BAE SYSTEMS

Visualization for Optimization

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UTP for design

CEDC

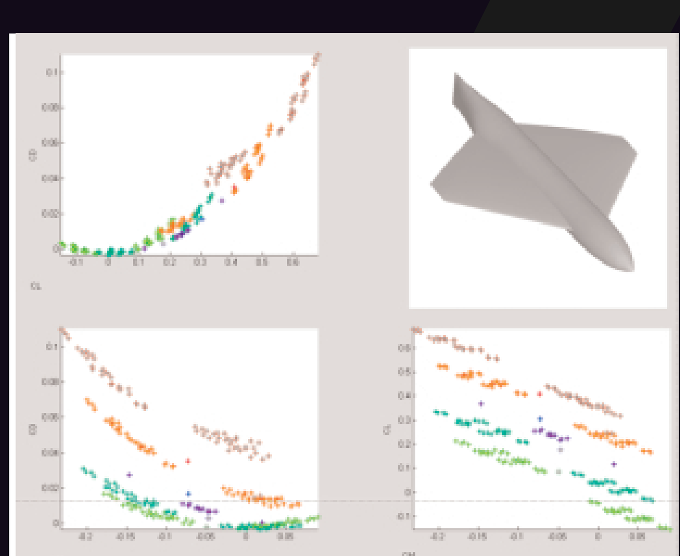

Figure 1: Scatter plot of 273 raw data points. Also illustrated an optimised body/wing configuration in the toy problem.

Aerodynamic design is complicated, so it requires designer intervention at every step. The role of the designer in this process is to confirm that everything up to the point he or she is at is consistent. The **visualization technology** presented in this poster has been designed specifically to help in this process. Computational evaluations, certainly for aerodynamic analysis are not guaranteed to converge for every case, particularly if the flow becomes 3D. Designers generally spend time inspecting evaluation results and making sure that they are correct. A toy problem that is none-the-less representative, which ranges between 2 and 22 design variables, is chosen for the illustrations of the visualization methodologies. A methodology is required in the first instance, after a number of evaluations have been performed, to identify any off trend results. Scatter plots are ideal for this purpose. The self-organizing map (SOM) also helps with this to give an overview.

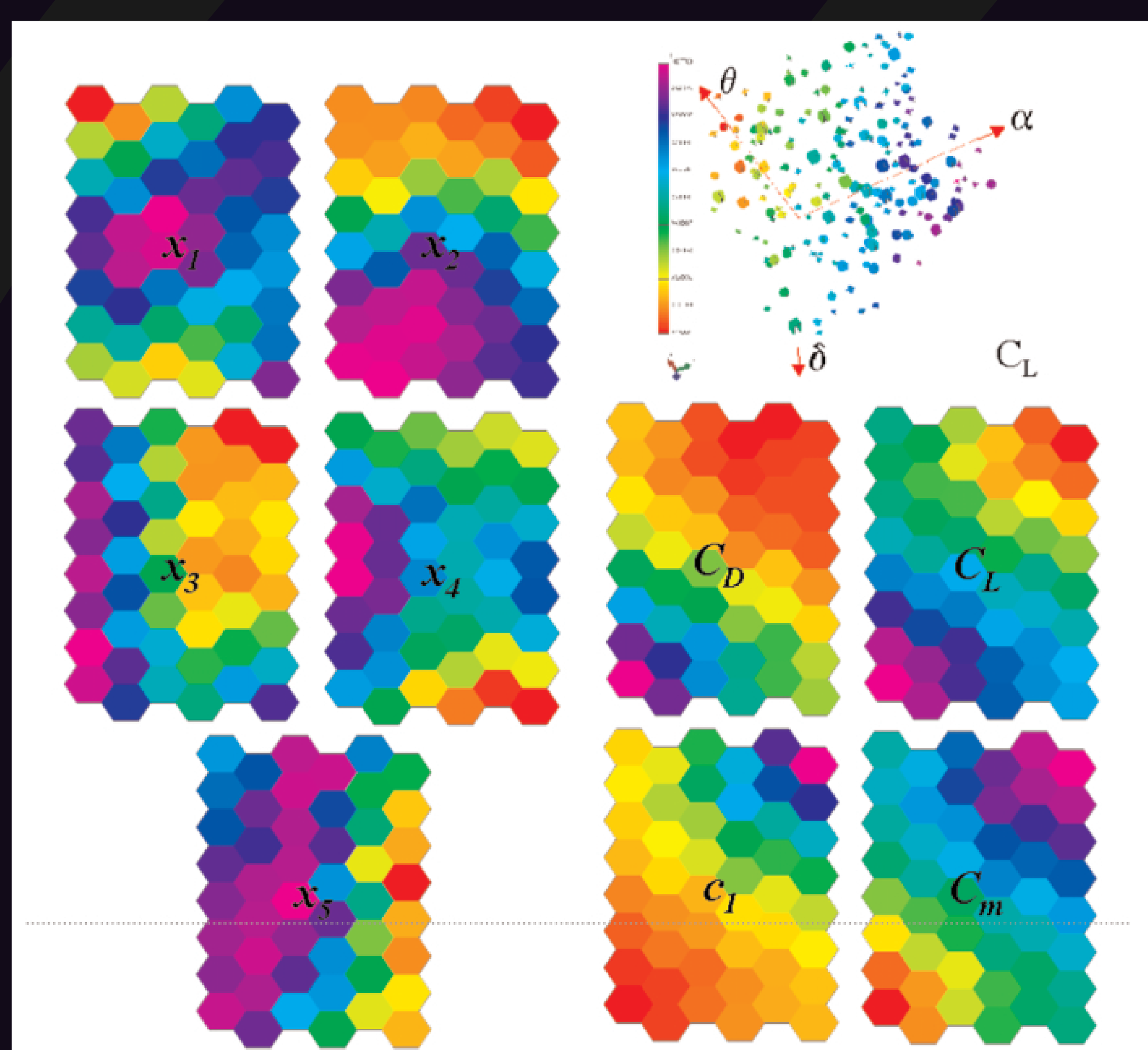

Figure 2: SOM representations of the design space

Response surface method technology eliminates inefficient design space sampling in the final stages of a gradient search optimization. The effect of smoothing through numerical noise via regression results in fewer basins of attraction. It also provides the amount of data required to enable **the hierarchical axes technique** (HAT) plots to be created. Several very sophisticated response surface techniques have been used here, which have advantages such **as statistical error, screening** and **user controlled regression**. A small number of less sophisticated methods may also be needed e.g. the Levenberg-Marquardt algorithm which minimizes the sum of squares error. This may be particularly useful if response surface fitting needs to be blind, for instance with very large numbers of dimensions.
There is a need to use **expected improvement** or current optimum and iterate to improve the difference between the raw data and response surface. A balance is required between the number evaluations in the **design of experiments** (DoE), the number of cycles in the CFD, the number of points in the initial DoE and the number of further evaluations used.
The use of one data set for training and a second for error analysis proved effective.

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Work is required to establish the relationship between the statistical measures of error with and without a second data set.
The use of the 4D HAT plot with screening to first reduce the number of design variables in the problem to 4D incurs what cost? Holding some of the design variables fixed reduces the number of degrees of freedom, and it appears that, in principle, problems having more degrees of freedom should have a better global optimum. This effect may be mitigated though by the fact that **multiple optima** and **numerical noise** are found in real problems, and therefore this may be hard to find without visualization.
Increasing the number of design variables in the plot incurs the penalty that the data is more difficult to manage: plotting packages work more slowly and zooms are necessary. Alternatives for merging dimensions will necessarily incur a loss in data structure.
The order of the design variables in the HAT plot is important and different HAT plots result from different variable orders. It is likely that the fast variables should be used as the least important variables as the change from tile to tile is hard for the eye to detect.
Screening methods currently used seem to give contradictory information at times. An alternative to this, in which a number of optimizations are used to gain insight into which variables are changing the most in the optimization problems is also likely to give different information. Further information on the relationships between different screening methods and perhaps additional more reliable methods are required.

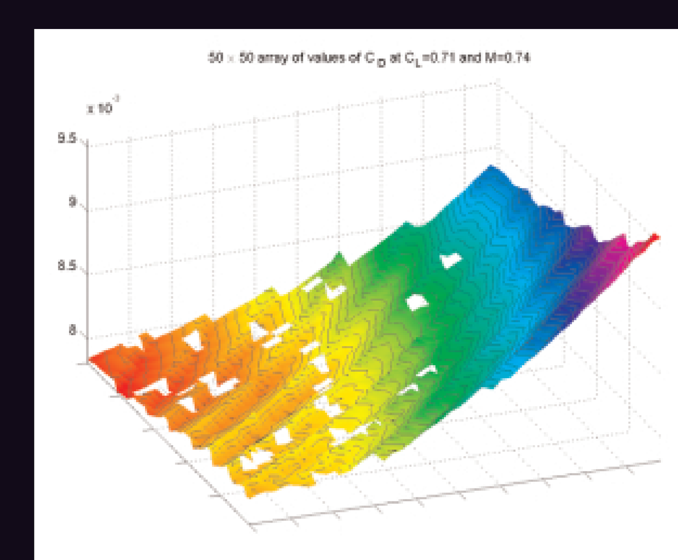

Figure 3: Full factorial grid of 50*50 samples of an aerofoil trailing edge design space.

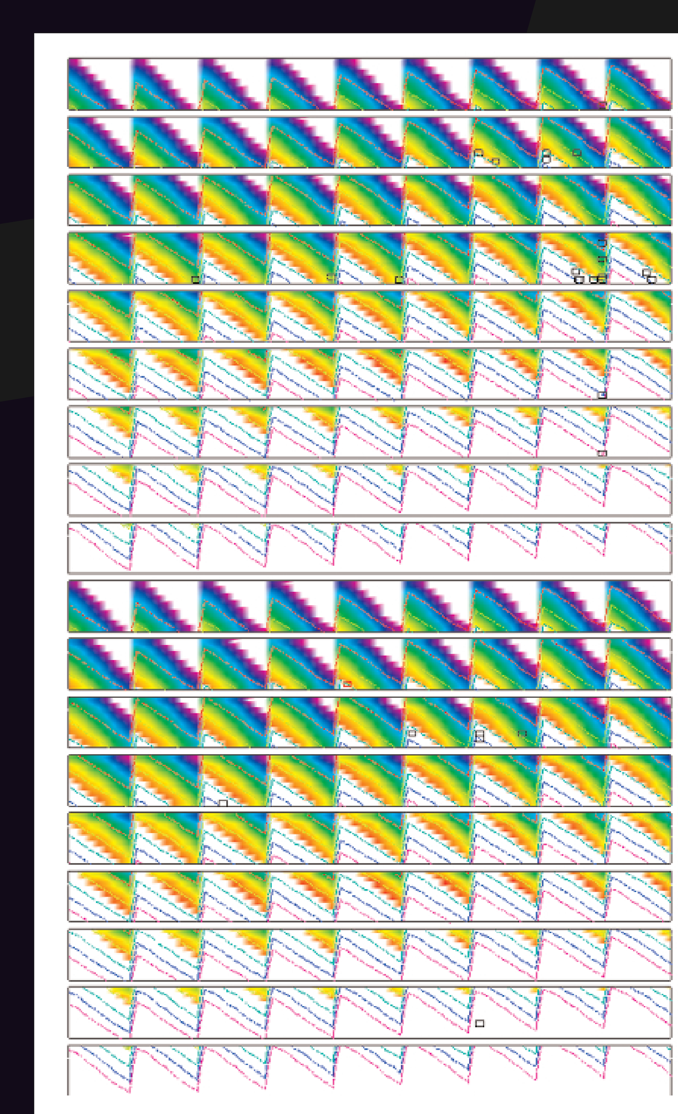

Figure 4: Zoom into 5D HAT plot. Also shown squares denote trace of simulated annealing optimization on response surface.

Glossary

HAT hierarchical axes technique
SOM self-organizing map
DoE design of experiments

University of Southampton