15th Triennial World Congress, Barcelona, Spain

CONTROL CONFIGURATION DESIGN USING EVOLUTIONARY COMPUTING

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Abstract: The control configuration design involves the choice of measurements and/or manipulations to be used in a feedback control loop. The selected variables should have an effect on the controlled outputs. The control law will result in unnecessary complex systems if the control configuration is not adequately considered. The approach studied here is employed to design a control configuration for the PI multivariable controller for the gas turbine engine, using multiobjective genetic algorithm as an approach for optimization and preference articulation. *Copyright © 2002 IFAC*

Keywords: gas turbines, genetic algorithms, multiobjective optimization, nonlinear system, PI controllers.

1. INTRODUCTION

High performance gas turbine engines (GTE) require complex controllers to maintain system stability and achieve strict performance and design criteria. The engine dynamics change drastically with changes in operating conditions of altitude and forward speed of the aircraft. These also change the required thrust that maintains these conditions and performs required maneuvers. These various operating points combine to form the flight envelope for a particular engine configuration. This indicates that the system dynamics vary with time and changes in operating demands and ambient conditions. 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. The engine is inherently non-linear with multiple inputs and outputs.

Computer aided control system design together with optimization based methods are extensively used to design suitable controllers to meet the desired performance specification. A typical control system for a gas turbine engine would include a set of controllers, PI say, for each operating point. Designing for each operating point requires satisfaction of multiple objectives. These objectives are often conflicting or competing. An elegant and powerful method for dealing with multiple objectives is the concept of Pareto optimality. Using this approach, the designer is no longer searching for a single optimum, rather a compromise satisfying the various objectives. Genetic algorithms (GAs) are amenable to multiobjective optimization (MO). This is because a GA works on a population of solutions instead of the traditional single point search. The search with this population can help achieve a faster and more comprehensive mapping of the trade-off hyper surface.

Genetic algorithms have been applied to control engineering in a variety of ways: control system design, robust control, multiobjective optimisation, system identification, system integration and real-time and adaptive control (Jones and De Moura Oliveira, 1995; Jones and Lin, 1998; Obayashi, 1996; Klaassen and Litz, 1998; Pashkevich and Pashkevich, 1998; Tan *et al*., 1995; Moin *et al.*, 1995; Linkens and Nyongesa, 1996).

Samar (1995) applied some mathematical tools to tackle the output measurement selection problem. Chipperfield and Fleming (1996) applied a multiobjective genetic algorithm (MOGA) to the SIMULINK linear Spey engine model for system integration. The approach studied here is employed to design a control configuration for the PI multivariable controller for the GTE.

2. MULTIOBJECTIVE GENETIC ALGORITHM

Multiobjective or multicriteria optimization and decision making refers mainly to simultaneous optimization in order to achieve optimal trade-off solutions satisfying various objectives. These objectives tend to be conflicting or competing. There is not usually one unique solution but rather a family of compromise solutions that need to be analyzed by a decision maker.

Multiobjective optimization can be expressed as follows:

Minimize: $F(x) = \{f_1(x), f_2(x), ..., f_n(x)\}$

Subject to: $g(x) \leq 0$

Where $g(x)$ is the constraint vector and $f_i(x)$ is the *i-th* objective function.

The set of trade-off solutions that express the best performance in all of the objectives is known as the Pareto or the non-dominated set. Any attempted improvement for a member of this set in one of the objectives will result in deterioration in performance in one or more of the other objectives.

The MOGA combines the characteristics of a powerful evolutionary optimization strategy 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 optimization methods (Fonseca and Fleming, 1995).

The work described in this paper uses the GA Toolbox (Chipperfield, *et al*., 1995) for Matlab™ together with the implementation of a MOGA as proposed by Fonseca and Fleming (1993). This tool allows the designer a simple but powerful method for articulating preferences progressively and interacting with the design process in real time to achieve the best results and gain further insight into the problem in question.

3. THE GAS TURBINE ENGINE

The engine under consideration is the Rolls-Royce Spey engine, which is a two-spool reheated turbofan, used to power military aircraft (Fig. 1). Linear and non-linear SIMULINK™ models are available for this engine.

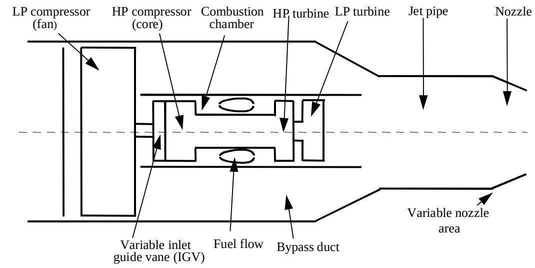

Fig. 1. The aero-engine

The engine 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 number (DPUP). These variables can be used to provide closed-loop control of the input variables. For the purpose of this work one of the engine set points is considered corresponding to 87% of thrust demand, at zero altitude and zero Mach number. For this operating point the system is required to meet the following (Silva, 1999):

- XGN ≥ 48.64 kN
- TBT ≤ 1713 ^{o}C
- LPSM ≥ 10%
- XGN rise time (XGN Tr.) ≤ 1.0 s
- XGN settling time (XGN Ts.) ≤ 1.4 s

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

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

- NL < 102%
- 0.25 < A8 < 0.34 m² (dry thrust limits)

The following multiple objectives were also addressed by MOGA:

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

4. CONTROL CONFIGURATION DESIGN

Modern engineering systems exhibit two distinct trends which have important implications for control theory (Reeves, *et al.* , 1991):

- the systems requiring control are becoming increasingly complex,
- increasingly stringent accuracy requirements are being imposed on the controlled systems.

As a result of these trends the critical issues for control systems design have become complexity and uncertainty. They are the premier issues in control system design for modern engineering systems. Correspondingly, an appropriate paradigm for control system design might be stated as follows: *minimize* *control system complexity subject to the achievement of accuracy specifications in the face of uncertainty*.

An important phase of a multivariable control design is the control law. However, if control configuration design is not addressed adequately before control law design begins, unnecessarily complex control systems may result. For industrial problems usually the number of candidate measurements and/or manipulations to find the best control configuration is very high. The system has many outputs to be controlled and usually has limited number of inputs. The selection of manipulations and measurements is related to disturbance rejection, plant stabilization and reference tracking.

It is desired to select measurements, which have a strong relationship with the controlled outputs, or which may quickly detect a major disturbance and which, together with manipulations, can be used for local disturbance rejection.

The selected manipulations should have an effect on the controlled outputs, and should have "close" dynamic response to the outputs and measurements. If the plant is unstable, then the manipulations must be selected such that the unstable modes are state controllable, and the measurements must be selected such that the unstable modes are state observable.

5. INPUT-OUTPUT PAIRINGS FOR THE GTE

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 the engine under consideration, a controller is planned to control three variables independently: XGN, LPSM and NH. For the three engine inputs, only three outputs can be controlled independently (Skogestad and Postlethwaite, 1995; Reeves, *et al*., 1991).

The first step is to choose from the available measurements, the ones that are in some sense better for control purposes. Any extra outputs, cannot be controlled independently, but may be made effective use of by the controller.

A good understanding of the plant's behavior can simplify the control structure design problem. Some candidate outputs may be preferred over others. Regarding the GTE control structure design, it is known that the static and total pressure ratios behave similarly, and that static pressures are easier to measure than total pressures (Samar, 1995). Taking account of the available sensors provided from outputs of the SIMULINK model, the choice of the five output measurements is made. For each one of the five output measurements, a look-up table provides its desired optimal value, the reference value, as a function of the operating point.

Engine thrust (one of the parameters to be controlled) can be defined in terms of NL, engine pressure ratio (EPR) and NH. One of these measurements gives better performance and is to be selected. Similarly, either the fan pressure ratio (FPR) or the by-pass Mach number (DPUP) can represent LPSM, and a selection between these two has to be made. The third output is NH, which is also important to be maintained within safe limits. NH is actually the HP compressor spool speed made dimensionless by dividing by the square root of the total inlet temperature and scaled so that it is a percentage of the maximum spool speed at a standard temperature of 288.15°K.

The outputs were subdivided into three subsets (Table 1), according to the input to be used for controlling the three variables of interest. Table 2 shows the six-candidate output sets resulted by subdividing the available outputs into three subsets and selecting one output from each subset.

Table 1 Possible input-output pairings

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

Table 2 Six candidate outputs set

Set Number	**Candidate controlled output**
1	EPR, DPUP, NH
2	NL, DPUP, NH
3	NH, DPUP, NH
4	EPR, FPR, NH
5	NL, FPR, NH
6	NH, FPR, NH

The approach studied here is employed to design a control configuration for the PI multivariable controller for the GTE. MOGA is used in order to establish the best choice amongst six different configurations proposed. Each of these configurations is characterized by a set of PI parameter gains to be optimized by the MOGA. The optimization for the choice of configuration is done simultaneously by adding another optimization parameter which is a flag value representing a particular configuration.

6. MOGA SEARCH FOR BEST PI CONTROL CONFIGURATION

A MOGA was used to implement the input-output pairings according to Table 1. Six different models for the six different candidate controlled output choices (Table 2), were evaluated by the algorithm to find the best configuration for the engine for control purposes, and a set of optimal controller gains for the two PI controllers, which are into the WFE and A8 loops respectively. The algorithm aimed at finding the best set of these controllers in one of the six different combinations of input-output pairings.

The controller parameters were encoded as 17-bit Gray-coded chromosome constructed of 5 sections (Fig. 2). The last section is a flag that gives the value corresponding to the one of the six engine models to be evaluated (Table 2). The first two sections give the values for the proportional and integral gains respectively for the fuel flow loop, and the next two sections give the values of the gains for the nozzle area loop. Standard two-point crossover and mutation are used. The MOGA parameters for selection, crossover and mutation probabilities are as detailed in Table 3. All the objectives were assigned the same level of priority. All constraints were assumed to have the same level of priority. Gain parameters in the interval $[10^{-5}, 1)$ were logarithmically mapped onto the set of possible chromosome values. The setting of the MOGA parameters, although of importance, is not seen as a critical issue.

P1	I1	P2	I2	flag

Fig. 2. General chromosome structure

Table 3 MOGA parameters for control configuration design

MOGA parameters	
Selection method	SUS
Crossover probability	95%
Mutation probability	5%
Selective pressure	-1.5
Population size	80 individuals
Number of generations	160 generations

7. INPUT-OUTPUT PAIRING RESULTS

The optimization of the controller assumes no *a priori* knowledge of the controller parameter values apart from that implicitly used in setting the parameter ranges.

After 160 generations of 80 individuals each, MOGA generated 136 non-dominated solutions for the two sets of PI controller gains. It was found that the best performance was for structures 1, 2 and 3 (Table 2). 109 solutions were for structure 1, 22 for structure 2, and 5 for structure 3. None was for structures 4, 5 or 6.

Considering all the objectives and constraints, all the 136 final solutions are equivalent. Further considerations can be made in order to identify particular controllers and/or configurations as the most suitable designs. The objectives representing the steady-state errors are all catered for adequately by all solutions and are thus ignored. The 136 solutions are now further ranked but only using the first 5 objectives. Other choices can be made according to whether a faster response is required or higher thrust rating, etc. A choice is made here to choose controllers that have the lowest TBT. An important observation has to be stressed here is that all of the original non-dominated solutions offer similar performances. The filtering approach used here is not intended to signify superior performance for the final controller. Rather, it is an aid to choosing one solution for convenience.

Fig. 3 shows the conceptual engine model for the new configuration designed. The model has two PI controllers, using fuel flow and nozzle area inputs to control EPR and DPUP outputs respectively. The input signal IGV is scheduled against the measured values of NH. Using a MOGA with the PI controller, it was found the outputs EPR, DPUP and NH to be the best for control purposes of XGN, LPSM and NH respectively. This is in agreement with the findings in Samar (1995).

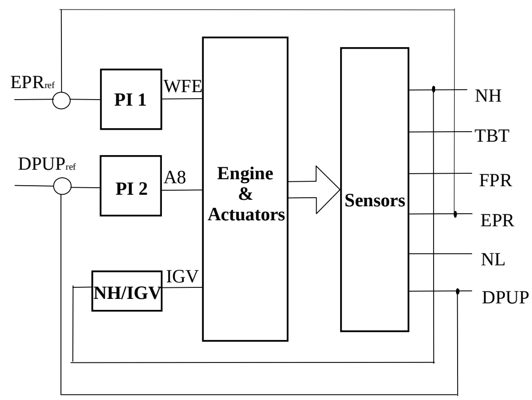

Fig. 3. Conceptual Spey model for the new configuration

Fig. 4 shows the trade-off graph of the objective values for the chosen solution of the PI controllers of the new control configuration, and the objective values for the Rolls-Royce set of parameters for the PI controllers.

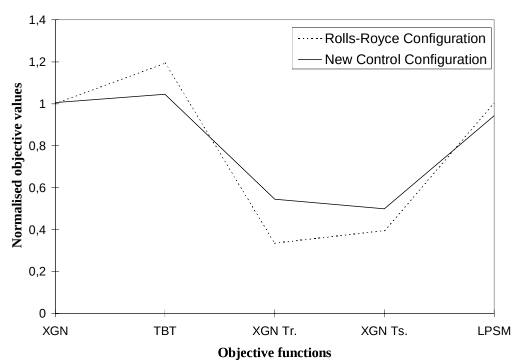

Fig. 4. Trade-off graph for two solutions for the control configuration of the GTE control system.

Fig. 5-8 show the engine step responses for the outputs XGN, NH, LPSM and TBT for the GTE simulated for the Rolls-Royce (RR) and the new configurations of the PI controller. All the responses are plotted against time in seconds, and the response values are all normalized such that unity represents the desired response.

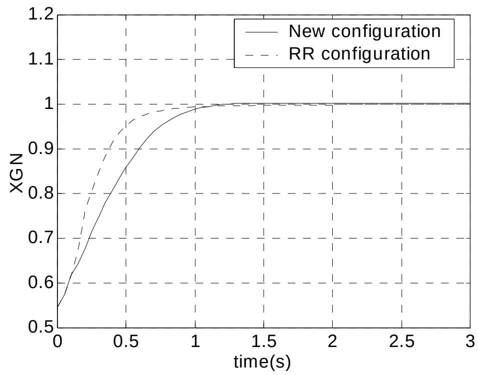

Fig. 5. XGN performance

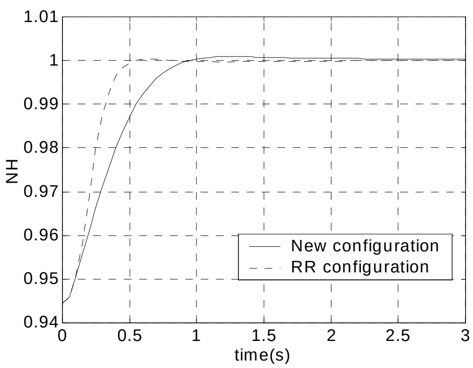

Fig. 6. NH performance

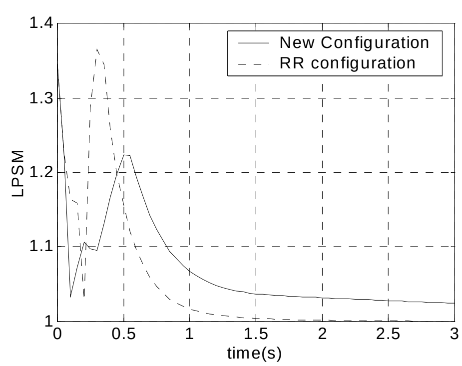

Fig. 7. LPSM performance

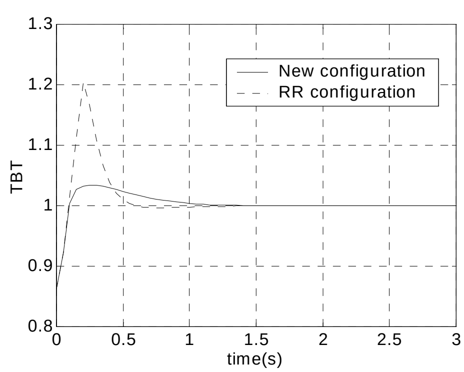

Fig. 8. TBT performance

The controllers for both the RR and the new configurations perform well in terms of rise time, settling time and steady state accuracy. The responses for XGN and NH are slightly faster for the RR configuration. The controller for the new configuration performs better for TBT and LPSM responses. Since, for both cases, the design specifications are satisfied, the solution taken here is not intended to signify superior performance for all the objectives. A choice was made here for a controller that gives the lowest TBT transient, as previously stated.

8. CONCLUDING REMARKS

This work presented a very powerful, yet rather simple, evolutionary computing approach for multivariable non-linear control configuration design. This approach uses a MOGA for optimization and multiobjective selection and preference articulation. This framework enables the designer to search a very complex design space without any need for assumed knowledge or gradient information. This flexibility allows more designs to be evaluated, taking into account more realistic performance optimizing objectives.

Directly designing the control system on a non-linear model in this way has many benefits, including preventing controllers that violate any of the system's physical constraints being assigned a good fitness value.

More work needs to be done on the following:

- to investigate the use of this technique to optimize the control configuration of the control system for the complete flight envelope of operating conditions,
- incorporating more performance measures,
- using other control structures,
- introducing other disciplinary objectives for an integrated design approach.

ACKNOWLEDGEMENTS

The first author gratefully acknowledges support of this research by FUNREI, 'Fundação de Ensino Superior de São João del Rei', Brazil. The authors also wish to thank DERA Pyestock for the Spey engine models.

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