VARIABLE COMPLEXITY MODELLING FOR EVOLUTIONARY GAS TURBINE CONTROL DESIGN

Valceres V. R. Silva, Wael Khatib and Peter J. Fleming

University of Sheffield, UK

ABSTRACT

Control systems design of complex non-linear system often involves the use of expensive computational models. To speed up the design process and to allow more designs to be evaluated, an inexpensive approach using variable complexity modelling (VCM) is introduced. A non-linear thermodynamic model of a gas turbine engine is used to evaluate a selection of designs for a multivariable PI controller configuration. Regression analysis is applied to fit polynomial models to this data for various control responses. These simple models are used to design the controller within the framework of a multiobjective genetic algorithm (MOGA). The final designs are checked using the original non-linear model. Good results indicate the viability of this approach for application to complex designs involving expensive computational models.

Keywords

Variable complexity modelling (VCM), non-linear systems, Optimisation, multiobjective genetic algorithms (MOGA).

Introduction

High performance gas turbine engines require complex controllers to maintain system stability and achieve strict performance and design criteria. The engine dynamics vary with time and changes in operating demands and ambient conditions. Moreover, the engine core endures very high temperatures and pressures. The engine control system has to protect against breaching the physical limits of the engine, maximum temperature for example, as well as the actual stability and performance requirements. Computer-aided control system design together with optimisation based methods are extensively used to design suitable controllers to meet the desired performance specification. Accurate thermodynamic models are usually complex reflecting the inherent non-linearity of the engine. These models are computationally expensive. This cost is more critical for design purposes where many model evaluations are required.

The engine under consideration in this study is the Rolls-Royce Spey engine which is a two-spool re-heated turbofan used to power military aircraft. The full thermodynamic model of the Spey engine was developed by J. Beard of DERA (P), French, (5). This model can be used to assess the steady-state performance of the engine. Various controllers can be tested using the model. Designing for an optimum control configuration involves many model simulations. A non-linear SIMULINK™ implementation of this model is used in this study. Actual model runs simulating a few seconds of operation requires a few minutes of CPU time on a standard workstation. This overhead cost can limit the number of design or redesign cycles.

Variable Complexity Modelling

Variable complexity modelling (VCM) is part of decomposition and approximation methods used frequently in multidisciplinary optimisation (MDO). MDO is usually associated with aero-structural design problems that involve the design of systems which are functions of more than one discipline, aerodynamics and structures for example, Khatib and Fleming (10), Balabanov et al (1), Giunta et al (6, 7, 8). Such techniques are used to overcome some of the main difficulties encountered in MDO; organisational complexity and computational cost. Low-fidelity analysis is often used to explore the design space to identify promising regions. This process is formalised by constructing response surfaces (RS). Response surfaces are polynomial approximations, usually quadratic, that model the objectives based on the given designs. The hope is that these design will form a near convex hull around the feasible design region. The RS approach helps reduce the complexity of the optimisation problem. The noise in the design space is also smoothed out. Providing the design space is not highly irregular, it is usually hoped that the RS models can model the global optima adequately. Regression analysis using least squares is usually used to fit the polynomial curves to the data. If n terms are chosen for the polynomial model, then the number of design points required to construct the model should be at least 1.5*n. In MDO problems, this limits the order of the polynomials to quadratic to avoid the problem referred to as the *curse of dimensionality*. Additional work might need to be done to construct the RS models depending on the nature and size of the problem. For regular and relatively small design spaces, the choice of points can be made using a variety of simple techniques to construct near-convex hulls. For larger problems with irregular spaces, other statistical techniques from the design of experiments domain are needed, an example would be the D-optimality criterion. This is an important and fresh issue in this field.

Designs obtained using this approach usually give a good indication of the near-optimal design. These designs can be fine tuned using the full models to arrive at the final solutions. The more accurate these RS models are, the less tuning shall be required in due course.

Multiobjective Genetic Algorithm (MOGA)

Most optimisation problems in control design are multiobjective in nature. Optimising to satisfy multiple objectives makes redundant the notion of a single global optimum. In such circumstances, the design space is searched for solutions that exhibit no preference over each other from a Pareto optimality point of view. These solutions form a set of trade-offs or non-dominated solutions. Evolutionary algorithms have found many successful applications in search and optimisation problems for control systems design and other applications. A multiobjective genetic algorithm (MOGA) combines the characteristics of a powerful evolutionary optimisation strategy in the genetic algorithm (GA) with the concept of Pareto optimality to produce solutions illustrative of a problem's trade-off set. A MOGA evolves a population of solution estimates thereby conferring an immediate benefit over conventional multiobjective optimisation methods that rely on single-point search.

The work described is this paper uses the GA Toolbox for Matlab™, Chipperfield et al (3), together with an implementation of a MOGA as proposed by Fonseca and Fleming (4).

SPEY Engine Multivariable PI Control Design

The SPEY gas turbine engine is a two-spool turbofan originally developed for military jets. There are three control inputs: fuel flow, inlet guide vane and nozzle area. Sensors provide various measurements which can be used to control engine performance. These include spool speeds, pressure, temperature, etc. These values can be used to evaluate other engine parameters such as thrust, flow rates and surge margins. The most important objective of the engine control system is to control thrust whilst regulating compressor surge margin. But compressor surge margin and thrust cannot be measured directly. Other measurable engine parameters are used to control these two most important variables after pre-set transformations. For example, thrust can be controlled through comparing pressure ratios and interpolating to find the relevant fuel flow readings.

Input-output Pairing For Closed-loop Control

The engine model has three inputs: fuel flow (WFE), exhaust nozzle area (A8) and inlet guide vane (IGV). Sensors provided from outputs of the engine model are high and low pressure spool speed (NH, NL), engine and fan pressure ratios (EPR, FPR) and Mach no. (DPUP). These variables can be used to provide various pairings of input-output for closed-loop control, since one input can control only one output independently, Skogestad & Postlethwaite (12).

Table 1 shows the possible combinations of inputs and outputs to control engine thrust, surge margin of the low pressure compressor and high pressure compressor spool speed respectively. These outputs were chosen because thrust and surge margin can be defined in terms of these measurable variables.

Applying MOGA to the non-linear Spey model, to search for the best output to be controlled by one of the inputs, the outputs in italics in Table 1 were found to be the best for control purposes, Silva & Fleming (11).

Table 1- Possible input-output pairings

Engine inputs	Feedback control outputs
WFE	*EPR*, NL, NH
A8	*DPUP*, FPR
IGV	*NH*

The complete design of a PI controller involves finding controller parameters covering various operating points defined by the high pressure spool speed to cover the thrust range of the engine. The gains of these controllers are then scheduled against the high pressure spool speed at which they were designed.

For the purposes of this work, we will consider one of these set points corresponding to 95% HP spool speed (NH%) at zero altitude and Mach no. The step response to a change in thrust demand of 62% to 87% is used to evaluate controller performance.

The system is required to meet the following design constraints:

- XGN ≥ 48.64 kN
- TBT ≤ 1390 °K (± 10 °C)
- LPSM ≥ 10%
- A8 = 0.28 m²
- XGN rise time ≤ 1.0 s
- XGN settling time ≤ 1.4 s

where XGN is the engine gross thrust, TBT is turbine blade temperature and LPSM is the low pressure compressor surge margin.

The following constraints (engine mechanical limits) are used to maintain the stability of the simulation:

- NL < 102%
- 0.25 < A8 < 0.34 (dry thrust limits)

The following multiple objectives were also addressed by MOGA:

- minimise steady-state error for NH, NL and A8
- minimise overshoot/undershoot for NH and NL.

Constructing Response Surface Approximations

For this particular problem, there are 4 controller gains required and they form the independent design variables. The low dimensionality of this problem precludes most of the difficulties associated with the RS approach. There is room for choosing higher order polynomials to achieve better approximations. Further, the choice of design points is also easier. This choice was done in two stages:

- Generating a coarse grid in 4 dimensions covering a certain range for the controller gains. The controller performance is evaluated for these points. A subset of this mesh is identified as the feasible design region.
- A fine grid is evaluated in the feasible region. These points are used to construct the RS models.

This kind of information is not often readily available using the traditional design approach. This mesh refinement helps make the search process more efficient. Further data filtering is possible by leaving out designs that do not meet the stated constraints. For some problems, filtering the data this way can make the design space less evenly distributed inside the mesh. As long as the model accuracy is maintained, this does not pose any serious problems. Certainly, in this case, no such problems are encountered.

In this implementation, around 1400 points were initially chosen from the coarse mesh covering a wide range of controller gains. These points are filtered to choose 245 points for RS model construction. Around 200 extra points are further chosen to assess the RS model performance.

To achieve low modelling errors, a polynomial of order 4 is used as follows:

$$y = c_o + \sum_{1 \le i \le p} c_i x_i + \sum_{1 \le i \le j \le p} c_{ij} x_i x_j + \sum_{1 \le i \le j \le k \le p} c_{ij} x_i x_j x_k + \sum_{1 \le i \le j \le k \le l \le p} c_{ij} x_i x_j x_k x_l \quad (1)$$

where y is the response or output to be estimated, c are the polynomial coefficients, x are the independent variables and p is the number of variables (p=4 here).

For a number of n_s = 245 points selected to construct the model, the remaining n_e = 200 points are used to evaluate the modelling error. The difference between the values predicted by the response surface and the actual values for the n_s points is the residual error. If the predicted value is yh and the actual value is y modelling error is:

$$\delta_i = | yh_i - y_i | \quad (2)$$

For i = 1, ..., n_e.

The average modelling error is:

$$\bar{\delta} = \frac{1}{n_e} \sum_{i=1}^{n_e} \delta_i \quad (3)$$

As the validation points are different to those used in constructing the RS, this equation gives an unbiased estimate of the modelling error.

Table 2 below gives values for residuals and modelling errors for the RS models for 10 outputs. Figure 1 shows the performance of the RS model in predicting the TBT response for the test data at the n_e design points.

Table 2- Error performance values for the RS models

output	**mean residual**	$\bar{\delta}$	**Design point**
Thrust	0.03	0.41	48.6 kN
TBT	0.67	13.26	1713 K
Rise time	0.006	0.06	1.0 s
Sett. time	0.04	0.5	1.4 s
LPSM	0.14	2.2	10 %
NH ss error	0.002	0.04	95 %
NL ss error	0.005	0.11	90 %
A8 error	0.001	0.01	0.27 m^2
NH ov'shoot	0.004	0.13	95 %
NL ov'shoot	0.001	0.49	90 %

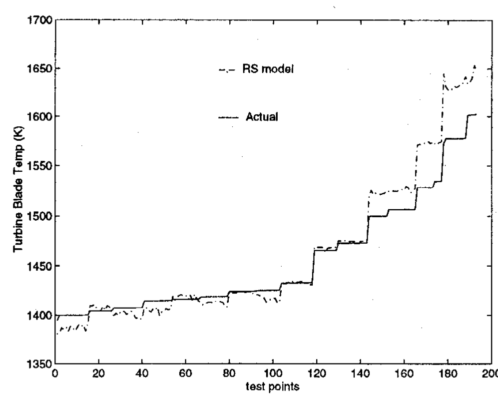

Figure 1. Turbine blade temperature output

MOGA Control Design using RS Models

Using 100 individuals, a MOGA is evolved over 100 generations to search for the best controllers satisfying the various objectives mentioned above. The controller gains are represented as Gray-coded bit strings or chromosomes. Standard two-point crossover and mutation are used. The actual evaluation time is literally a few minutes of a standard workstation. The same scenario using the full model will require in excess of day to execute on the same machine.

The user interface of the MOGA (Figure 2) shows the progress of the search process. It allows the designer or decision maker to alter goals and preferences in a progressive manner as the search moves forward. Each solid line in the graph represents a solution. The goal values are denoted by X. Lines crossing above the X indicates that the respective goal is not met.

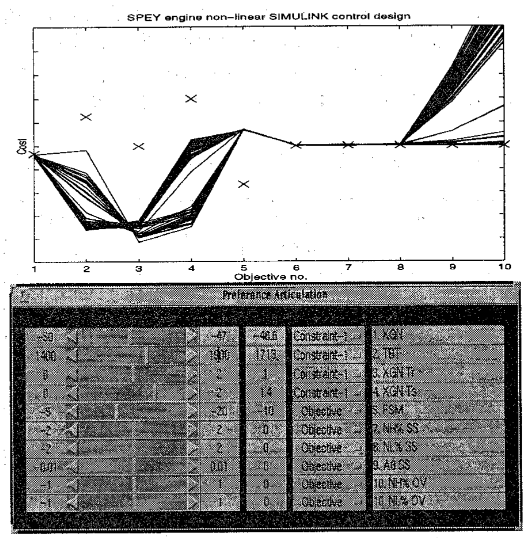

Figure 2. MOGA user interface

Results

The MOGA finds a set of nondominated designs for the PI controllers. To reduce the size of this set, some of the objectives are tightened further. We Choose controllers with fastest responses in terms of thrust rise and settling times. We also look for controllers with minimum overshoot and good tracking performance in terms of steady state (ss) errors. These modified preferences reduce the number of controllers to a subset of similar gain ranges. The final designs for the PI controllers are checked using the full thermodynamic model. The actual and predicted values for the ten objectives are almost identical (Table 3).

Table 3- RS Modelling errors

output	$\bar{\delta}$	*output*	$\bar{\delta}$
Thrust	0.008	*NH ss error*	0.001
TBT	5.21	*NL ss error*	0.0
rise time	0.004	*A8 ss error*	0.0
sett time	0.016	*NH ov'shoot*	0.0
LPSM	0.001	*NL ov'shoot*	0.007

The step response curves for some of the outputs (normalised) further illustrate that these controllers are good designs that meet all the original design specifications.

Figures 3 and 4 show a fast and steady response for the engine. The thrust response in particular is of great importance for a military aircraft, both in terms of speed of response and attaining adequate thrust values.

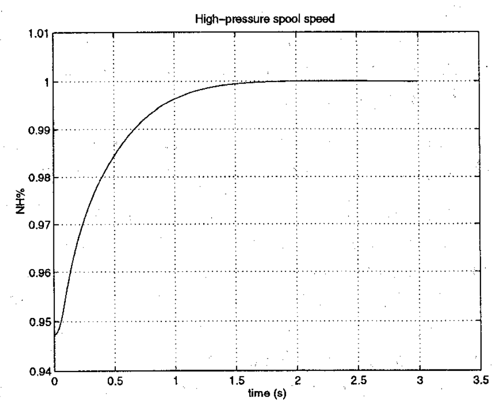

Figure 3. High-pressure spool speed

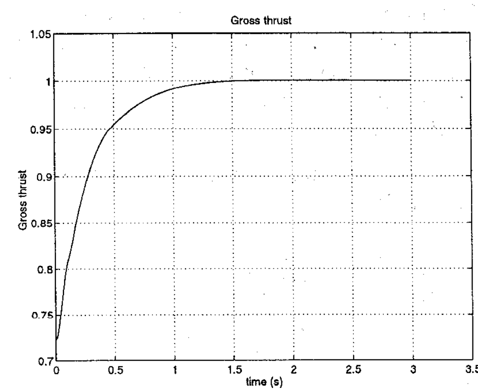

Figure 4. Gross thrust

In figure 5, we observe how the turbine blade temperature is maintained within the allowable physical range avoiding deformation of the blades.

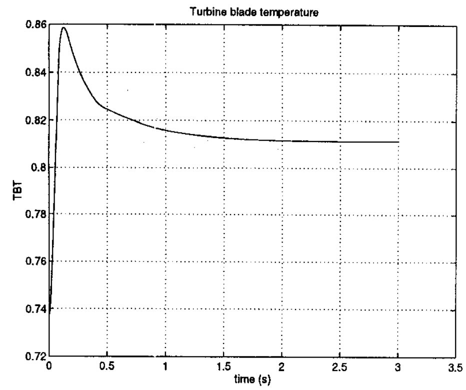

Figure 5. Turbine blade temperature

In order to maintain a robust and stable engine operation, the surge margin has to be a minimum of 10%. Figure 6 shows that in this case, a low pressure surge margin of nearly 14% is achieved and maintained.

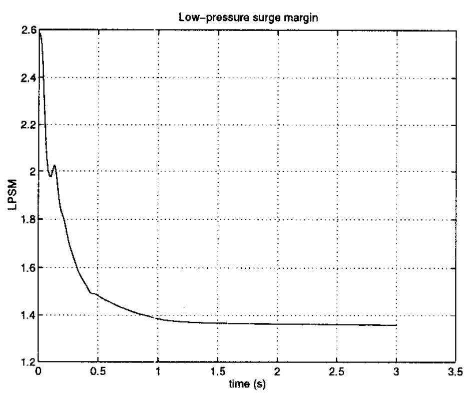

Figure 6. Low-pressure surge margin

The MOGA design process was repeated for the same objectives and parameters but using the full engine model. The run-time cost is many orders of magnitude higher. No better designs are achieved with this approach than before. In fact, the latter design process was helped slightly by using the knowledge gained in constructing the RS models about the range for the controller parameters. Such information is not usually present and the MOGA might have to search longer to arrive at similar results. The range of gains found using both approaches is quite similar.

Conclusions

VCM techniques like the RS models allow the designer the freedom to explore the design space more freely in search for the best design region(s). Once near optimal designs are established this way, fine tuning can be carried out if necessary using the full models.

The initial cost of establishing the RS models is more than offset by the savings in the design process. Further, these models are re-usable at no extras cost. The construction of the models sheds more light on the design problem and helps design optimisation in the process.

If necessary, more complex data fitting techniques such as genetic programming (GP) or neural networks (NN) can be used. This, however, can lessen the effect of one of the attractions of this approach, that of simplicity. Least square polynomials are more than adequate for this problem. Problems of higher dimensionality and less smoothness might require a more eloquent point selection method such as D-optimality.

Further work is under way to investigate the use of this technique to do a complete controller design for the complete flight envelope of operating conditions. This work is not limited to PI control. The emphasis is on performance optimisation control. This efficient modelling approach is one tool towards achieving good control implementations that meet that target.

Acknowledgements

The first author gratefully acknowledges support of this research by CAPES, 'Coordenação de Aperfeiçoamento de Pessoal de Nível Superior' and FUNREI, 'Fundação de Ensino Superior de São João del Rei', Brazil. The authors also wish to thank DERA Pyestock for the Spey engine model. The second author wishes to acknowledge the support of EPSRC (CASE Award) and BAe PLC Sowerby Research Centre especially Dr Phil Greenway.

References

1. Balabanov, V., Kaufman, M., Knill, D.L., Haim, D., Golovidov, O., Giunta, A.A., Haftka, R.T., Grossman, B., Mason W.H., and Watson, L.T., 1996, "Dependence of Optimal Structural Weight on Aerodynamic Shape for a High Speed Civil Transport". Proceedings of the 6th AIAA/NASA/USAF Multidisciplinary Analysis and Optimization Symposium, Bellevue, WA, 599-612. (AIAA Paper 96-4046)

2. Chipperfield, A. & Fleming, P. J., 1996, 'Systems integration using evolutionary algorithms'. International Conference on Control'96 - IEE Conference Publication n° 427, 1, 705-710.

3. Chipperfield, A., Fleming, P. J., Polheim, H. & Fonseca, C., 1995, "Genetic Algorithm Toolbox for

use with MATLAB©," Version 1.2: Department of Automatic Control and Systems Engineering, University of Sheffield, England.

4. Fonseca, C. M. & Fleming, P. J., 1993, "Genetic algorithms for multiobjective optimization: formulation, discussion and generalisation," In Genetic Algorithms: Proceedings of the Fifth International Conference (S. Forrest, ed.), San Mateo, CA: Morgan Kaufmann.

5. French, M., 1993, "Multivariable control demonstration on a Spey engine ", Interim Report no. 2, Document no. ACER 10068, Engineering Dept. – Bristol, Rolls-Royce.

6. Giunta, A. A., Dudley, J. M., Narducci, R., Grossman, B., Haftka, R. T., Mason, W. H. & Watson, L. T., 1994, "Noisy Aerodynamic Response and Smooth Approximations in HSCT Design", AIAA Paper 94-4376.

7. Giunta, A.A., Balabanov, V., Burgee, S., Grossman, B., Mason, W.H., Watson, L.T., and Haftka, R.T., 1996, ``Parallel Variable-Complexity Response Surface Strategies for HSCT Design", Proceedings of the NASA Ames Computational Aerosciences Workshop 95, Editors: Feiereisen, W.J. and Lacer, A.K., NASA CD Conference Publication 20010, Moffett Field, CA, 86-89.

8. Giunta, A.A., Balabanov, V., Kaufman, M.D., Burgee, S., Grossman, B., Haftka, R.T., Mason, W.H. and Watson, L.T., 1997, ``Variable-Complexity Response Surface Design of an HSCT Configuration", Proceedings of ICASE/LaRC Workshop on Multidisciplinary Design Optimization, SIAM, Philadelphia, PA, 348-367.

9. Giunta, A.A., Narducci, R., Burgee, S., Grossman, B., Haftka, R.T., Mason, W.H., and Watson, L.T., 1995, ``Variable-Complexity Response Surface Aerodynamic Design of an HSCT Wing", Proceedings of the 13th AIAA Applied Aerodynamics Conference, San Diego, CA, 19-22, 994-1002. (AIAA Paper 95-1886)

10. Khatib, W. & Fleming, P. J., 1997, "An introduction to evolutionary computing for multidisciplinary optimisation", GALESIA'97, Glasgow, UK, 7-12.

11. Silva, V. V. R. & Fleming, P., 1997, "Multiobjective non-linear robust control design for gas turbine engines using evolutionary computing". Mathematical Theory Networks Systems Conference - MTNS'98, 'Universidade de Padova', Italy.

12. Skogestad, S. & Postlethwaite, I., 1996, "Multivariable feedback control - Anaysis and design", John Wiley & Sons Ltd, Chichester, England.