DYNAMIC MODELLING FOR CONDITION MONITORING OF GAS TURBINES: GENETIC ALGORITHMS APPROACH

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Abstract: The problem of model-based condition monitoring of aero gas turbine engines is considered. Genetic algorithms are applied for the dynamic modelling of aero engines by estimating parameters of the linear reduced-order model. The use of genetic algorithms affords flexibility in the choice of performance metrics. Real engine data is used to investigate the performance genetic algorithms and this approach is compared with traditional modelling techniques used in industry.

Keywords: Aero engines, genetic algorithms, condition monitoring.

1. INTRODUCTION

Gas turbine engines are widely used in many fields of human activity and reliable engine condition monitoring can produce substantial benefits. Condition monitoring of the power plant is especially important in aircraft operation, which strongly depends on the health of the engine and its control system, and where a single fault can lead to disastrous results. Benefits of condition monitoring include not only improved flight safety but also reduced maintenance costs.

Health monitoring employs direct physical and indirect model-based methods for investigating the current state of the engine components. Direct methods include visual inspection, detecting metal particles in lubricant oil, X-ray, vibration and ultrasonic examination. Another group of methods are based on mathematical modelling of the engine operation. Modelling of normal operation and faults enables recognition of changes to be conducted (Isermann, 1993).

Of all condition monitoring methods, the model-based approach is most promising for the real-time condition monitoring of such complex systems as aircraft gas turbine engines. Mathematical modelling methods can detect abrupt and, more importantly, gradual changes in the system performance due to wear and deterioration of its components (Basseville 1988, Isermann 1993, Chen and Patton 1999). Additional maintenance following the changes detected can prevent serious flight accidents due to equipment faults.

Most current engine condition monitoring systems employ static models for diagnosis. However, precise condition monitoring must account for the dynamic nature of the engine. Utilization of model-based approaches for condition monitoring of gas turbine engines faces the problem of finding a compromise between the complexity of the model and the accurate prediction of engine parameters. A very complex model is difficult for identification and simulation in real time. On-line model-based engine fault detection and isolation (FDI) requires reduced order engine modelling.

This paper is focused on application of genetic algorithms for on-line dynamic modelling of aero engines. The main advantage of genetic algorithms is flexibility in selection of an objective function to be optimized. This allows to organize the engine reduced order model parameters identification based on minimisation of the model long term prediction error. Real engine data is used to demonstrate performance of genetic algorithms in comparison with traditional modelling techniques used in industry.

2. MODEL-BASED CONDITION MONITORING IN DUAL-LANE ENGINE CONTROL

In digital controllers of aero engines, dual-lane redundancy is often introduced. These systems include two identical sets of transducers, wiring, A/D and D/A converters and control computers. This hardware redundancy improves the reliability of the information measurement channels in the case of a single fault. Both lanes simultaneously measure engine parameters during the controller operation and mutually exchange the current data. This enables condition monitoring to be conducted via the comparison of the measurements of engine parameters gathered from both lanes. One lane is controlling the engine operation, whilst the other channel is waiting in "hot back-up".

Consider a dual-lane control system with two identical lanes. Experimental data is obtained from two information channels, which measure the same input and output signals. Figure 1 presents a generalized schematic of a gas turbine engine. The test was performed at the sea-level static engine test-bed. Amongst the variables measured, fuel flow into the combustion chamber W_f and high pressure (HP) and low pressure (LP) shaft speeds N_{HP} and N_{LP} are considered.

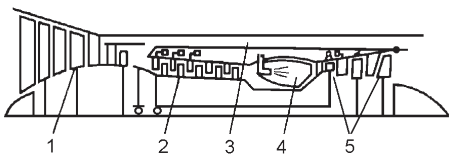

Fig. 1. Generalized schematic of gas turbine engine: 1) fan (LP compressor); 2) HP compressor; 3) bypass duct; 4) combustion chamber; 5) HP and LP turbines

Since two independent transducers measure the same variable, an information redundancy exists. Figure 2 shows HP shaft speed measurements from both lanes and the difference between them. In order to detect single-sensor faults like drift and malfunction, the maximum allowed measurement difference is considered in two lanes, as demonstrated by Kulikov et al. (1995). However, this method does not provide sufficient information to detect the faulty transducer and faults in the engine itself. This problem is resolved via accurate modelling of the engine and its controller to produce the third "virtual" lane in a majority-voting scheme.

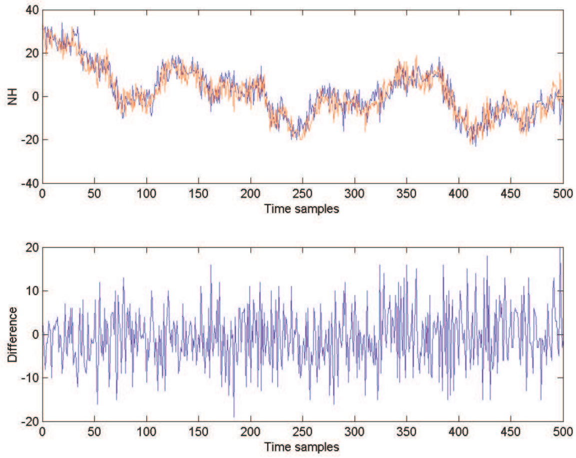

Fig. 2. Data from measurement channels (top) and difference (bottom)

Explicit modelling of the gas turbine engine is rather complex, and its real-time computations are extremely intensive, so simplified real-time models are required. These models can be obtained by use of systems identification methods for modelling of the normal engine behaviour. A general scheme presented in Figure 3 shows the use of on-board engine modelling in condition monitoring of a dual-lane control system and the lane-to-lane switching logic. Note that in the case of a double fault in both lanes, the engine control can be temporarily performed using the digital model output as a feedback. This increases the system reliability.

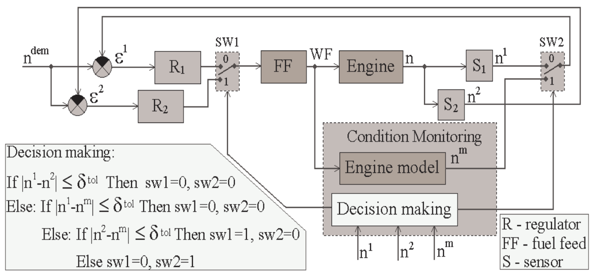

Fig. 3. Model-based condition monitoring in dual-lane control

A generalized scheme of engine model-based condition monitoring and diagnostic is presented in Figure 4. A simple fault model is the signal exceeding the allowed threshold. The total duration of fault confirmation and lane switching must not exceed the critical time limit for the system. The fault confirmation probability $P_{confirm}$ increases with the time of the parameter being outside the allowed band.

Simultaneously, the successful switching probability P_{switch} (fault accommodation) decreases, as shown in Figure 5.

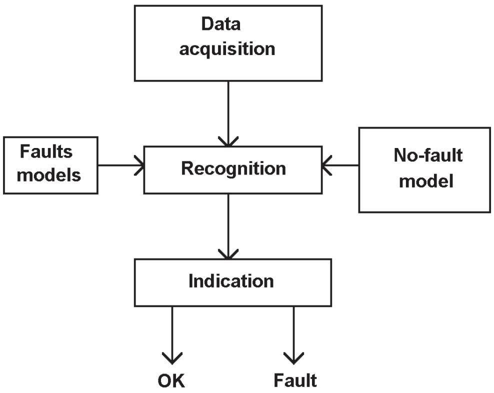

Fig. 4. Model-based condition monitoring and diagnostics

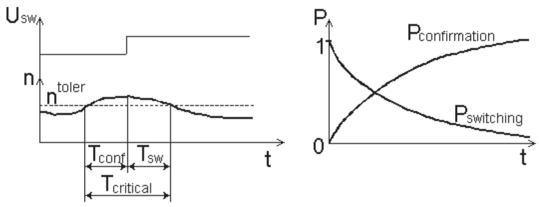

Fig. 5. Example of fault model and switching probability

The engine model utilized in condition monitoring must be sufficiently accurate and operate in real time. These requirements make general engine models ineffective, as they do not account for individual engine characteristics within the fleet. Individual modelling of flight and environmental conditions is not always feasible in real time. In order to use simplified models for condition monitoring purposes, on-line identification must be performed during the engine operation.

3. REDUCED ORDER ENGINE MODELLING

On-line model-based engine health monitoring requires reduced order engine modelling. The engine performance based full thermodynamic model is about 26th order. This can vary for different engines. This model is very complex to be used in real-time applications. Linearisation of this model faces the problem of initial model inaccuracy.

Aero engine operates at a number of power levels at different altitudes and Mach Numbers. Engine degradation and even fuel quality affect engine operation. With this in mind it is necessary to adapt the engine model to the engine current operation or identify the model parameters on-line.

In this paper identification based engine health monitoring problem is considered. Real engine data gathered from normal engine closed-loop operation at the engine test-bed and in flight are used to perform identification of the simplified dynamic model of the engine. It is not possible to apply special excitation signals in flight due to safety reasons. In addition, it is necessary to monitor identifiability conditions for closed-loop identification as the engine operates under closed-loop control.

Figure 6 shows implementation of the proposed condition monitoring scheme. The longest engine operating in the flight envelope is cruising. As soon as the engine transition to cruise operation is finished the engine data are gathered and analysed by the system to check closed-loop identifiability conditions. If identification is possible then the simplified model of this particular engine for current operation conditions is identified. This can take 10-20 sec. Then for some time (up to several hours) this model can be used in condition monitoring scheme. As soon as the engine operating changes, this process should be repeated again to obtain a new model.

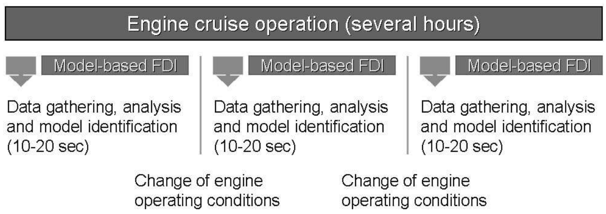

Fig. 6. On-line engine model based FDI scheme

A number of different methods have been implemented for identification of the simplest first order model of the engine. Engine fuel flow has been used as the input of the model and high pressure shaft speed has been used as the model output $\Delta N_{HP}(t) = a.\ \Delta N_{HP}(t-1) + b.\ \Delta W_f(t-1)$.

Table 1 Reduced order engine model parameter estimation

Method	ε	a	b
Exhaustive search	9.1319	0.9004	0.0123
Genetic algorithm (600 generations)	9.1324	0.8919	0.0123
Genetic algorithm (100 generations)	9.1523	0.8988	0.0126
Gradient method	10.9881	0.9100	0.0109
Engine thermo-dynamic model linearisation	19.7420	0.8804	0.0106
Least Squares	21.6924	0.9069	0.0064

Table 1 shows comparison of different methods performance, where ε is mean squared long-term prediction error, *a* and *b* are parameters of the model. One of the results here is that genetic algorithms and gradient method outperform the least squares method as the latest minimises only one step ahead prediction error.

The gradient method faces the problem of selecting the gradient search parameters, selecting different parameters gives different results. Genetic algorithms overcome this problem and shows very similar performance to the extensive search methods. Genetic algorithms can be computationally very extensive for implementation in real-time application but they produce good results even for a small number of generations passed. This requires sensible selection of the number of generations to be used.

Another important result is that parameters of obtained models are very close to the performance based linear model. This gives confidence in closed-loop identification and shows that the engine model is identified, not the model of the closed-loop.

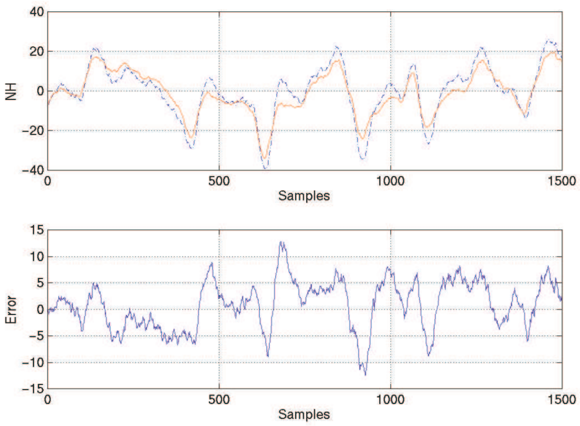

Fig. 7. Least Squares approach: engine model output (solid) compared with the real engine data (dashed)

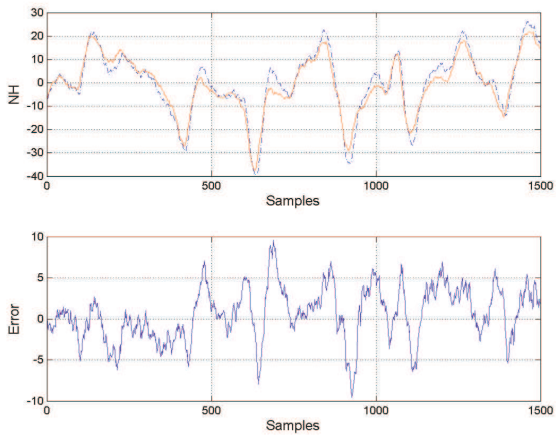

Fig. 8. Recursive estimation (gradient search): engine model output (solid) compared with the real engine data (dashed)

Figures 7 - 9 show performance of the identified models compared with real engine data. It is possible to see that even first order model estimated by genetic algorithm gives reasonably good performance for this particular operating conditions and can be used for engine health monitoring.

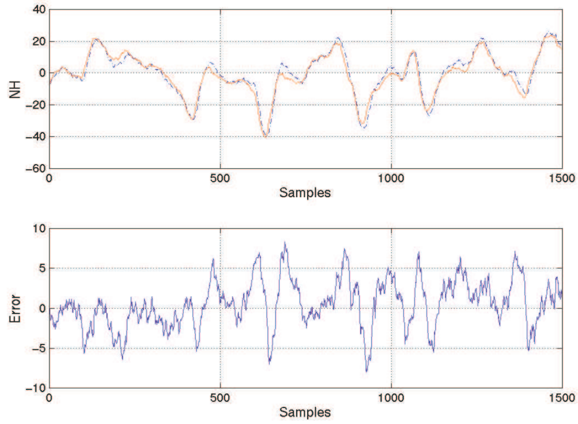

Fig. 9. Genetic algorithms approach: engine model output (solid) compared with the real engine data (dashed)

4. CONCLUSIONS

This paper presented a concept of gas turbine engine on-line identification based fault detection and isolation. The proposed technique allows using simple dynamic models for the engine health monitoring during the engine cruise operation.

Performance of different methods for identification of reduced order engine model has been compared. It was shown that genetic algorithms outperform least squares and gradient methods generally used in industry.

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