Multi-disciplinary optimization of turbine components with the aid of surrogate modeling techniques

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Abstract: Turbomachinery components design and optimization process requires a multi disciplinary approach. These components are designed and optimized for aerodynamic efficiency with robust mechanical integrity requirements. Further analyses are also required for thermal stresses, rotor dynamics, acoustics and other design requirements. The analyses require different tools (in-house and commercial) which must be integrated within a fully automated process. The calculation time for these calculations, particularly for CFD, could be a limiting factor for the number of iterations used. In order to ensure the widespread adoption of this automated process throughout the design and engineering organisation a generic process framework is being developed together with supporting software tools. This allows different types of analysis to be included in the framework process and the resulting analysis process to be easily applied to different design problems. This paper presents the approach to integrate multi-disciplinary tools within an automated process and describes the use of surrogate modeling techniques to reduce the time to execute these calculations. The development and use of the analysis framework process and supporting tools is also described.

Keywords: Isight, Coupled Analysis, Design Optimization, Multi-disciplinary Optimization, Seals, Turbines.

1. Introduction

Alstom Power is a global leader in power generation systems, products and services. Computer-aided design (CAD) and engineering (CAE) tools are used extensively in our product design and analysis processes. A typical product or component design process involves the use of computational fluid dynamics (CFD), and finite element (FE) models for stress and life analysis. Analyses of vibration and heat transfer behaviour are also required. These analyses tend to be computationally costly, typically the CPU time for running one analysis case can range from minutes to hours. For this reason, design optimisation using full engineering analysis is often impractical. A pragmatic approach is to use surrogate models to support the design optimisation process. With the appropriate choice of surrogate model type and good sampling plan, the surrogate model can closely approximate the response function.

Ensuring the widespread adoption of optimisation techniques throughout the design and engineering organisation requires a simple way of introducing automation and optimisation into analysis processes in different disciplines and for different applications. The Methodologies for Tools department has developed an automated build process applied to standardised process templates which provides this, allowing the complexity of setting up the automation and optimisation and handling of different analyses to be captured in the template processes.

This paper describes the process templates and the build process, the use of surrogate models generated from the results of the CAE analysis, and gives examples of the process applied to steam turbine design.

2. CAE process automation

The Methodologies for Tools department has performed many CAE optimisation projects using Isight, some of these using robust design and Design For Six Sigma (DFSS) techniques. These have been set up on a case-by-case basis, building on previous experience and covering several types of analysis; CFD, FE, Heat Transfer, Vibration analysis, and also applying coupling between different analyses. These projects have been used for research into optimisation methods, and have demonstrated great potential benefits.

Optimisation of a CAE analysis (e.g. CFD, FE) is typically set up by an expert in the type of analysis gradually building the process into an Isight model for each specific case, and applying optimisation once the analysis process has been automated. This procedure must be repeated for each new case and therefore requires significant Isight model development effort.

In order to deploy the techniques throughout the design and engineering organisation, the lessons learned from the earlier research have been used to develop a flexible, deployable CAE process comprised of Isight process templates and supporting tools including a program which builds process models for specific analysis cases from a process templates.

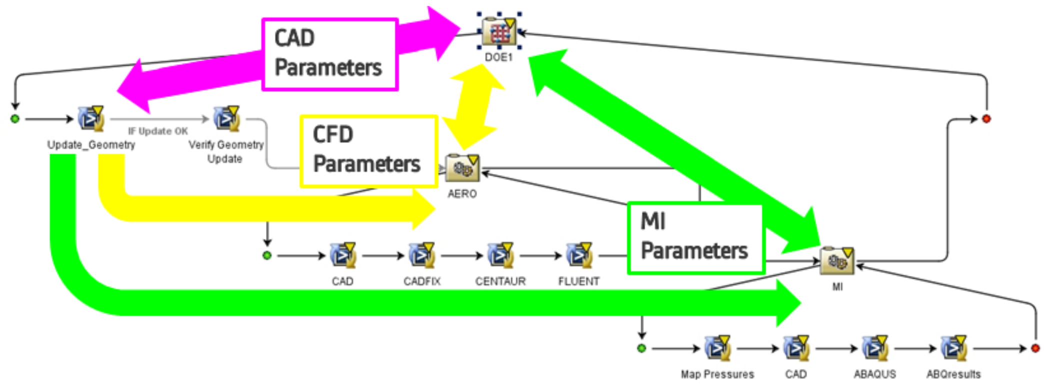


Figure 1. Template process model for CFD and MI analysis, showing mapping of parameters between components

The use of a standardised automation process applicable to different types of problem and to different types of analysis reduces this duplication of work and simplifies the set-up task for each new analysis. A further benefit is that improvements made to the process are available to all users.

A basic 'framework' process template has been designed to allow different types of CAE analysis to be incorporated easily. An example of CFD and Mechanical Integrity (MI) analyses integrated into the framework process is shown in Figure 1.

3. Automatic generation of CAD-CAE analysis process models

3.1 Automated parameter extraction from CAD models

The most obvious difference between two different applications of a CAE analysis is often the geometry. Usually geometric parameters will be included in the control factors of the optimization. Therefore the geometry must be parameterised so that it can be controlled by the automated process and these parameters must themselves be included in the process model.

Changes to the model geometry will affect other dimensions which need to be measured, either to be used as constraints on the optimisation, or as inputs to the CAE analysis. These measurements must also be defined in the CAD model.

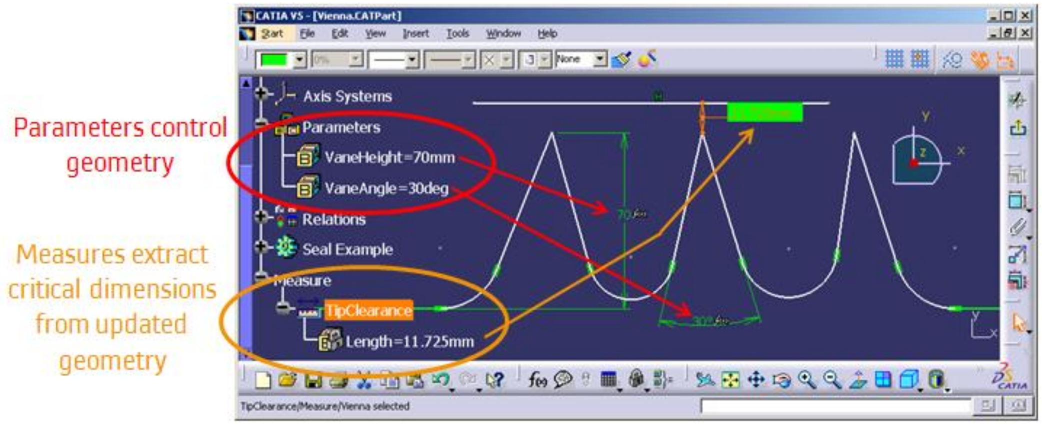


Figure 2. Parameters and Measures in a CATIA CAD part

The process model building program uses simple text files to define and set parameters and dimensions in the process model when it is built from the template process. The text files are themselves generated by another program which interrogates the parameterised CAD geometry (Figure 2).

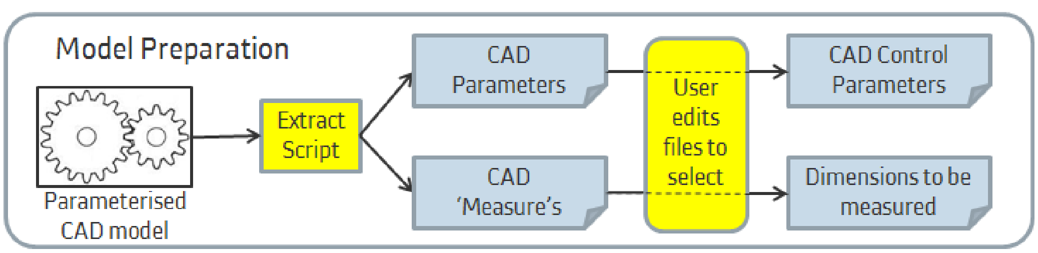


Figure 3. Flowchart of CAD Model Preparation process

This allows different geometries with different parameterisations to be controlled by a standard process.

3.2 Automated CAE geometry generation

A CATIA CATScript program applies the parameter values to the CAD geometry and takes measurements from the updated geometry. Each CAE analysis process also runs a similar program to apply CAE-specific operations to the CAD model and generate the form of the geometry required by the CAE analysis (Figure 3).

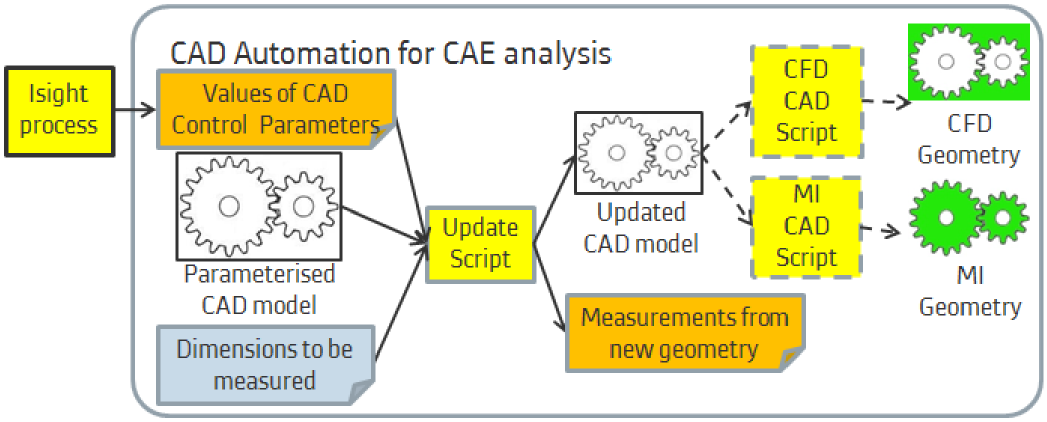


Figure 4. Flowchart of CAD Model Preparation process

3.3 Automated generation of CAD-CAE analysis process models

Because the Isight process needs to contain an internal parameter for each CAD model parameter and dimension, these must be inserted into the template process. The process builder program does this. The builder program also copies and maps parameters between Isight process components and sets up the data exchange operations between input and output files (Figure 4).

The template process contains many configuration parameters and also some parameters used to control the process builder program. These parameters are grouped in the template process using Isight's parameter grouping capability. As the process builder inserts the new parameters these are put into new groups. (Figure 5)

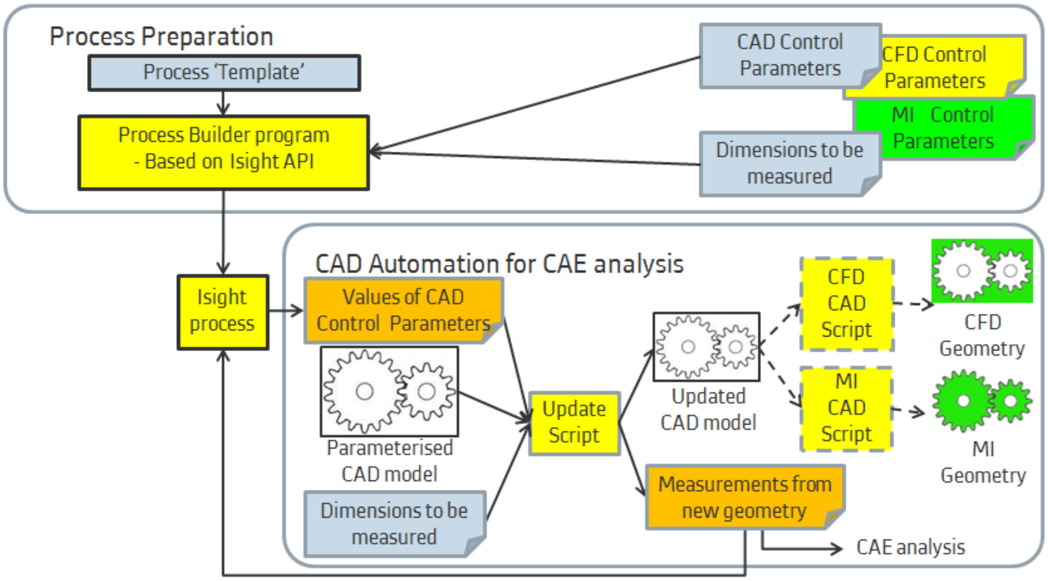
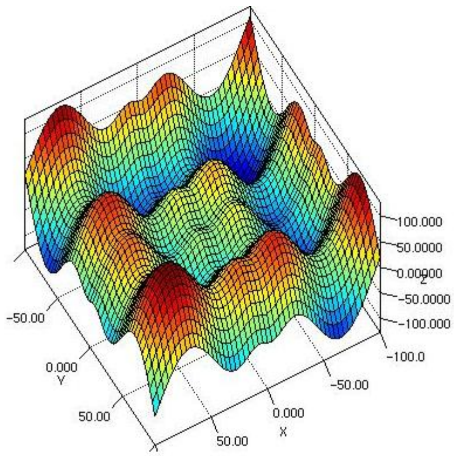


Figure 5. Flowchart of CAD Model Preparation process

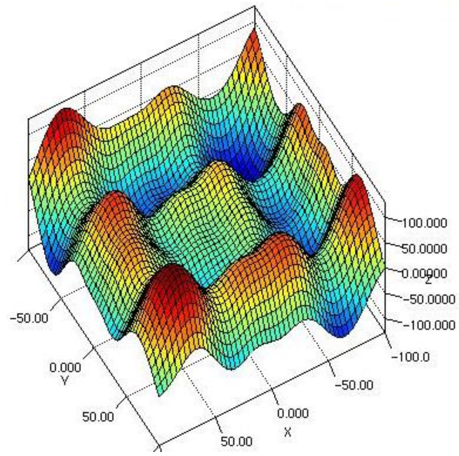
Isight expert knowledge is captured in the template process, allowing the CAE domain expert to run complex automated processes using their domain knowledge.

4. Optimisation using Surrogate Models

At Alstom Power, the Methodology for Tools department has benchmarked different types of surrogate models, including polynomial response surface model (RSM), radial basis function (RBF) and Kriging, against a number of test functions with different response characteristics. Kriging coupled with optimised Latin hypercube has been found to be highly flexible and has outperformed the other benchmarked models in most cases, ranging from the relatively smooth response surfaces to the highly non-linear multi-modal problems. (Figures 6 and 7)



(a) True function



(b) Kriging

Figure 6. Kriging vs true response for 2D Schwefel function

Once confidence has been established with a surrogate model, it has been applied to engineering design optimisation. The test cases shown in this paper relate to the turbomachinary design, where the response surfaces are not explicit analytical functions but solutions from a host of engineering tools. For these test cases, the main objective is not to obtain a high fidelity approximation model throughout the design space, but to achieve improved performance. Both test cases are single objective optimisation problems. In one case, the objective is to minimise the leakage flow through a labyrinth seal in an Alstom steam turbine. In the other case, the objective is to maximise the aerodynamic efficiency of a steam turbine. Using an optimised Latin hypercube sampling plan, a Kriging model was constructed for each case. Optimisation was then performed on the surrogate model to find the optimal design point. The design variables were then fed into the full engineering analysis, to evaluate the true response at this "optimal" point. This true response was compared to the optimal objective function obtained from full optimisation runs, with certain computation budget constraints. A description of these test cases and results is provided in the following sections.

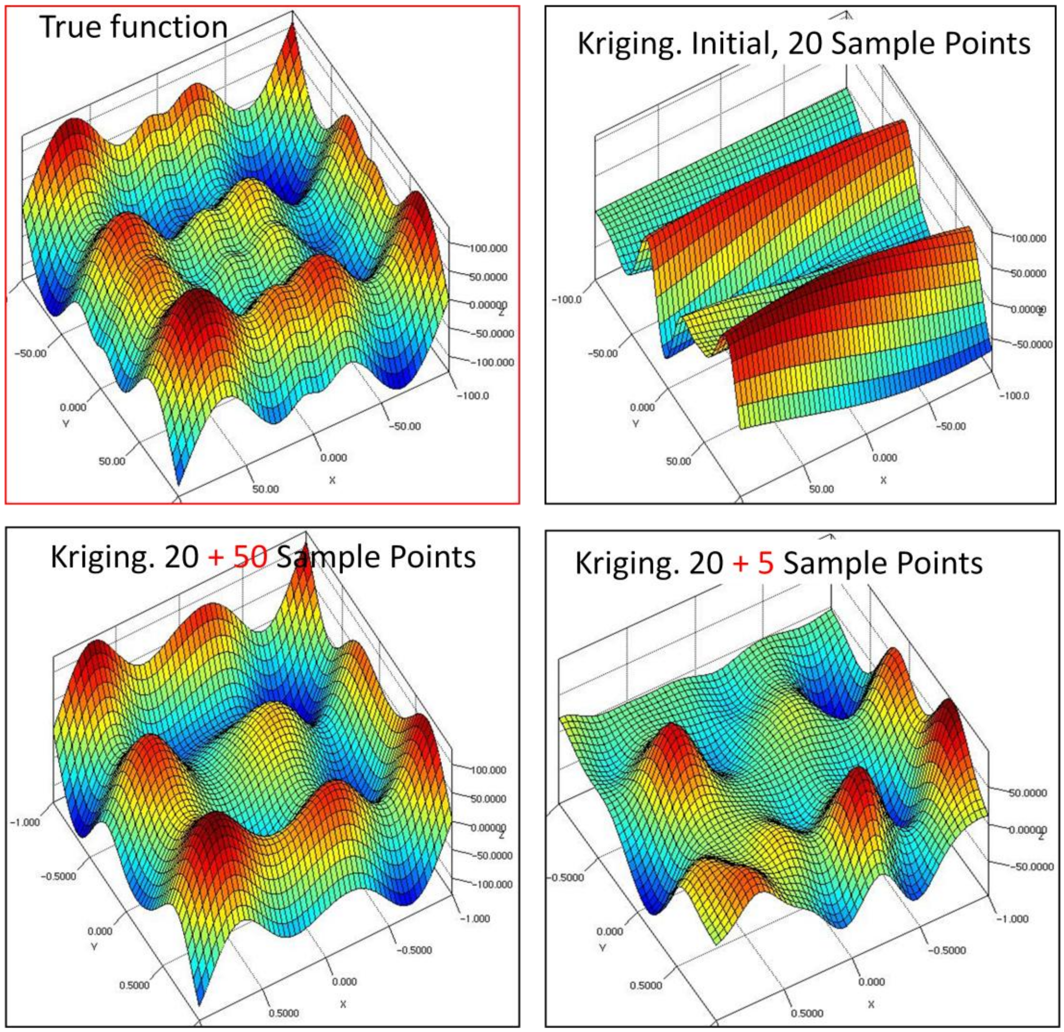


Figure 7. Adaptive sampling applied to Kriging model of 2D Schwefel function

5. Example: Seal Leakage reduction

The unavoidable leakage flow between the rotor and the static components erodes the turbine efficiency. Seals are used to reduce the leakage flow. For the labyrinth seal optimisation test case, the objective is to minimise or control the leakage flow through the optimal design of the seal geometries, while the boundary conditions are determined by the main flow. The leakage flow is dependent on a number of geometric design parameters, such as the mean thickness and tip thickness, height, and lean angle of individual fins.(Figure 8)

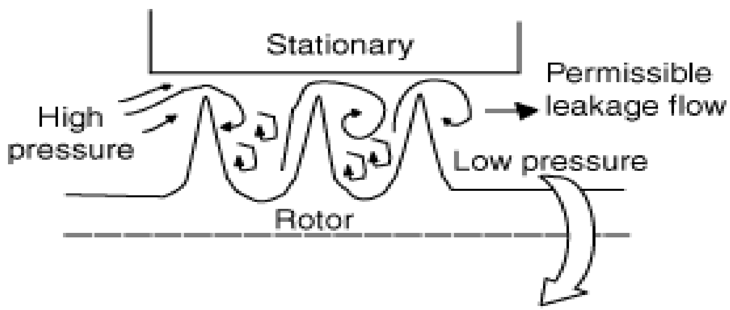


Figure 8. Schematic of labyrinth seal between turbine rotor and static components

This analysis used CATIA V5 for geometry creation, Centaur for Mesh generation and Fluent as the CFD solver. Typical computational time for a single calculation was about 15 min.

Through Design of Experiments, the number of main geometric design variables affecting the leakage flow was screened to four. A Kriging model of the leakage flow versus these four parameters was created, using an optimised Latin hypercube with 50 points. In the search for the optimal solution, a 50 level full factorial sweep was carried out within the design parameter boundaries, resulting in 6.25 million evaluations of the surrogate function that takes about two minutes on a single core of a PC with 2.66GHz Intel Core(TM)2 Quad CPU. This optimal point was then fed into the full engineering analysis to obtain a validation value, which was then compared with the results obtained by full optimisation. The full optimisation was conducted using the downhill simplex or evolutionary algorithm in Isight, prescribing a budget of 1000 evaluation points for each of these algorithms.

The lowest leakage flow from the initial 50 points optimised Latin hypercube has been used as the reference for assessing the optimisation results. With surrogate model assisted optimisation, leakage flow reduction of 1.1% has been achieved. By comparison, full optimisation achieved a leakage reduction of 0.8% using downhill simplex, and a reduction of 1.4% using the evolutionary algorithm. While these results clearly show the benefit of surrogate model assisted optimisation, they also indicate its limitations.

A further study used the same test case to investigate the performance and suitability of different types of surrogate models (Badjan, 2013). Surrogate models tested included Polynomial models, Radial Basis Functions, Kriging and two types of Neural Network – Feed-forward Back-Propagation (FFBP NN) and Dynamic Threshold (DTNN). Some of the normalised results from this study are shown in Figure 9.

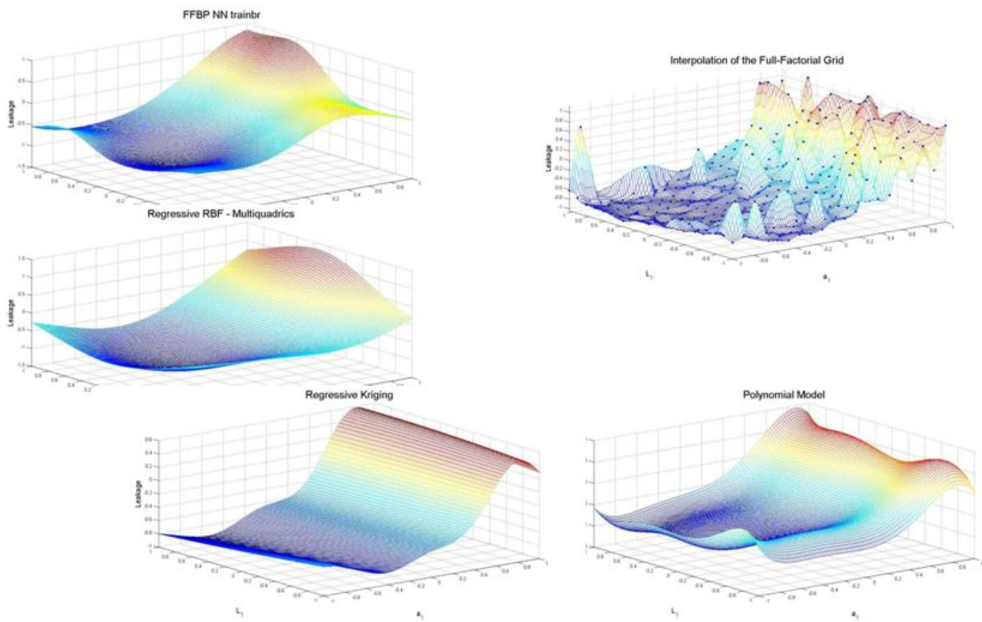


Figure 9. Seal Leakage surrogate models and interpolation of Full Factorial Design of Experiments study

6. Example: Turbine flow path design optimisation

The objective of this test case was to maximise the aerodynamic efficiency for a given turbine flow path design. The aerodynamic efficiency is strongly affected by the distribution of flow and pressure field along the flow path. The aerodynamic efficiency was calculated using the Alstom in-house tool Prel.

There were initially 11 independent design variables for this study, defining both the geometry and operating conditions. Using DOE screening, the 6 most significant parameters were selected for optimisation.

A Kriging model was created for the aerodynamic efficiency, using these 6 parameters as independent variables, and 100 optimised Latin hypercube sampling points. A full sweep was performed on the Kriging model using 20 levels for each parameter to search for maximum efficiency, which made 64 million calls to the surrogate model and takes about one hour on a single core of a PC with 2.66GHz Intel Core(TM)2 Quad CPU. A further Prel run was carried out to validate the predicted efficiency at the surrogate model derived optimal point.

The surrogate assisted optimal solution was compared to the solutions from full optimisation, using a downhill simplex or evolutionary algorithm in Isight. The Prel calculation is "very fast", each evaluation taking about 10 seconds. For the downhill simplex, 1000 evaluations were allocated. For the evolutionary algorithm, 10,000 evaluations were allocated, which takes just over a day to complete.

The optimal solutions are normalised against the original 100 Latin Hypercube points. The lowest efficiency of the sampling plan was normalised to 0, and highest to 1. The surrogate assisted optimal solution achieved a normalised efficiency 1.048. By comparison, the "full" optimal solution returned a value of 1.025 and 1.038 for the downhill simplex and evolutionary algorithm respectively.

It is clear that the downhill simplex quickly converges to a local optimum: the optimal solution was obtained at 112th evaluation. For the evolutionary algorithm, the current optimal was obtained at 3482nd out of 10,000 iterations. It is likely that the evolutionary algorithm can obtain a better solution if more iterations were allocated. Nevertheless, the usefulness of surrogate-assisted optimisation is clearly demonstrated in this case.

7. Conclusion

The application of optimisation techniques offers great benefits in turbine component design. The computationally expensive nature of many CAE simulations, especially CFD, necessitates the use of surrogate models for many of these analyses. Work on different aspects of turbine component design has demonstrated the effectiveness of surrogate models for design optimisation.

A standardised automated integrated CAD-CAE process framework and supporting tools is under development in the Methodology for Tools department of Alstom Power to facilitate widespread adoption of surrogate-model based optimisation throughout the engineering design organisation. This framework simplifies the automation of complex multi-disciplinary CAE processes and thereby the generation of surrogate models of turbine components for their optimisation.

8. References

1. Badjan, Gianluca, "Evolution of Surrogate Modelling Methods for Turbo-Machinery Component Design Optimisation", MSc thesis, University of Trieste, 2013