Accelerated Whole Engine Structural Design Process Based on Data Reuse

Leran Wang

leran.wang@soton.ac.uk

Petru-Cristian Cimpoesu and David Toal

University of Southampton

Southampton

United Kingdom

Alessandro Anobile

Rolls-Royce plc.

Derby

United Kingdom

ABSTRACT

The design of complex engineering systems, such as a gas turbine engine, is often decomposed into system design and subsystem/component design. Both the system and subsystem designs normally go through several design iterations. For each iteration, a series of analyses, simulations, optimisations and, at times, experiments are carried out to find the optimum. Traditionally, the data generated in one design iteration is not fed explicitly into the next iteration. This is because a new design iteration can often start with structural changes and the new design is considered to be topologically different from the previous design. Most existing design optimisation techniques cannot leverage the data across multiple design iterations and each design iteration has, therefore, to start almost from scratch. This paper presents a novel structural design process that is capable of accelerating both the component level and system level design by reusing data from previous design iterations. A case study of multiple design variables and topology changes in three components of a whole engine model (WEM) is carried out and it demonstrates that the proposed method employing surrogate modelling and data reuse technologies can significantly reduce analysis costs from one design iteration to the next.

NOMENCLATURE

DI	Design Iteration
DOE	Design Of Experiment
FBH	Front Bearing Housing
HP	High Pressure
IMC	Intercase
IP	Intermediate Pressure
LP	Low Pressure
MAE	Mean Absolute Error
R2	Coefficients of Determination
RMSE	Root-Mean-Square Error
TBH	Tail Bearing Housing
UHBR	Ultra-High Bypass Ratio
WEM	Whole Engine Model

1 INTRODUCTION

A whole gas turbine engine consists of many interacting components and simply combining the optimal individual components often may not lead to an optimal system [1]. Although it is preferable to analyse each component within a whole engine scenery, the large number of finite elements required to build a WEM inevitably leads to long simulation times. A reduced-order model, such as a medial surface model, has been proven to be able to accurately represent the WEM while reducing computational cost [2]. Figure 1 shows a medial surface model of an Ultra-High Bypass Ratio (UHBR) engine. It is used as the whole engine scenery for the case study presented in Section 2.2. In this paper, a medial surface model is also referred as 2D model as its elements are 2D, compared to a 3D model which is made of 3D elements e,g tetrahedral elements.

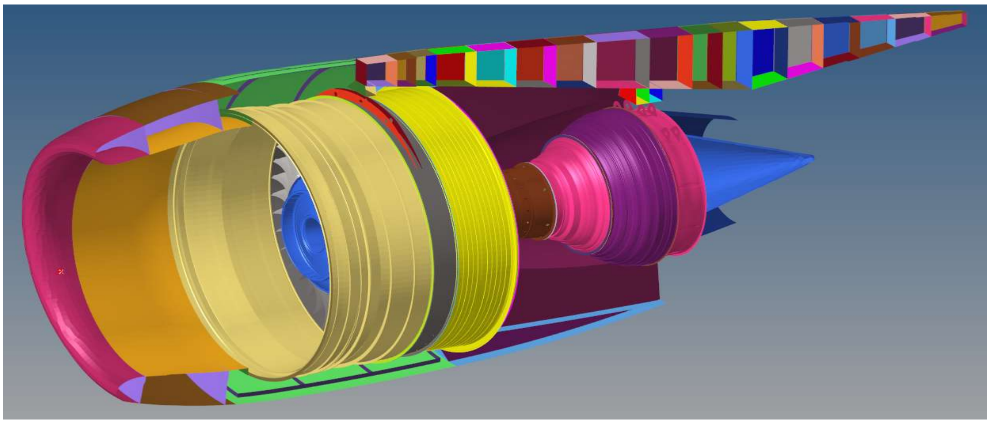


Figure 1 UHBR whole engine model

Although the simulation of a 2D WEM is much faster than a 3D WEM, it is still too computationally expensive to fully explore the design space by directly using the 2D WEM. Therefore design processes often focus on component design only, to be then verified at system level later. More advanced approaches could employ surrogate models constructed from a limited number of computational simulations to account for whole engine response while working on component design. In these cases, a design of experiment (DOE) is constructed and simulated to build surrogate models of the design objective function(s) and constraints with respect to the design variables. The design space, represented by these surrogate models, is then searched for an improved design. In these approaches the design variables are traditionally continuous and, once a topological change is made to the initial component design, the whole process needs to be repeated. The analysis of a new topology is independent of the existing results related to the previous topology although the two topologies are likely to be similar and there might be considerable correlations between their respective results.

A surrogate model uses an approximate mathematical model to predict the behaviour of a complex engineering system. In the application considered in this paper, the surrogate model is also required to be able to handle categorical/integer-valued variables. This is because the aforementioned topological changes are not described by continuous variables. Among many existing types of surrogate models such as radial basis functions, support vector machines and Bayesian networks etc. [3][4], some are adapted to incorporate categorical/integer-valued variables [5][6]. Others argue that continuous surrogate-based optimization algorithms are well-suited for expensive discrete problems [7]. Kriging [8] is chosen as the surrogate model not only for its popularity and flexibility but also for its successful applications in aero engine design [9][10]. Over the years, variants of Kriging have been developed to handle multi-fidelity problems (co-Kriging) [11] and discrete variables (categorical-Kriging) [12][13].

This paper focuses on data reuse from one design iteration to the next relying on the categorical-Kriging model application. As during a gas turbine engine design process, a large amount of analysis data is generated after each design iteration. The data can include both simulation and experimental results. Other work reported in literature explores the benefits of data reuse at different engineering phases. In [14], the data from engine production is linked back to the engine design stage to form the "digital twin"; in [15], the CAD/CAM data is reused for manufacturing cost estimation; and in [16], a similarity metric is proposed to measure the potential of data reuse.

2 METHODOLOGY

2.1 WORKFLOW

This paper presents a novel computational method based on data reuse technologies that aims to exploit the correlation of the results between topological changes and reduce the analysis cost from one design iteration to the next (Figure 2). In order to reuse the data from a previous design iteration of a baseline topology, a smaller DOE is constructed from simulations of the updated topology. Instead of building surrogate models from this new DOE only, categorical Kriging models are built combining the set of results from the baseline DOE with the smaller DOE of the updated topology. The correlations of analysis results between design iterations are explored when building the categorical Kriging models. The details of Kriging and categorical Kriging (also called multi-output Kriging) are discussed in depth in [13]. This paper focuses on their application in whole engine design process with data reuse. Using a generic UHBR engine as case study, the accuracy and consistency of the categorical Kriging models are presented in Section 3.2 and 3.3. Section 3.4 compares the results of two WEM optimisations with and without data reuse.

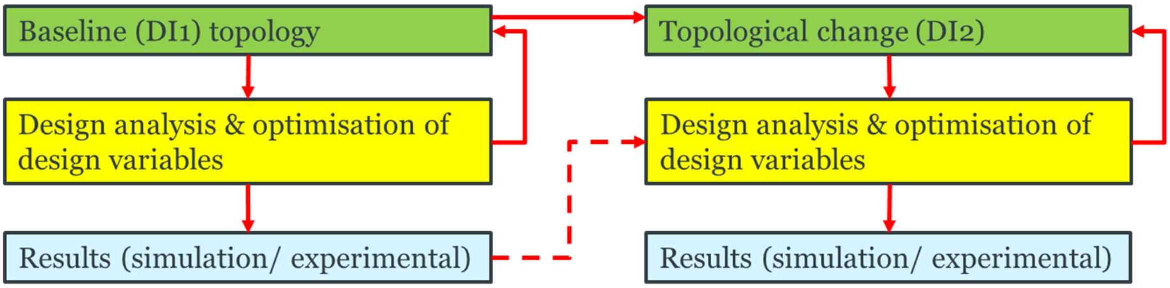


Figure 2 Data-reuse to accelerate design study after topological design change

2.2 CASE STUDY

A generic UHBR engine (Figure 1) with a sea-level static load case is chosen as the case study. Three components, the FBH, intercase and TBH, are used as component design examples. To identify the design variables that have the largest impact on the engine performance under the specific load case, an OptiStruct freesize optimisation of the baseline 2D medial surface whole engine model is carried out. The optimisation objective is to reduce whole engine mass. The constraints are nine tip clearances across the engine, including fan, five compressor stages and three turbine stages. Figure 3 shows the optimisation results with locations of high sensitivity highlighted. Some of the locations can be identified as vane thickness, casing thickness and bearing locations etc. Five design variables from the identified, high-impact regions, are chosen for each component.

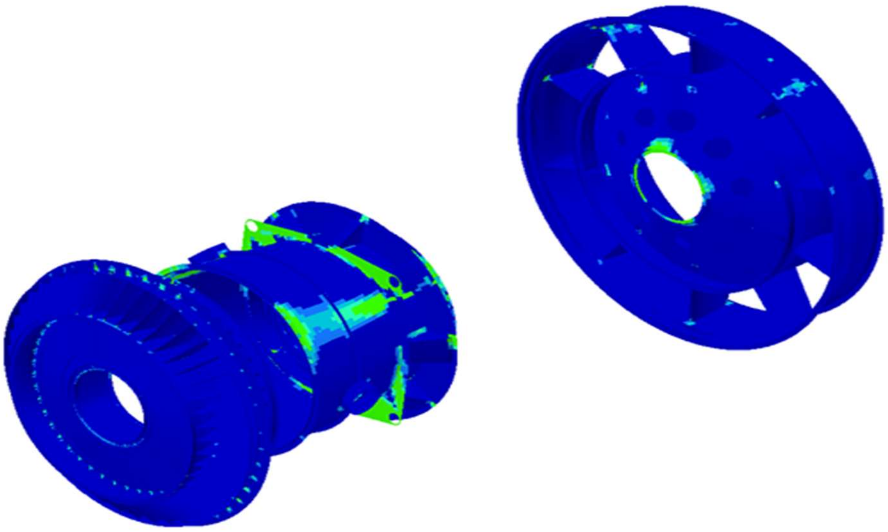


Figure 3 OptiStruct freesize optimisation to identify important design variables for system performance (highlighted areas are those with the greatest reduction in element thickness)

In addition to the five design variables, a topological change is introduced to each component to form a "baseline" geometry and an "updated" geometry. This resembles the scenario where design variables are optimised within a design iteration while a new topology starts a new design iteration. For the intercase, the baseline geometry uses a rib stiffener on the front casing (Figure 4(a)) and the updated geometry uses an iso-grid stiffener (Figure 4(b)). For the TBH, the number of vanes is increased from 5 to 12 (Figure 4(c) and (d)). For the FBH, the number of vanes is reduced from 30 to 20 (Figure 4(e) and (f)). Note that the engine component figures shown in this paper are simplified and not true to scale for confidentiality reasons.

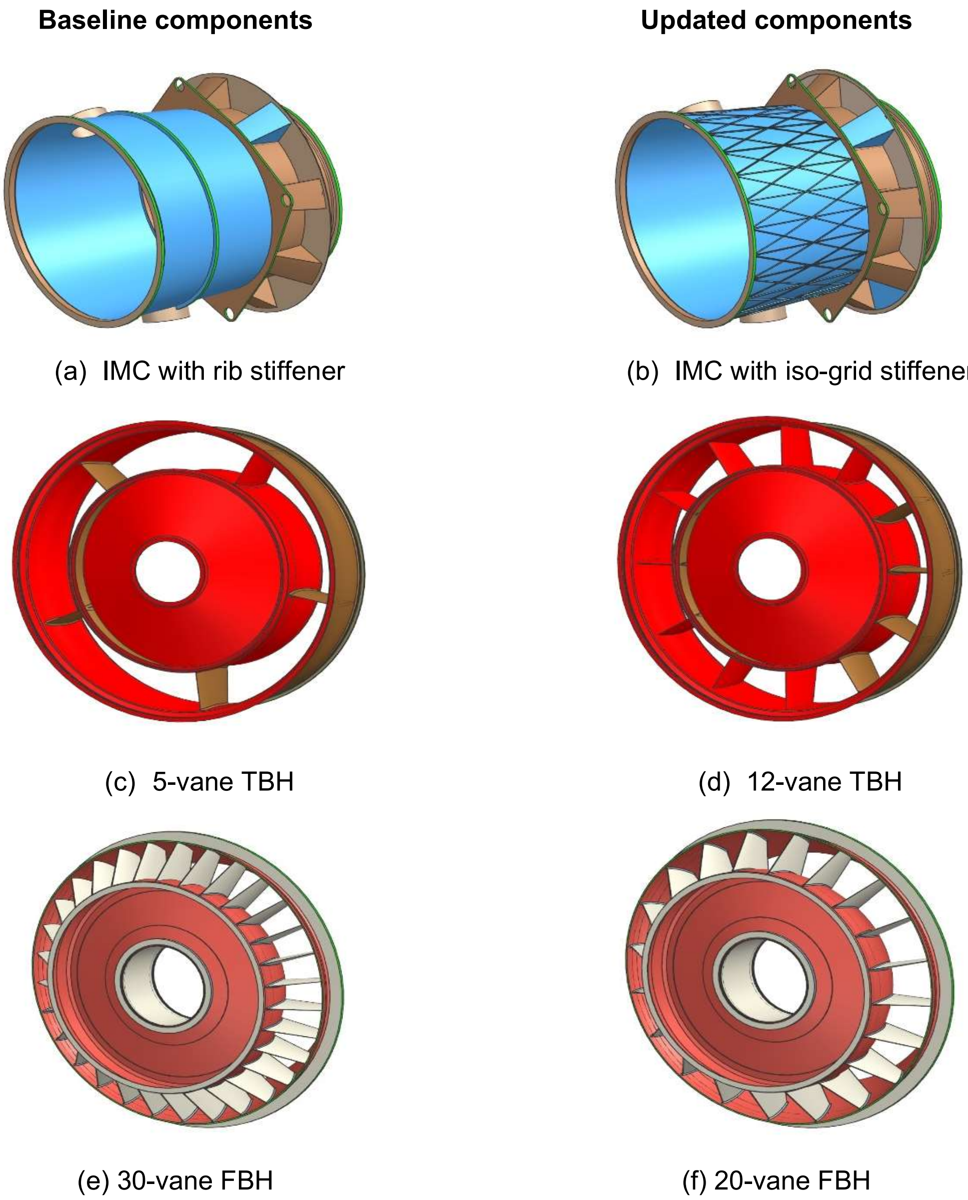


Figure 4 Topological component design changes

Although the present study focuses on the optimisation of these three components, all the simulation results are obtained from a whole engine model. Engine mass is chosen as the design objective. Nine tip clearances are chosen as the constraints. The tip clearances are extracted from engine components other than the FBH, intercase and TBH. A MATLAB script is used to automatically generate the DOE which includes changing the design variables, 3D meshing the component, assembling the whole engine model, solving in Altair OptiStruct and extracting results. Kriging models are generated from the DOE results using the proprietary, Rolls-Royce, software suite CM02 [13].

3 RESULTS

3.1 SURROGATE MODELS OF "TRUE" SYSTEM RESPONSES

"True" system responses are needed to measure the accuracy of the categorical Kriging models generated from the proposed data-reuse methods. Kriging models of each component are constructed from a 50-point DOE of finite element simulations. Three components, intercase (IMC), FBH and TBH, are chosen here as component design examples as they are all key components for whole engine structural strength. Each component has ten Kriging models (mass and nine tip clearances). Table 1 to 3 lists the coefficients of determination (R2), root-mean-square error (RMSE) and mean absolute error (MAE) of the least accurate model for each component. It can be seen that even the worst-case scenario model has high accuracy therefore these Kriging models are regarded as indicative of the "true" system responses in the following sections. It is worth noting that the FBH has a lower accuracy level; this is because the responses of the constraints are less sensitive to FBH variables, therefore the effect of noise is higher, decreasing the surrogate model quality. The DOEs in the following sections are constructed by sampling these Kriging models of "true" system responses instead of running extra FE simulations. This enables the performance of the data-reuse strategies to be statistically quantified. The results presented in this paper focus on the accuracy and consistency of the surrogate models built from new data-reuse methods.

Table 1 IMC surrogate model accuracy

	Krig min R2	Krig max RMSE	Krig max MAE
Baseline ICC 50pt FE DOE (true response)	0.9742	4.7049%	10.7842%
Iso-grid ICC 50pt FE DOE (true response)	0.9738	4.8569%	13.4791%

Table 2 TBH surrogate model accuracy

	Krig min R2	Krig max RMSE	Krig max MAE
5-vane TBH 50pt FE DOE (true response)	0.9807	2.8686%	6.7598%
12-vane TBH 50pt FE DOE (true response)	0.9754	3.5750%	9.2119%

Table 3 FBH surrogate model accuracy

	Krig min R2	Krig max RMSE	Krig max MAE
30-vane FBH 50pt FE DOE (true response)	0.8339	11.5286%	23.7311%
20-vane FBH 50pt FE DOE (true response)	0.8299	11.4203%	24.2505%

3.2 DATA-REUSE AT COMPONENT LEVEL

The first set of examples demonstrates data-reuse at single component level. This essentially means only one component is updated while the rest of the engine remains the same. Two indicators of the Kriging model's quality are accuracy and consistency. The accuracy refers to the Kriging model's ability to predict the behaviour of the underlying engineering system. The consistency refers to whether the Kriging model is sensitive to the DOE used, as different DOEs can lead to differently performing models. The accuracy of the Kriging model is calculated by sampling the model at 1000 points and comparing these predictions with the "true" system responses. This is then repeated 25 times using different DOEs enabling a mean and a worst performance to be determined. The model's consistency is judged by considering both the mean and the worst performance.

Using the intercase as an example, Kriging models of the baseline design are constructed from a 20-point DOE. Using traditional methods, another 20-point DOE is needed when the topology is updated with the iso-grid stiffener. However, the proposed approach only requires a 5-point DOE of the new topology when reusing the 20-point DOE of the original baseline topology in order to achieve the same level of accuracy and consistency. For comparison, the results of the Kriging models generated from the 5-point DOE of the updated geometry is also calculated. Table 4 lists the results for the baseline intercase, the updated intercase with and without data-reuse. As expected, the Kriging models from only a 5-point DOE are unreliable. But the categorical Kriging models, needing only 5 extra analyses, have similar accuracy and consistency as the original 20-point Kriging models.

Table 4 Data-reuse for IMC design

Kriging method \ Model accuracy	mean				worst		
	R2	RMSE	MAE		R2	RMSE	MAE
20pt DOE of baseline IMC	0.98	1.98%	1.49%		0.73	11.37%	8.17%
5pt DOE of iso-grid IMC	0.60	13.55%	10.97%		0.01	41.76%	33.70%
20pt baseline + 5pt iso-grid IMC categorical Kriging	0.98	2.06%	1.59%		0.74	11.56%	8.65%

Similar results are obtained from the TBH and FBH designs (Table 5 and 6). In all cases, the results show that the proposed approach only requires a small number of DOE points of the new topology to achieve the same level of prediction accuracy when reusing baseline analysis data. Note that the worst-case scenario numbers from the different components are less aligned. However in all cases there is a significant improvement in consistency when data is reused.

Table 5 Data-reuse for TBH design

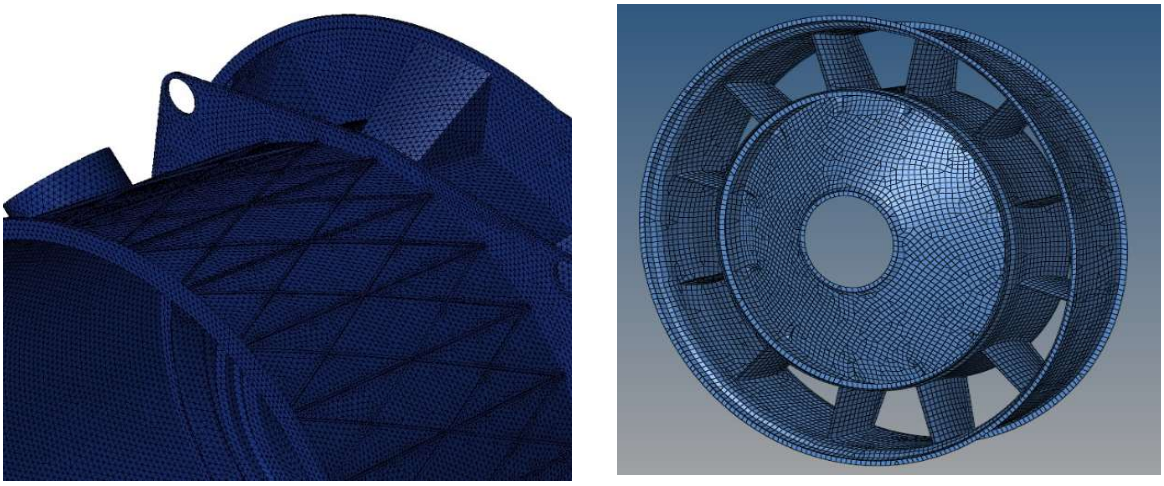
Kriging method \ Model accuracy	mean				worst		
	R2	RMSE	MAE		R2	RMSE	MAE
20pt DOE of 5-vane TBH	0.99	0.84%	0.64%		0.97	3.55%	2.75%
5pt DOE of 12-vane TBH	0.61	13.48%	10.83%		0.01	36.49%	29.21%
20pt 5-vane + 5pt 12-vane TBH categorical Kriging	0.97	3.16%	2.46%		0.37	30.02%	24.73%

Table 6 Data-reuse for FBH design

Kriging method \ Model accuracy	mean				worst		
	R2	RMSE	MAE		R2	RMSE	MAE
20pt DOE of 30-vane FBH	0.98	1.29%	0.98%		0.50	13.00%	9.94%
5pt DOE of 20-vane FBH	0.46	14.88%	11.97%		0.01	39.73%	32.54%
20pt 30-vane + 5pt 20-vane FBH categorical Kriging	0.96	3.28%	2.61%		0.40	34.83%	28.84%

3.3 DATA-REUSE AT SYSTEM LEVEL

In practice, it is often the case that multiple components are updated simultaneously by different component design teams. Therefore the whole engine scenery does not stay the same. This example investigates such a case, in which both the intercase and the TBH are topologically changed. The example is simulated from the intercase designer's perspective, which means that the intercase is modelled as 3D whereas the rest of the engine is modelled as 2D. The intercase is changed from a rib stiffener to an iso-grid stiffener and the number of TBH vanes is increased from 5 to 12. The medial mesh of the new TBH is generated and replaces the old TBH in the whole engine model (Figure 5 (b)). The 3D mesh of the new intercase (Figure 5 (a)) is then integrated with the updated whole engine scenery.



(a) 3D IMC with iso-grid (b) 2D 12-vane TBH

Figure 5 Two components are updated at the same time

There are now three categories:

- Cat1: 20pt baseline 3D IMC + baseline 2D TBH
- Cat2: 5pt new 3D IMC + baseline 2D TBH
- Cat3: 5pt new 3D IMC + new 2D TBH

Analysis results of Cat1 and Cat2 can be obtained from single component designs as described in previous section. As Cat3 represents a new whole engine configuration, a new 50-point DOE is obtained to construct the Kriging models of the "true" system responses. The accuracy of these Kriging models is in line with the data listed in Table 1, with minimum R2 above 0.95. The "true" system responses are then sampled 5 times to build the Kriging models of Cat3. Table 7 lists the performance of Kriging models for each individual category.

Table 7 System level Kriging models

Model accuracy / Kriging method	mean				worst		
	R2	RMSE	MAE		R2	RMSE	MAE
20pt baseline 3D IMC + baseline 2D TBH (cat 1)	0.98	2.08%	1.63%		0.74	11.56%	8.65%
5pt DOE of new 3D IMC + baseline 2D TBH (cat 2)	0.60	13.55%	10.97%		0.01	41.76%	33.70%
5pt DOE of new 3D IMC + new 2D TBH (cat 3)	0.63	12.87%	10.43%		0.01	40.02%	33.09%

In this example, the target is to predict the behaviour of the new whole engine model (Cat3) with data reuse. There are two historical data sets (Cat1 and Cat2) that can be reused. It is still assumed that the baseline design requires a 20-point DOE and any subsequent topology update only requires 5 extra points. There are three different combinations involving Cat3. Table 8 lists the performance of categorical Kriging models from different combinations of each category.

Table 8 System level data-reuse for IMC design

Kriging method \ Model accuracy	mean R2	mean RMSE	mean MAE		worst R2	worst RMSE	worst MAE
cat1+cat2+cat3	0.93	4.22%	3.30%		0.15	21.06%	17.28%
cat2+cat3	0.71	11.12%	8.95%		0.01	37.28%	30.42%
cat1+cat3	0.95	3.89%	3.04%		0.49	20.89%	17.15%

It can be seen that combining Cat1 and Cat3 leads to the best results for both accuracy and consistency. Although the results are not as good as in single component examples, reusing analysis data still greatly improves the resulting models' quality.

3.4 OPTIMISATION OF AN UPDATED WEM

In most engineering design applications, the purpose of accurate surrogate modelling is not only for prediction but also for optimisation. The Kriging and cat-Kriging models of the whole engine with three updated components are optimised to reduce the total mass of the three components of interest (FBH, IMC and TBH). The optimisation parameters are the 15 design variables used before (5 from each component). The range for each variable is ±40% of baseline value. The constraints are 9 tip clearances with no more than 1% increase from the baseline value. To demonstrate the benefit of data reuse, Kriging and cat-Kriging models are employed within a surrogate-based optimisation where results from infill points at the location of optima predicted by the surrogates are iteratively added to each surrogate model. The search of the resulting surrogate models employs a genetic algorithm with this search and the construction of the surrogates at each iteration performed using the proprietary, Rolls-Royce, optimisation suite, CM02 [13]. Figure 6 plots the total mass as percentage of the baseline value against the number of surrogate model update iterations. For both the Kriging and cat-Kriging, each point represents a new sample of the updated whole engine model. However, the cat-Kriging also reuses the sampling points of the old whole engine model.

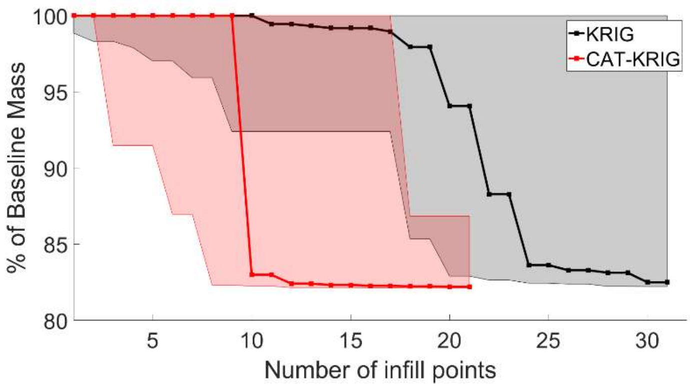


Figure 6 WEM optimisation with and without data reuse
(solid lines – average performance; shaded areas - 95% confidence bounds)

Due to the stochastic nature of genetic algorithm, both optimisations are repeated multiple times to assess their overall performances. In Figure 6, the solid lines are the average optimisation results of the Kriging (black) and cat-Kriging (red) models. The shaded areas represent the 95% confidence bounds, i.e. the result of a single optimisation has 95% chance falling into the shaded area. It can be seen that the optimisation of both models reaches a similar optimum, i.e. around 17% of mass reduction is achievable through optimisation. However, the cat-Kriging model with data reuse converges much faster than the simple Kriging model.

4 CONCLUSION AND FUTURE WORK

A novel computational method based on data reuse technologies is presented and validated. By reusing analysis results of previous design iterations, only a small number of simulations are needed to build a surrogate model with a high level of prediction accuracy. A case study of multiple design variables and topology changes in three subsystems demonstrates that surrogate modelling and data reuse technologies can significantly reduce analysis costs from one design iteration to the next.

The results indicate that though reusing analysis data generally improves the surrogate models' quality, the level of improvement can vary with the type of data being reused. Therefore some analysis to select the most appropriate data to reuse in the model can be beneficial. The future work will investigate how to carry out this type of analysis. Some research work is also needed to understand better how far the updated model can differ from the baseline while still having the benefits in re-using old data. The work so far has been based on a subsystem designer's perspective. In the future it might be useful to apply similar approach on system level in order to assist the decision making in whole engine design. Another area of interest for future developments is in understanding the correlation evolution going further with the iterations and how to get benefit in re-using better-correlated older data.

ACKNOWLEDGEMENTS

The research leading to these results has received funding from Innovate UK, under the Collaboration Across Business Boundaries (COLIBRI) project (Ref no. 113296).

REFERENCES

[1] Yong, H. K., et al. (2019). "Multi-fidelity Kriging-assisted structural optimization of whole engine models employing medial meshes." Structural and Multidisciplinary Optimization, 60(3): 1209-1226.

[2] Wang, L., et al. (2020). "Structural topology optimisation of a gas turbine engine and nacelle integration components employing a medial surface representation." Proceedings of the 1st Aerospace Europe Conference, Bordeaux, France. 25 - 28 Feb 2020.

[3] Queipo, N., et al. (2005) "Surrogate-based analysis and optimization." Progress in Aerospace Sciences, 41: 1–28.

[4] Simpson, T., et al. (2001) "Metamodels for computer-based engineering design: Survey and recommendations." Engineering with Computers, 17(2): 129–150.

[5] Garrido-Merchán, E. and Hernández-Lobato, D. (2019) "Dealing with Categorical and Integer-valued Variables in Bayesian Optimization with Gaussian Processes." Neurocomputing, 380: 20-35.

[6] Saves, P., et al. (2021) "Constrained Bayesian Optimization over Mixed Categorical Variables, with Application to Aircraft Design." Proceedings of AeroBest, Lisbon, Portugal. Jul 2021.

[7] Karlsson, R., et al. (2021) "Continuous Surrogate-Based Optimization Algorithms Are Well-Suited for Expensive Discrete Problems." Proceedings of Artificial Intelligence and Machine Learning, 48-63.

[8] Krige, D. (1951) "A statistical approach to some basic mine valuation problems on the witwatersrand." Journal of the Chemical, Metallurigical and Mining Engineering Society of South Africa, 52(6): 119-139.

[9] Brooks, C., et al. (2011) "Multifidelity design optimisation of a transonic compressor rotor." Proceedings of 9th European Turbomachinery Conference, Istanbul, Turkey, 21st-25th March.

[10] Wankhede, M., Bressloff, N. and Keane, A. (2011) "Combustor design optimisation using co-kriging of steady and unsteady turbulent combustion." Proceedings of ASME Turbo Expo 2011, Vancouver, Canada.

[11] Toal, D. J. J. (2015) "Some considerations regarding the use of multi-fidelity Kriging in the construction of surrogate models." Structural and Multidisciplinary Optimization, 51 (6): 1223-1245.

[12] Lin, Q., et al. (2021) "Multi-output Gaussian process prediction for computationally expensive problems with multiple levels of fidelity." Knowledge-Based System, 227(107):151.

[13] Toal, D. J. J. (2023) "Applications of multi-fidelity multi-output Kriging to engineering design optimization." Structural and Multidisciplinary Optimization, 66: 125.

[14] Martinsson, J., et al. (2021). "Exploring the Potential of Digital Twin-Driven Design of Aero-Engine Structures." Proceedings of the Design Society, 1521-1528.

[15] Letaief, M. B., et al. (2020). "An approach of CAD/CAM data reuse for manufacturing cost estimation." International Journal of Computer Integrated Manufacturing, 33(12): 1208-1226.

[16] Martinsson Bonde, J., et al. (2023). "A similarity-assisted multi-fidelity approach to conceptual design space exploration." Computers in Industry, 151.