal management of power train, the overall modeling of the subsystems and their interactions, and the identification of certification requirements of this new class of aircraft [2]. Exploring the design space would allow to better understand response of the design parameters to the desired requirements and constraints and the interaction between the different subsystems, including possible contrasting effects. This process, however, is significantly computationally heavy [5].

Different competing approaches are being developed for this issue. In this paper we propose a methodology based on Set-Based Design, but alternative methods include the Margin Allocation method of Guenov et al. [3] or the Margin Value method of Brahma and Wynn [4]. Margin-based approaches seek to identify the amount of overdesign such it would compensate any uncertainty or late design change without compromising the target requirements. However, it comes at an increased cost, hence these approaches try to minimise the amount of added margin and limit it to specific parameters. Instead, Set-Based Design is a general design methodology whose principles is to generate as many configurations and delay critical design decisions as much as possible [6]. The candidate configurations are evaluated in parallel and the least desirable discarded, this allows the designers to manage unexpected problems and uncertainties which under traditional, point-based, design approaches would require a total re-design [7]. Indeed, SBD has been recently investigated for the problem of designing products under flexible requirements [8].

Previous work at Cranfield focused on implementing these principles for design space exploration. The developed framework, named Augmented Design and Optimisation (ADOPT) [11], combines Set-Based Design to generate many configurations using discrete levels of input parameters, discard the unfeasible and undesirable ones, and convert the surviving ones in bounded optimisation problems. Figure 1 shows the flowchart of ADOPT.

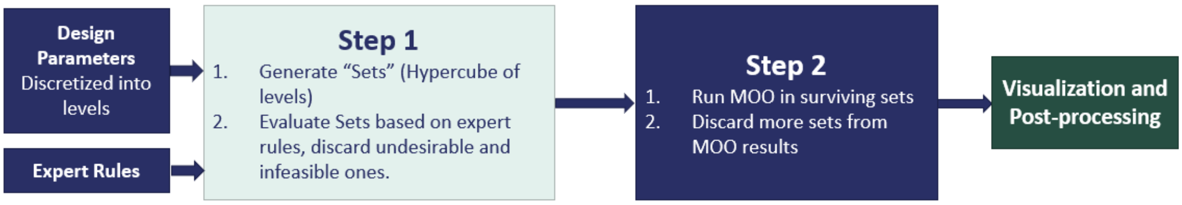

Figure 1. ADOPT Flowchart

However, the major drawback of this framework is the necessity of expertise on the system under design to construct if-else expert rules capable to filter out unfeasible and undesirable configurations, otherwise the combinatorial explosion from input parameters makes the entire methodology impractical to use. The identification of the feasible design space that satisfies user-defined requirements is a major challenge in SBD methodologies. Previous approaches include fuzzy set theory [9] and the use of Bayesian network classifiers [10] to overcome the need of an analytical mapping between the design space parameters and the requirements. Nonetheless, both approaches lack a quantification of the uncertainty of the mapping procedure, where the output of the process is just a discrete classification as desirable or undesirable of each subset.

2. Methodology

The present methodology focuses on extending ADOPT [11] by replacing the rule-based filtering system of Step 1 with a probabilistic one. This is achieved by using a statistical surrogate model which predicts the response of the system under design together with its standard deviation. The statistical surrogate used is the Gaussian Process algorithm implemented in the Python library `scikit-learn` [12].

The user defines the probabilistic requirements as an unequal relationship between a i-th response of the system $y_i = f(X)$ and its i-th limit value $\overline{g_i}$ (Eq. 1).

$$P\left(y_i \geq \overline{g_i}\right) \geq P_{target} \tag{1}$$

The procedure to evaluate the probability of a set to satisfy the requirements is as follows:

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(i) From the set sample a number of input parameters X^k using Latin Hypercube sampling.

(ii) Calculate the mean μ_i^k and deviation σ_i^k of each i-th response with the statistical surrogate model.

(iii) Calculate the probability of each sample to satisfy the requirements (Eq. 2):

$$P^k(y_i \geq \overline{g_i}) = \Phi\left(\frac{\mu_i^k - \overline{g_i}}{\sigma_i^k}\right) \tag{2}$$

where Φ is the Gaussian Cumulative Distribution Function.

(iv) Finally count how many samples have $P^k > P_{target}$ over the total amount of samples, this constitutes the set probability to satisfy the i-th requirement.

If multiple requirements are present, the total probability is calculated by multiplying all the individual probabilities and assuming conditional independence. Once every set has been evaluated, those with a probability under an user-specified threshold are marked for discard and do not get evaluated in Step 2. Those that survive, get converted into a Multi-Objective optimisation problem where the parameter levels that constitute the set are used as input boundaries. Optimisation is performed using the Python library `pymoo`, which implements the Multi-Objective Optimisation algorithm LSGA-2 [13]. Given the large amount of evaluations of the objective function, modeling should be as computationally cheap as possible. Surrogate methods such as Radial Basis Function interpolation, Kriging, and more recently, Artifical Neural networks, can be introduced to replace costly simulations. While not present in the presented test case, these approaches should be considered in the definition of the system model [14].

After all optimisations have been run, results are stored in a .csv format for visualisation and post-processing. An interactive web-based visualisation tool is being developed alongside the described methodology. The multi-dimensionality of the output data requires multiple types of graphs where data can be selected and visualised on multiple axes. A convenient form is the parallel coordinates plot [15], which can be augmented if combined with scatter plots [16]. All the graphs presented in this paper are generated using this tool.

3. Test Case

The selected test case is the design of a parallel hybrid-electric propulsion system to be fitted on an ATR-42 class regional aircraft. A diagram of the architecture is shown in Figure 2, where Table 1 contains the efficiencies of each component assumed for modeling. The simulation code used is an in-house tool that calculates the required power for each part of the mission (climb, cruise, descent) with the classic Specific Excess Power equations from flight mechanic theory [17]. Then, by applying the chain efficiency of the propulsive system, it calculates the required fuel and battery masses. The code updates the calculated take-off mass and iterates until it converges on fuel and battery mass. Table 2 contains the parameters of the mission segments.

Parameters that define the design space are presented in Table 3. The framework is tasked to find the best energy management strategy given the different values of battery energy density and motor power density.

The optimisation problem is defined in Equation 3, where M_{fuel} is the fuel consumed in the mission and TOM is the take-off mass. The selected constraints limit the take-off mass to a 7.5% increment over the ATR-42-600 maximum take-off mass, and ensure that the minimum overall system efficiency η_{total} is above 0.4. These values are also used as requirements for the probabilistic filtering in Step 1, where each sample must have $P \geq 0.5$.

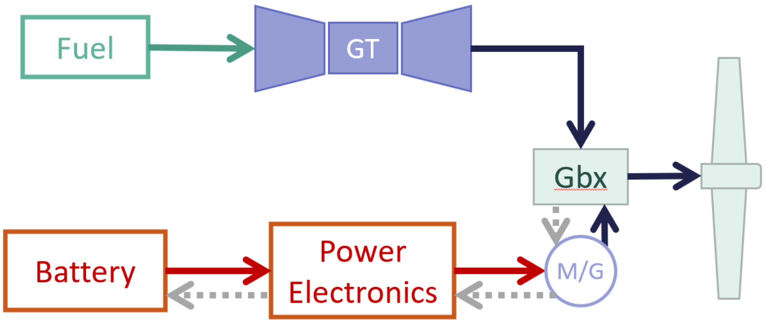

Figure 2. Propulsion system configuration. The greyed-out path is an unused energy recovery connection.

Table 1. Efficiency values for each component.

Propeller	0.9
Gearbox	0.99
Gas Turbine	0.40
Electric Motor/Generator	0.95
Power Electronics	0.94
Battery	0.95
Cabling	0.995

Table 2. Mission Parameters.

	L/D	V_{TAS} [m/s]	V_z [m/s]	Range [km]	Altitude [m]
Climb	16.00	107.44	9.4	59.21	-
Cruise	14.50	154	-	555	5181
Descent	16.00	114.48	-6	98.85	-

Table 3. Efficiency values for each component.

Input Parameter	Symbol	Range	Levels
Climb Degree of Hybridisation	DOH_{cl}	0.1 - 0.9	3
Cruise Degree of Hybridisation	DOH_{cr}	0.1 - 0.9	3
Battery Energy Density	e_b	200 - 500 Wh/kg	3
Motor Power Density	p_{mg}	6000 - 8000 W/kg	3

$$\begin{aligned}
&\text{given} && X = \{DOH_{cl},\ DOH_{cr},\ e_b,\ p_{mg}\} \\
&\underset{X}{\text{minimise}} && M_{fuel},\ TOM = f(X) \\
&\text{subject to} && TOM \leq 20000\,kg \\
& && \eta_{total} \geq 0.4
\end{aligned} \tag{3}$$

4. Results

The total number of sets generated with the input from Table 3 is $3^4 = 81$. However, only 15 sets were retained as the probabilistic filtering identified them as the most desirable. Figure 3 presents in Parallel Coordinates form all the generated combinations, where the colors refer to the total probability to satisfy all the requirements (marked in bold). It is clear that the levels with the highest degrees of hybridisation, both for climb and cruise, are marked with low total probability since the battery weight would be above the 20000 kg MTOM constraint. Similarly, the lowest level of Battery energy density is marked with low probability for the same reason.

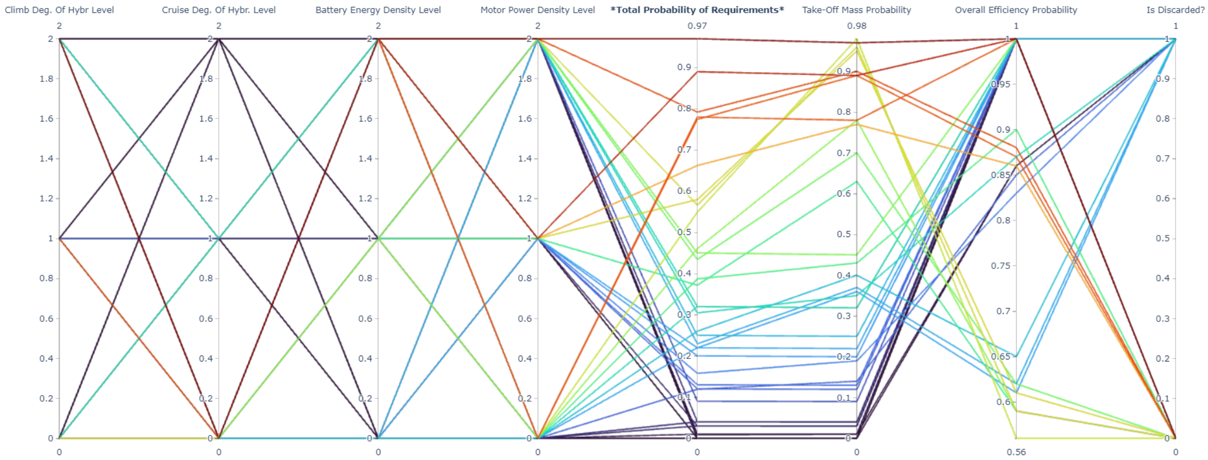

Figure 3. Step 1 results

Results from the multi-objective optimiser within the surviving sets are shown in Figure 4. The trade-off between take-off mass and burned fuel mass is clearly visible by the colouring. It is also evident how the cruise degree of hybridisation has the highest impact in the objectives, while the climb degree of hybridisation does not show a clear tendency. Finally, the optimiser selected the highest possible value of battery energy density available in each level: 400 Wh/kg for level 2 and 500 Wh/kg for level 3. Figure 5 shows the trade-off between the two objectives compared with the baseline data of an ATR-42. The two lines represent the two different values of battery energy density.

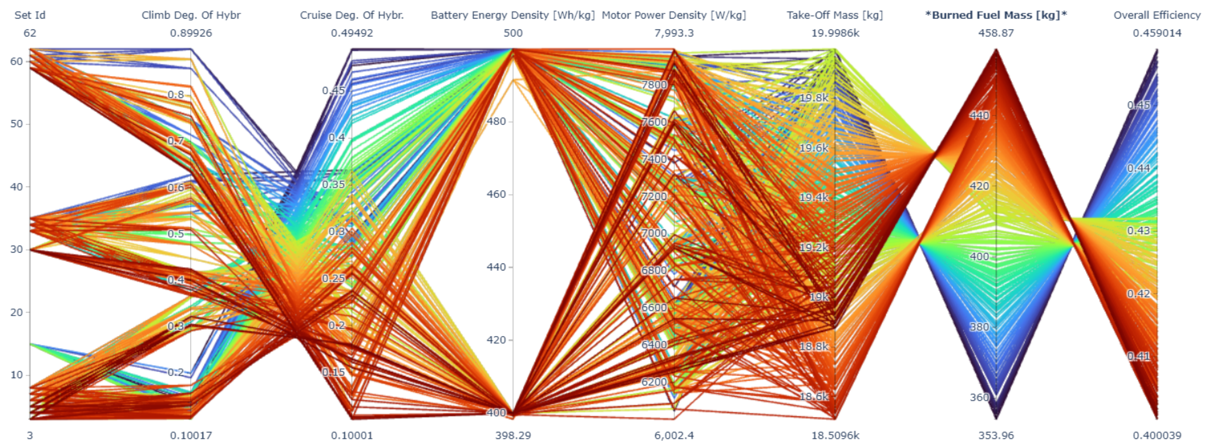

Figure 4. Step 2 results

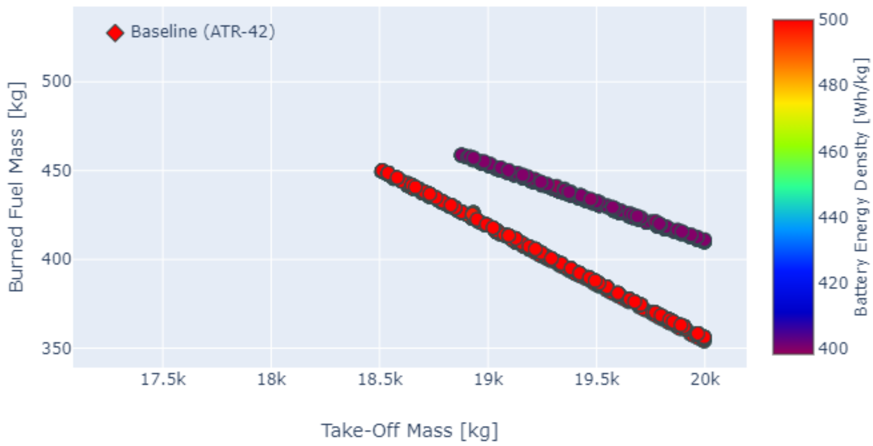

Figure 5. Pareto Front of Step 2

To demonstrate the effectiveness of the probabilistic evaluation and filtering, the same optimisation problem was run without Step 1 and without constraints. The result of this experiment is shown in Figure 6.

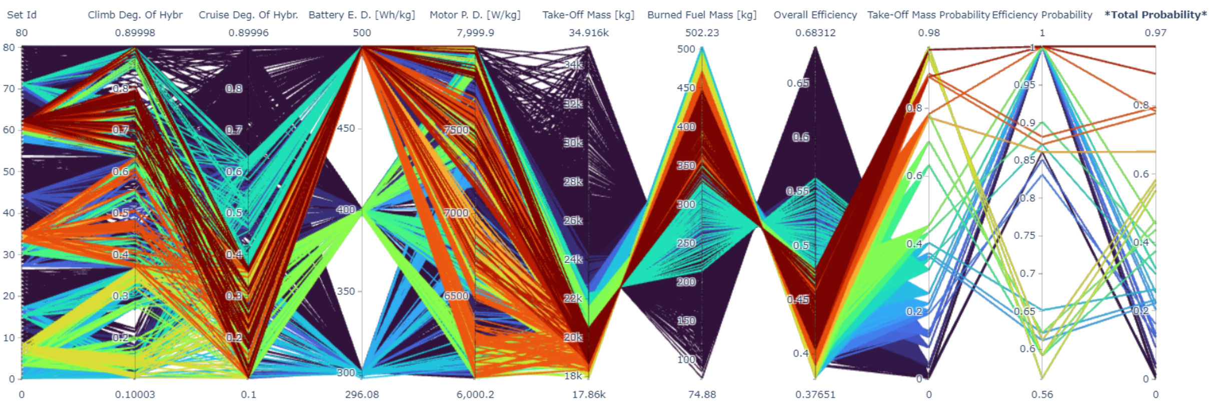

Figure 6. Step 2 results without filtering

Table 4. Effectiveness of Probabilistic Filtering

	With Filtering	Without Filtering	Change %
Number of Sets	15	81	-81.48%
N. of function evaluations	20780	107130	-80.60%
Total optimisation run-time (s)	12.85	86.22	-85.09 %

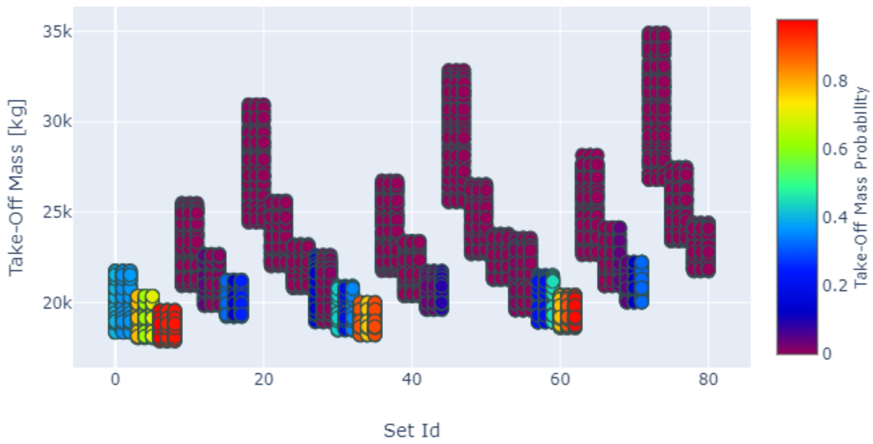

Figure 7. Take-Off Mass vs Sets vs $P(TOM < 20000\ kg)$

By inspecting the total probability and comparing with Figure 4, it is clear the surrogate statistical model was capable to mark with low probability all those sets that were not able to satisfy the requirements (and therefore constraints). In particular, the take-off mass constraint was the most restrictive, as shown in Figure 7: each line represents one set whose vertical extent is the range of take-off mass values.

Finally, Table 4 presents the comparison of the optimisation on the whole design space with the filtered one: with the probabilistic filtering it is possible to reduce the number of function evaluations and the total optimisation run-time by more than 80%.

5. Conclusion

Most conventional aircraft design methodologies cannot accommodate the exploration of innovative concepts such as hybrid-electric propulsion. Complexity and uncertainty pose a significant challenge in the understanding of this propulsive technology. We proposed a methodology based on Set-Based Design and enhanced it with a probabilistic approach, where the designer does not have to use experience to drive the design space exploration but instead use data and encode their requirements in a probabilistic form. This allows the consideration of the unknown impact to the design process and development of a propulsion system when new technologies are explored. With the exemplar test case we demonstrated that our approach is capable of filtering out the undesirable areas of the design space and use the optimisation results to reveal the behaviour of the system under design. Future research will focus on extending these capabilities by introducing an uncertainty quantification scheme parallel to the optimiser, in order to evaluate the sensitivity of each optimal point to the input parameters. This extra step would add more information to further discard sets of design solutions with low robustness when technological uncertainties are considered during the early development stages of the system.

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