Robust structural design of a simplified jet engine model, using Multiobjective optimization

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http://www.soton.ac.uk/~cedc/posters.html

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UTP for design

Robustness

Until recently it was normal in engineering design to simply use the most important design goal as a single objective during optimization. Robustness is intrinsically multiobjective in nature, as the optimal robust solution includes two goals - robustness and optimality. Robustness is measured using the variability of the performance characteristics, i.e. (stress levels, fuel consumption, weight etc) with regards to external variation of some design measures i.e. (thickness, structural load, temperature, shape, etc). (see Figure 1). Current project aimed to pave a way of procedures and method that can be used to find a light-weight, fuel efficient, engine structure that is least sensitive towards external load conditions.

The model

The WEM structure shown in Figure 2, is modelled in MSC NASTRAN and the casing thicknesses within each super element are defined by a thickness value in the corresponding PSHELL cards. This allows automatic variation of the thicknesses by the optimization algorithm. For each set of 15 thicknesses 200 load variations were performed on the model using multiple right hand side computations in order to minimise the computation time. These 200 runs are a predefined set of loads, selected using a Latin Hypercube algorithm, and allow the variance of the reaction forces to be estimated. The following quantities are defined as objective functions:

Objective 1 - Minimum {Standard Deviation of the internal reaction forces over the 200 load variations STDEVFMPX} - minimization of this function would produce the most robust design;
Objective 2 - Minimum {Mean value of the internal reaction forces over 200 load variations, MEANFMPX} - minimization of this function will produce a design with least reaction forces;
Objective 3 - Minimum {Mass} - This will produce the lightest design;
Objective 4 - Minimum {Mean value of the specific fuel consumption, SFC} - this will give us the most economical engine.

Affordability

With advances of multiobjective algorithms the aim now is to produce a set of designs which in each case are better than the rest for at least one criterion. Such a set is called a Pareto front. Engineers and designers then sit together and compare different requirements and select the best trade-off. This allows several design goals to be considered simultaneously and actively searched, aiming to obtain as many designs as possible which are evenly distributed and widely spread around the objective space. In real engineering problems the cost of evaluating a design is probably the biggest obstacle that prevents extensive use of optimization procedures. In the multiobjective world the cost is multiplied because there are multiple expensive results to obtain. The research being presented, has managed to utilize state of the art scientific, computational and visualization methods that makes this process affordable for a busy, standard setting environment such as the Whole Engine Model (WEM) division at Rolls Royce PLC, Derby, UK. Well known multiobjective algorithm NSGA2 has been combined intrinsically with surrogate technology and novel updates generation approach. It has been shown that this solution can bring computation times from 6 months to 24 hours.

Parallel computations

Those having experience with multiobjective computations may conclude that using 15 design variables and 4 objectives is a relatively complex and tough challenge. Computationally the above task can be very expensive. Each new set of thicknesses takes 20 - 25 minutes to analyze on a 1 GHz CPU. This includes pre and post processing, as well as the finite element solving run. It is known that strategies based on genetic algorithms generally require a large number of function evaluations. For a problem of this dimension it is realistic to say that a minimum of 20000 evaluations would be needed to obtain a good Pareto front. This corresponds to over a year´s worth of computations on a single processor. It is for this reason that large multiobjective real life optimization has been avoided until recently.

The same number of function evaluations takes just under two weeks if 30-off 1 GHz CPUs are used in parallel. Instead of receiving results for one set of thicknesses we get results for 30 sets in 25 minutes. Genetic algorithms are very convenient for parallel computations of this sort. The entire population can be run at once, therefore if its size is set as a multiple of the available processor units one can perform the analysis very efficiently.

With the use of surrogate models one does not need to carry out all the 20000 evaluations needed by direct search. Guided by advanced surrogate update strategies it is possible to obtain good convergence in just over 1600 evaluations, which take approximately 26 hours on a 30 processor computing cluster.

An interesting comparison is shown in Figure 3, where runs of differing lengths are compared: on the left is a short run with just 200 set of solves and on the right a longer one with over 1600. In the right hand plot one can see that the region close to the most robust design is very narrow. The left hand plot shows that the pointed and narrow region was not discovered when fewer evaluations were performed. Both figures represent the same information but lead to completely different conclusions, this highlights the importance of affording sufficient depth to any search.

Visualization

Figure 4 and 5 are an attempt to show 4 objectives on two dimensional plots. The idea of using glyphs instead of axes is not new. On these graphs one can see that size of the circle and colour indicate the remaining two objectives (good designs are at the blue end of the colour scale and have small circles). These plots may appear chaotic at first sight, however they become a very powerful tool once the designer is trained to interpet them. It is easy to see all 4 objectives simultaneously and one can then choose the best design. Our investigation showed that the point designated with a brown diamond symbol has a good overall performance.

Summary

This paper demonstrates that by appropriate combination of the latest computer science advances, efficient surrogate techniques and properly updated models it is feasible to obtain valuable information in a relatively short time. At current prices a 30 CPU computer cluster can be purchased for around $15000, this is a tiny fraction of the benefits that such an investment can provide. Multiobjective optimization is no longer a thing to avoid, it is affordable and gives valuable insights.

Acknowledgements

This work was performed with the support of Rolls-Royce as part of the EC funded Vivace project. For more information on this project please refer to the project website;
http://www.vivaceproject.com/

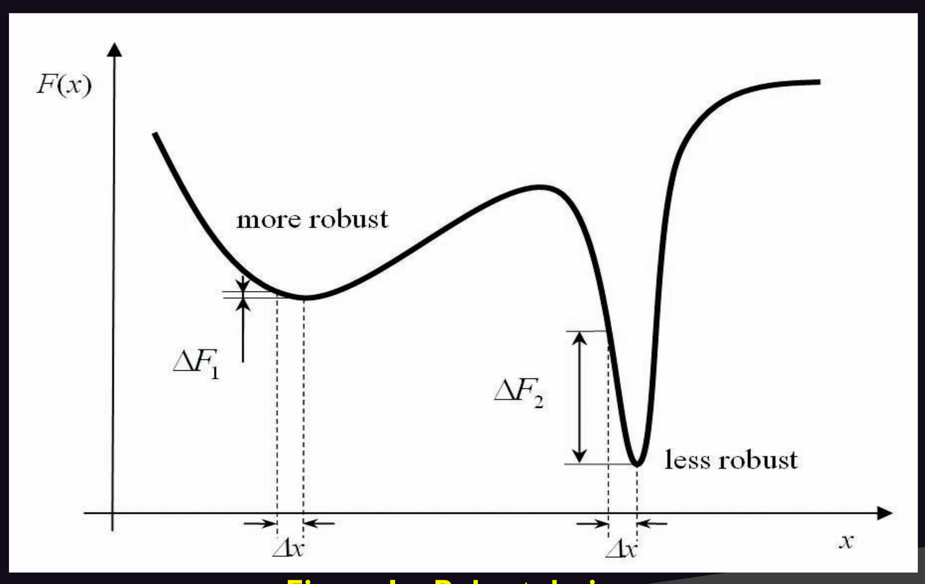

Figure 1 – Robust design

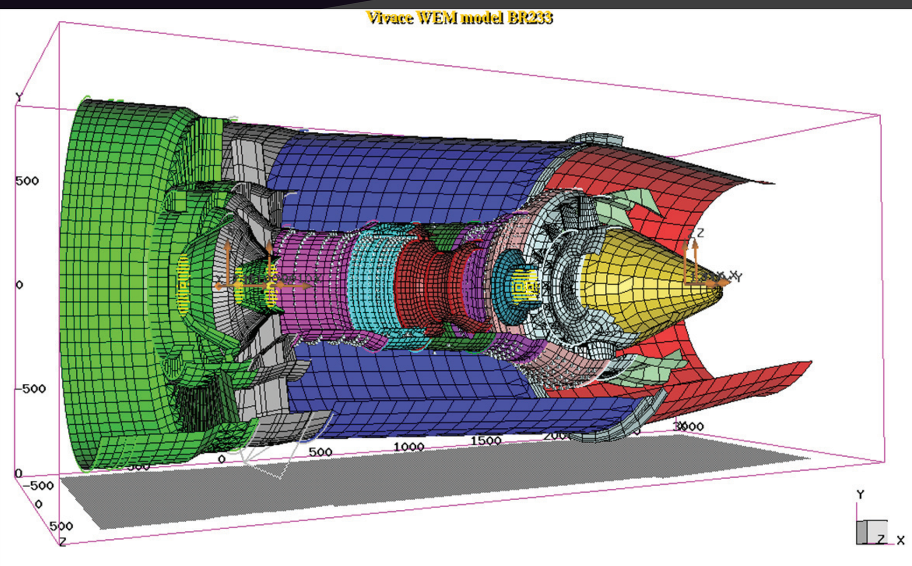

Figure 2 – Simplified Jet Engine model

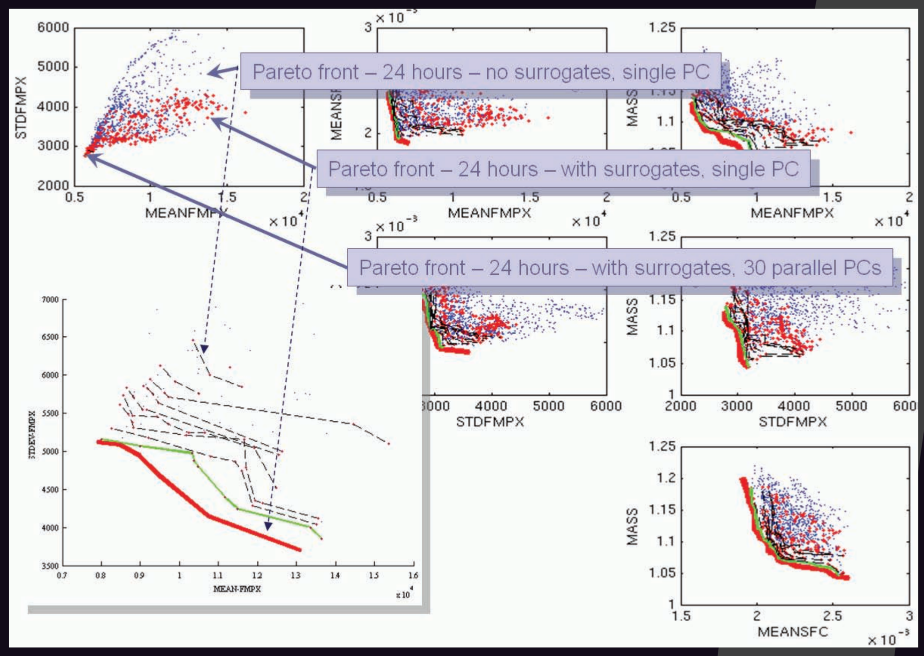

Figure 3 – Pareto front achieved using a low number of function evaluations (200) (left); A simplified version of Figure 8 – 1629 function evaluations (right)

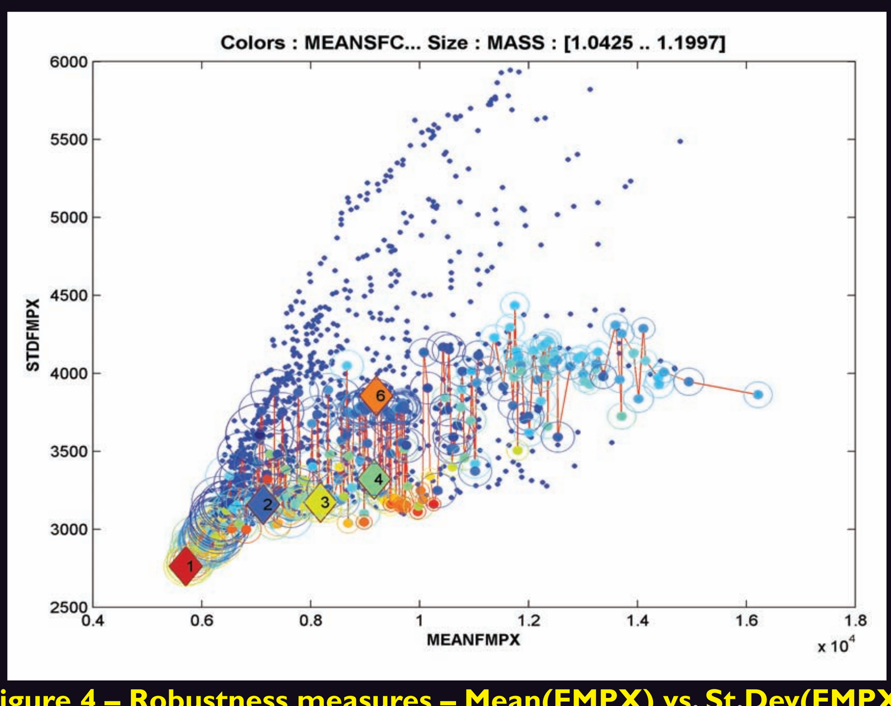

Figure 4 – Robustness measures – Mean(FMPX) vs. St.Dev(FMPX)

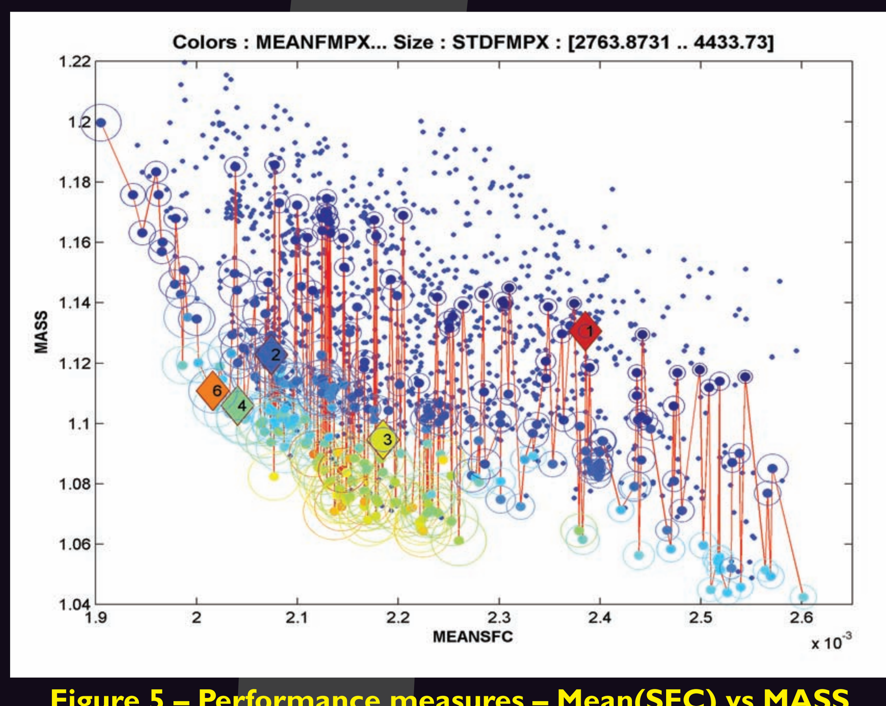

Figure 5 – Performance measures – Mean(SFC) vs MASS

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