MODEL-BASED CONTROL AND DIAGNOSTIC TECHNIQUES FOR OPERATIONAL IMPROVEMENTS OF GAS TURBINE ENGINES

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ABSTRACT

Gas turbines operational requirements continue to become more demanding in response to the need for extended component life, increased reliability and improved overall efficiency. To support these requirements, new model-based gas turbine control and diagnostics concepts have been introduced.

Traditionally gas turbine control system transforms real engine limits, into limits which are based on measured engine variables. As a result of that, engines operate with increased safety margins and thus with non-optimal performance. To overcome this problem model based control concepts have been proposed. Model based control approach exploits real-time on-line engine models to estimate control feedback signals, enabling the implementation of novel control methods.

Model-based diagnostics employs engine models tuned to match the observed engine state in the same manner as model-based control. The residual deviations between predicted and sensed parameters are modelled, again usually as variations in component losses and flow capacity, and the best match is used to identify likely component degradation modes and faults.

The use of model based techniques to diagnose and adaptively manage degradation of engine component characteristics is crucial for operational effectiveness of gas turbines. This paper gives overview of current and evolving model-based techniques and discusses benefits of these concepts in operational management of the gas turbines.

NOMENCLATURE

DDM Data Driven Modelling
EHM Engine Health Monitoring
GPA Gas Path Analysis
LEC Life Extending Control
MBT Model Based Tracking
MBD Model Based Diagnostics
MBP Model Based Prognostics
MBIA Model Based Isolation & Accommodation
MBC Model Based Control
MPC Model Predictive Control
PBM Physics Based Modelling

INTRODUCTION

Model based techniques exploit real-time engine models to estimate gas turbine internal conditions, enabling in that way implementation of novel control and diagnostic methods. Model-based information is the foundation of many diagnostics and control strategies, ranging from simple thresholding to sophisticated pattern recognition methods.

Engine performance is represented by a set of so-called health parameters. These health parameters deviate from initially healthy baseline values as the engine components degrade. Estimation of health parameters from engine data is often referred to as ***gas path analysis*** (Urban, 1972, 1974). The use of weighted-least-square estimation (Doel, 1992, 1993) and Kalman Filters (Kobayashi et al., 2003, 2005), are widely used for gas path analysis (GPA). More recently various techniques such as Neural Networks (Ogaji, 2003), Bayesian Belief Networks (Lee et al., 2010), Genetic Algorithms (Sampath et al., 2003), Polynomial Functions (Cerri et al.,2011) and different hybrid methods (Volponi et al., 2005, 2007) have been explored for use in performance fault diagnosis and tracking.

Most gas turbine diagnostics tools are based on engine steady state measurements, because during engine life most of the time engine will operate at steady state conditions. However, significant diagnostic content can be found in transient operation of engine, and hence transient gas turbine performance deterioration and diagnosis were analyzed by many researchers (Merrington, 1988, 1993, Meher-Homji and Bhargava, 1992, Bird and Schwartz, 1994).

Engine models used in gas turbine diagnostics fulfill two main purposes. Firstly they are used to determine ***performance baseline*** in order to calculate differences between measurements and such a baseline. Secondly they are used for obtaining ***fault signatures***, which represent different engine faults and degradation mechanisms.

We can also recognize two different approaches in gas turbine diagnostics. Goal of ***system identification technique*** is to determine gas turbine fault parameters that minimize difference between measured engine variables and model-based variables usually obtained by physics based models (PBM). Second approach is based on ***pattern recognition technique*** and mostly uses data-driven models (DDM). Once when fault pattern is available, a data-driven recognition tool is usually trained without detailed knowledge of the gas turbine system, and used for diagnostic purposes.

The ***data driven models***, e.g. artificial neural network models, give relationship between input and output variables that can be obtained on the basis of available real data without the need of gas turbine system knowledge. This can be seen as an advantage over physics based models, because this approach has a theoretical possibility to exclude model inaccuracy from diagnostic process. Disadvantage of data driven approach is reduced availability of data that can be used to form a representative fault classification because of the occasional occurrence of faults and on the other hand high cost of real fault simulation on a test bed.

The ***physics based models***, e.g. thermodynamic models, require detailed knowledge of the gas turbine, and generally present more or less complex software. Physical models usually consist of set of different component models. Behaviour of single components is described by physical equations or by using component characteristics, which are obtained using rig tests or various prediction tools. The main drawback of physics based modelling approach is that model inaccuracy can cause elevated errors in estimation of fault parameters.

GAS TURBINE PERFORMANCE MODELLING

Gas turbine thermodynamic models are physics based models, and they are extensively used for simulation of ***steady state*** and ***transient*** behaviour of gas turbine engines. Over the years steady state thermodynamic models establish themselves as a main tool in gas turbine gas path analysis. Mathematically, these are ***non-linear steady state models***, represented by system of algebraic equations reflecting mass, heat and energy balance for all components operating under stationary conditions. Steady state thermodynamic model computes vector $\boldsymbol{y}$ of gas path monitored variables, as a function of steady state variables $\boldsymbol{x}$, control variables $\boldsymbol{u}$ and operating conditions $\boldsymbol{v}$:

$$\boldsymbol{y} = \boldsymbol{g}(\boldsymbol{x}, \boldsymbol{u}, \boldsymbol{v}) \tag{1}$$

To describe various types of gas turbine deterioration and faults such as fouling, tip rubs, erosion, etc., this set of equations could be augmented with an additional state vector $\boldsymbol{h}$ containing health or fault parameters characterizing different engine degradation modes:

$$\boldsymbol{y} = \boldsymbol{g}(\boldsymbol{x}, \boldsymbol{h}, \boldsymbol{u}, \boldsymbol{v}) \tag{2}$$

For given steady state operating point above model can be reduced to:

$$\boldsymbol{y} = \boldsymbol{g}(\boldsymbol{h}) \tag{3}$$

Simplified model can be obtained by linearization of nonlinear dependency between gas path $\boldsymbol{y}$ and health $\boldsymbol{h}$ parameters determined for a fixed steady state operating conditions:

$$\delta\boldsymbol{y} = \boldsymbol{H}\delta\boldsymbol{h} \tag{4}$$

This ***linear steady state model*** connects vector of $\delta\boldsymbol{h}$ small changes of the health or fault parameters with a vector $\delta\boldsymbol{y}$ of the corresponding relative deviations of the monitored variables by influence matrix $\boldsymbol{H}$.

Although most of the diagnostics methods are developed at steady state, current trend demonstrates increasing interest in the diagnostics during transient operation (Loboda et al., 2006). Dynamic physics based models are used to describe behaviour of engine under transient conditions. ***Non-linear dynamic model*** is described with following generalized system of equations:

$$\dot{\boldsymbol{x}}(\boldsymbol{t}) = \boldsymbol{f}_x(\boldsymbol{x}(\boldsymbol{t}), \boldsymbol{u}(\boldsymbol{t}), \boldsymbol{v}(\boldsymbol{t}), \boldsymbol{t}) \tag{5.1.}$$

$$\boldsymbol{y}(\boldsymbol{t}) = \boldsymbol{g}(\boldsymbol{x}(\boldsymbol{t}), \boldsymbol{u}(\boldsymbol{t}), \boldsymbol{v}(\boldsymbol{t}), \boldsymbol{t}) \tag{5.2.}$$

where x and u stand for the state and the input variables, respectively, and $\boldsymbol{t}$ is the time. In steady state conditions, the left hand side in above equation (Eq.5.1.) is zero, and it degenerates into algebraic equation or system of equations. Second equation (Eq. 5.2.) is output equation that describes system output variables $\boldsymbol{y}$.

Many existing model-based methods are designed with assumption that the system exhibits linear behaviour in the neighbour of a steady-state operating point, and therefore linearization-based method are used. By linearizing the engine model (Eq. 5.1 and 5.2.) around a nominal operating conditions, i.e. $\boldsymbol{x}_0$ and $\boldsymbol{u}_0$, following ***linear dynamic model*** is obtained:

$$\dot{\boldsymbol{x}}(\boldsymbol{t}) = \boldsymbol{A}(\boldsymbol{t})\boldsymbol{x}(\boldsymbol{t}) + \boldsymbol{B}(\boldsymbol{t})\boldsymbol{u}(\boldsymbol{t}) \tag{6.1.}$$

$$\boldsymbol{y}(\boldsymbol{t}) = \boldsymbol{C}(\boldsymbol{t})\boldsymbol{x}(\boldsymbol{t}) + \boldsymbol{D}(\boldsymbol{t})\boldsymbol{u}(\boldsymbol{t}) \tag{6.2.}$$

where $\boldsymbol{A}(\boldsymbol{t}), \boldsymbol{C}(\boldsymbol{t})$ and $\boldsymbol{B}(\boldsymbol{t}), \boldsymbol{D}(\boldsymbol{t})$ are state and input distribution matrices, respectively, for the linear state and output equations.

Above equations (Eq. 6.1. and Eq. 6.2.) represent a ***linear time-varying model***, and in this general form, system matrices are functions of time. Further simplifications in the gas turbine model could be introduced by assuming that the system parameters are constant in time. In that case the system model simplifies to ***linear time-invariant model***, which can be described with following set of equations:

$$\dot{\boldsymbol{x}}(\boldsymbol{t}) = \boldsymbol{A}\boldsymbol{x}(\boldsymbol{t}) + \boldsymbol{B}\boldsymbol{u}(\boldsymbol{t}) \tag{7.1.}$$

$$\boldsymbol{y}(\boldsymbol{t}) = \boldsymbol{C}\boldsymbol{x}(\boldsymbol{t}) + \boldsymbol{D}\boldsymbol{u}(\boldsymbol{t}) \tag{7.2.}$$

where elements of system matrices A, B, C and D can be treated as constants.

Approaches that involve linearizing engine dynamics around steady state conditions and subsequent blending of parameters and controllers for selected operating points can lead to rather complicated procedure. In addition, when the effects of various faults are included into account, modelling complexity could be significantly increased, which makes design of model-based techniques and their real-time implementation very difficult. Therefore, future ***model-based control*** (MBC) and ***model-based diagnostic*** (MBD) systems will benefit significantly from new methods that are directly based on intrinsic nonlinearities of the engine dynamics.

Dynamic modelling

The accurate modelling of engine behaviour is complex task, because of the large number of effects that have to be taken into account. For example, if compressor and combustor stability effects are considered by simulation tool, high frequency gas volume dynamics should be included in the model. These high dynamic effects are in the range of 1 kHz and are usually neglected by the dynamic models. On the other hand, heat transfer effects and shaft inertia associated with the low frequency dynamics, are crucial for the dynamic behaviour of engine and control system, and are often considered by gas turbine transient models. When gas dynamics is not modelled, range of model sampling frequency reduces to 10 Hz.

Typically dynamic models have a component-oriented architecture where an engine model is composed of modules representing individual components (Schobeiri, 1994, Visser and Broomhead, 2000, Camporeale et al., 2006, Panov, 2009). The different component models are usually connected via conservation laws for mass, momentum and energy. The component models include conservation of mechanical energy for engine shafts, heat-soaking effects for metal parts (blades, discs and casing), and conservation of thermodynamic energy within different gas volume in the engine. This modelling approach generally leads to a set of non-linear differential equations, which can be solved by appropriate numerical methods such as integration algorithms.

The detailed dynamics model of gas turbine engine can be expressed with a system of non-linear differential equations in state space:

$$\begin{aligned} \dot{\boldsymbol{x}} &= \boldsymbol{f}_x(\boldsymbol{x},\boldsymbol{u},\boldsymbol{v}) \\ \boldsymbol{y}_m &= \boldsymbol{g}_m(\boldsymbol{x},\boldsymbol{u},\boldsymbol{v}) \\ \boldsymbol{y}_n &= \boldsymbol{g}_n(\boldsymbol{x},\boldsymbol{u},\boldsymbol{v}) \end{aligned} \tag{8}$$

where $\boldsymbol{x}$ is state coordinate vector, $\boldsymbol{u}$ is control vector and $\boldsymbol{v}$ is vector of operating conditions. Vector $\boldsymbol{y}_m$ contains measurable observable parameters and vector $\boldsymbol{y}_n$ non-measurable parameters.

As a gas turbine engine undergoes internal changes, these changes may be manifested in performance degradation. To account for this degradation original state and output equations could be augmented with an additional state vector $\boldsymbol{h}$ containing health parameters:

$$\begin{aligned} \dot{\boldsymbol{x}} &= \boldsymbol{f}_x(\boldsymbol{x},\boldsymbol{h},\boldsymbol{u},\boldsymbol{v}) \\ \boldsymbol{y}_m &= \boldsymbol{g}_m(\boldsymbol{x},\boldsymbol{h},\boldsymbol{u},\boldsymbol{v}) \\ \boldsymbol{y}_n &= \boldsymbol{g}_n(\boldsymbol{x},\boldsymbol{h},\boldsymbol{u},\boldsymbol{v}) \end{aligned} \tag{9}$$

The vector $\boldsymbol{h}$ contains health parameters that indicate the engine health conditions. Health parameters are usually represented by efficiencies and flow capacities of the engine components. As they deviate from their normal health conditions, the performance delivered by each component degrades, and this can be recognized as a shift in component characteristics (Razak, 2007). Generally speaking, we can recognize two main reasons for engine performance deviation: ***engine-to-engine variations*** and ***engine deterioration***.

The engine-to-engine variation accounts for manufacturing and assembly variation found in new engines, and it is based on engine parameter measurements of a sample of the engine population. This engine-to-engine variation, adds a normally distributed random value to the nominal value of each measured engine parameter.

Over the lifetime of operation, engine components will undergo some amount of degradation. This deterioration may be ***gradual*** or ***abrupt***. Some of the known ***deterioration mechanisms*** are seal and secondary flow leaks, clearance increases, erosion and fouling. While engine health deterioration is normal aging process that occurs in all engines as a result of usage, abrupt abnormal event such as foreign object damage are not predictable as they happen unexpectedly.

PERFORMANCE TRACKING

Since the gas turbine model represents “nominal” engine, it must be adapted or tuned to the performance of the real engine as it deviates from nominal baseline with time. To mitigate this problem, tuning of engine model can be performed so that model aligns to actual engine being monitored using ***model based tracking*** (MBT) approach (Fig. 1.). The idea behind this approach is to minimize the deviations or modelling errors of engine model that runs in parallel to gas turbine, by correcting parameters of “nominal” engine’s behaviour. This approach effectively removes the uncertainty introduced with engine to engine variability, different disturbances, unknown initial conditions and modelling simplifications.

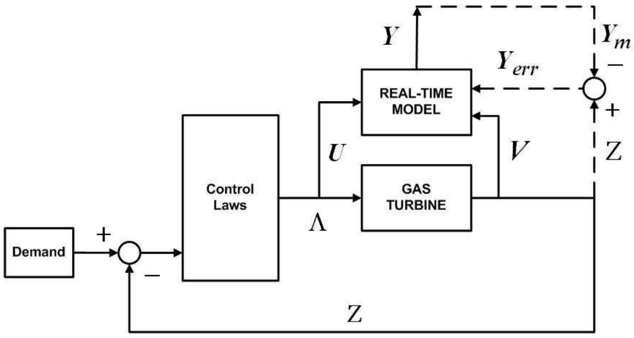

Fig. 1. Performance tracking

The tracking methods are usually based on the errors between the measured engine variables and the corresponding simulated variables, where generated errors are used to correct engine component characteristics. The measured variables $\boldsymbol{z}$ are compared with simulated variables $\boldsymbol{y_m}$, and then corresponding simulation error vector $\boldsymbol{y_{err}}$ is multiplied by a matrix $\boldsymbol{K}$, where resulting vector is used to correct the model state variables $\boldsymbol{x}$ and health parameters $\boldsymbol{h}$. Therefore dynamic model described with system of equations Eq. 9., expanded with tracking filter takes following form:

$$\begin{aligned}
\dot{\hat{\boldsymbol{x}}} &= \boldsymbol{f}_x\left(\hat{\boldsymbol{x}},\hat{\boldsymbol{h}},\boldsymbol{u},\boldsymbol{v}\right)+\boldsymbol{K}\left(\boldsymbol{z}-\hat{\boldsymbol{y}}_{\boldsymbol{m}}\right)\\
\hat{\boldsymbol{y}}_{\boldsymbol{m}} &= \boldsymbol{g}_{\boldsymbol{m}}\left(\hat{\boldsymbol{x}},\hat{\boldsymbol{h}},\boldsymbol{u},\boldsymbol{v}\right)\\
\hat{\boldsymbol{y}}_{\boldsymbol{n}} &= \boldsymbol{g}_{\boldsymbol{n}}\left(\hat{\boldsymbol{x}},\hat{\boldsymbol{h}},\boldsymbol{u},\boldsymbol{v}\right)
\end{aligned} \tag{10}$$

where function $\boldsymbol{K}$ represents gain matrix, which determines model correction and sensitivity to measurement and modelling process noise. Vectors $\hat{\boldsymbol{x}}$ and $\hat{\boldsymbol{h}}$ represent the estimates of the state variables and health parameters, and vectors $\hat{\boldsymbol{y}}_{\boldsymbol{m}}$ and $\hat{\boldsymbol{y}}_{\boldsymbol{n}}$ represent the estimates of the measurable and non-measurable model outputs, respectively. Gain matrix $\boldsymbol{K}$ can be designed using linear quadratic theory to form Kalman filter gain matrix (Dewallef and Leonard, 2003, Tagashira et al., 2009). Non-linear observer described with Eq. 10. is called Extended Kalman Filter and requires continuous evaluation when engine operating point is moving.

DIAGNOSTICS

Fault detection and isolation play a critical role in enhancing the engine reliability and reducing operating cost of gas turbine engines. Engine component degradation and faults may occur in various degrees of severity and at various locations, and numerous scenarios are possible. We can distinguish three general classes of engine faults, namely, ***sensor***, ***actuator*** and gas turbine ***component faults***.

The detection process evaluates the residuals between measurements and estimates, and monitors if a fault has occurred. The approach commonly used for model–based diagnostics (Fig. 2.) is composed of two steps (Jaw and Wang, 2006). First step consists of generation of residual signals from measurements and their nominal values:

$$\Re(\boldsymbol{t})=\boldsymbol{z}(\boldsymbol{t})-\boldsymbol{y_m}(\boldsymbol{t}) \tag{11}$$

followed by calculation of normalized relative deviation $\Delta\boldsymbol{z}$ for measured variables from their nominal values:

$$\Delta\boldsymbol{z}(\boldsymbol{t})=\frac{\Re(\boldsymbol{t})}{\boldsymbol{\sigma y_m}(\boldsymbol{t})} \tag{12}$$

where standard deviation $\boldsymbol{\sigma}$ accounts for measurement uncertainty and it is calculated based on the assumption of Gaussian distribution for measurement noises. Second step contains comparison of residuals with thresholds to make fault detection decisions:

$$\Delta\boldsymbol{z}(\boldsymbol{t})>\boldsymbol{\gamma} \tag{13}$$

In order to diagnose gas turbine faults under transient conditions above equation for normalized relative deviation (Eq. 12.) could be transformed into following form (Li, 2003):

$$\Delta z(t) = \frac{\int_{t_0}^{t} [z(t) - y_m(t)] dt}{\sigma \int_{t_0}^{t} y_m(t) dt} \tag{14}$$

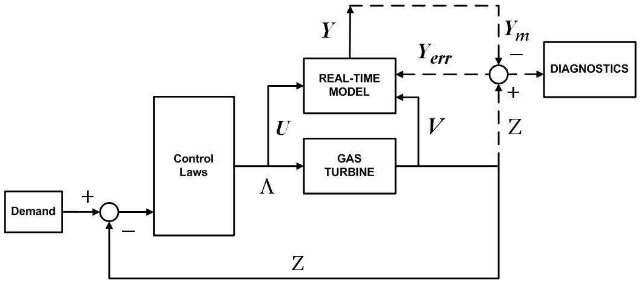

Fig. 2. Diagnostics

ISOLATION

Once a fault is successfully detected, the next step is to isolate particular fault from other potential faults. The goal of fault isolation is to identify which degradation state variable, i.e. health parameter has exceeded the alarm threshold:

$$\hat{h}(t) > \varepsilon \tag{15}$$

In reality there is a very wide range of different engine faults. Classification of faults is usually based on different criteria, and generally they can be divided into ***single*** and ***multiple faults***. It would be ideal to address all these faults (sensor, actuator and component faults) under one unified diagnostic framework, and several researchers have investigated the development of such diagnostic framework (Tang et al., 2010).

In practice, for the analysis of the engine degradation, engine faults have to be divided into the limited number of ***fault classes***. Typically it is considered that every fault class corresponds to one engine component. For example, compressor fouling and turbine erosion are considered as two different component fault classes. Compressor fouling fault class is detectable with decreased compressor efficiency and capacity, and erosion of turbine component can be detected as increase in turbine capacity and decrease in turbine efficiency.

To isolate the diagnostic information, a classifier is added to model-based detection process, and numerous techniques have been applied in the past as a ***classification engines*** (Li, 2002). Detection process consists of a preliminary variable selection and computation of variable residuals. Subsequently, further features such as health parameters are calculated by using previously determined variable residuals. And finally, after feature selection process, the determined features are subjected to classifications, where classification engine isolate final fault state.

ACCOMMODATION

The goal of fault accommodation system is to regain operability and maintain stability after a fault has been detected and isolated. The output of the diagnostic system triggers the accommodation, i.e. actuator control adjustments, to achieve stability margins in a faulted engine that are equal to or greater than the pre-fault values (Fig. 3.).

A successful ***model based isolation and accommodation*** (MBIA) strategy should protect engine stability and operability under steady state and transient conditions. Due to large number of possible accommodation parameters, they have to be carefully balanced to ensure the overall stability of the gas turbine and its subsystems (Rausch et al., 2005).

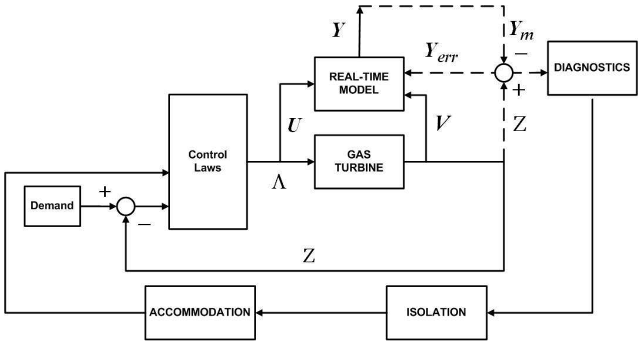

Fig. 3. Isolation and accommodation

PROGNOSTICS

Prognosis is the ability to predict the remaining useful life of a component based on engine performance. The main task of prognostics is to predict how performance degradation will deteriorate to an unacceptable level, which can be summarized as follows:

$$\Delta \mathbf{z}(\boldsymbol{t}+\boldsymbol{d}) > \boldsymbol{\kappa} \tag{16.1.}$$

$$\hat{\boldsymbol{h}}(\boldsymbol{t}+\boldsymbol{d}) > \boldsymbol{\mu} \tag{16.2.}$$

where $\boldsymbol{\kappa}$ is the acceptable performance limit for useful service and $\boldsymbol{\mu}$ is the corresponding state variable, i.e. health parameter degradation limit, and $\boldsymbol{d}$ is time to failure or remaining useful life of the component.

Prognostics holds central place in ***prognosis based asset management***, and it has potential to contribute towards reducing the operating cost of running gas turbines. Condition based component lifing and inspection, instead of operating to fixed intervals, is based on engine health, where component state\level of damage and plant profitability dictate when optimal inspection should take place (Cerri et al., 2008).

It is common practice to base damage calculation on a fleet average loading cycle mix. Using ***model based prognostic*** (MBP) technique it is possible to perform these calculations for each engine, taking into account engine to engine variation and specific engine application. Damage assessment could be done for selected critical components and could account different failure mechanisms. This proactive approach can be used to perform engine specific schedule maintenance and logistic activities.

Following current practice engine components are retired with useful life remaining. Introducing prognosis based management components will realize their life entitlement, because the life prognostics will be based on actual engine performance. This would lead towards lower engine operational costs and a shift from current practice, i.e. fixed predetermined maintenance intervals (Hindle et al., 2006).

LIFE EXTENSION

Gas turbine engine components operate under cyclic loading conditions and harsh environments, and hence they are subjected to deterioration. This component deterioration is generally described by damage evolution. Due to elevated temperatures and operational stresses, the design life of a hot section component is significantly reduced compared to that of a cold section component. The most common failure modes for a gas turbine engine include: low cycle fatigue (LCF), high cycle fatigue (HCF), thermo mechanical fatigue (TMF), creep, rupture, corrosion, oxidation and erosion.

The most important aspect of ***life extending control*** (LEC) concept is the identification of the type of damage that is most life limiting. TMF, creep and rupture are the main candidates for damage control and life extension on a continuous operation basis. Creep and creep rapture are primary damage modes for turbo-machinery, and these damage modes are further aggravated by extreme temperature cycles. By reducing temperature gradients in hot section components, significant life extension of critical components could be achieved. These thermal gradients in hot section components induce thermal stresses, which eventually can cause component failure. Especially during engine acceleration and deceleration high thermal gradients could be achieved, and hence a control policy that reduces engine transients can significantly influence remaining life of critical components (Guo et al., 2005).

The control strategies should be re-evaluated to include operating cost, and extending the life of engine is one approach to achieve that. In this way, maintenance cost could be potentially reduced if the life of engine is considered as an objective during the design of the engine controls philosophy. Disadvantage of life extension control concept, lies in the fact, that performance and life of engine are in opposition of each other. However, utilization of intelligent engine control algorithms can drastically increase the engine life, with minimum sacrifice in engine performance (Behbahani et al., 2006). Further development of damage models for turbine engines, should lead to implementation of online damage models in real-time that will allow for more robust damage prevention (Fig. 4.).

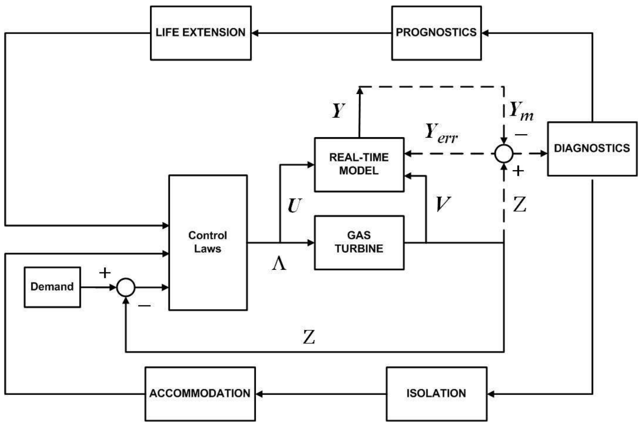

Fig. 4. Prognostics and life extension

MODEL BASED CONTROL

Model based control (MBC) explicitly uses virtual parameters created by on-line gas turbine engine models (Fig. 5.). Not all of the engine variables can be measured, or they can be measured only with reduced accuracy. Using real-time on-line engine models it is possible to obtain non-measured engine variables, such as temperatures, pressures and mass flows at relevant engine stations. By using those ***virtual measurements*** it is possible to calculate the dynamic responses of parameters, which are not available or data are affected with high measurement lags or low update frequencies. Another benefit that integrated real-time engine models can offer is ***analytical redundancy*** of existing sensors, which has been considered to be more cost-effective then commonly used ***hardware redundancy***.

Since the component characteristics change significantly during service interval, these control systems must sense degradation and damage to multiple components and adapt to it. This adaption can range from provisions to trim control constants and schedules, through to automated modifications of characteristics of individual components based on sensed parameters. Proposed control methods include numerous strategies such as clearance and compressor stability control, blade flutter and combustion instability suppression (Lietzau and Kreiner, 2001, Turevskiy et al., 2002). In addition, as previously discussed, life extending control also has potential to reduce impact of thermo-mechanical fatigue on hot components life caused by transients and short-term over-fuelling.

Various control philosophies such as adaptive (Fuller et al., 2006), active (Gastineau, 2001, Garg et al., 2010), and predictive control (MPC) (Essen and Lange, 2000, Brunell et al., 2004), have been explored for use in model based control concepts. Below is a brief description of model based control strategies that can enhance existing gas turbine control functions.

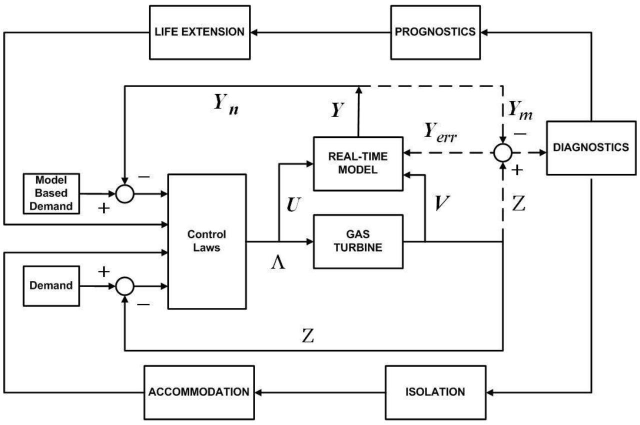

Fig. 5. Model-based control

Turbine life

Typically, the turbine component is protected by the engine control parameter, which is based on the measured gas temperature. The temperature of the combustion gases leaving the combustor is not directly controlled because measurement of the extremely high temperature at the inlet of the high pressure turbine is very difficult and impractical. Hot gas temperature is usually measured by a plurality of thermocouples disposed either at the outlet of turbine section or between high pressure and low-pressure turbine. At these engine stations, energy has been already extracted from hot gas, and gas temperature is correspondingly reduced to a suitable level, which may be practically measured.

Because the thermocouple probes at the turbine exit are constructed for accuracy and durability, but not for quick response, temperature measurement results in a lag with relatively slow response as compared to that of the critical turbine hardware. Although consideration of this temperature lag is not critical for engine accelerations of long duration, the delay becomes most significant when attempting to accurately compensate for thermocouple dynamics during rapid accelerations of short duration.

In order to prevent transient temperature overshoot from damaging turbine, model based temperature limiting control parameter provided by an on-line engine model can be used by control system to avoid or limit the temperature peaks that occur during rapid engine accelerations (Panov, 2011). Moreover, by introducing LEC strategy, this limitation of transient behavior could be adjusted to accommodate current component degradation level.

Depending on the degree of detail of the used simulation model, metal temperature of turbine vanes\blades or the hot gas temperature at the high-pressure turbine inlet can be used as a virtual measurement. To provide these virtual measurements, engine model has to capture effects associated with gas dynamics (volume packing) and heat soaking, which requires model sampling frequency in the range of 100 Hz.

Compressor stability

Operating range of compressors is limited by the onset of flow instabilities. Compressor aerodynamic instabilities are generally categorized in two distinct classes: rotating stall and surge. Surge is violent instability characterized by one-dimensional fluctuation in mass flow through the compression system. The occurrence of surge is preceded by the stalling of some compressor blade row elements, and it is characterized by regions of reduced or reversed flow that rotate around the annulus of the compressor. Especially during fast transient manoeuvres, such as rapid acceleration, a stall of the flow around the compressor blades, leading to compressor surge should be avoided. However, the distance of the current operating point to the stability line usually cannot be measured by available engine instrumentation.

Conventional control system overcome this measurement deficiency by imposing a limit on gas generator shaft acceleration or/and deceleration by using fuel schedules based on measured variables such as compressor delivery pressure to prevent compressor instabilities.

On-line model integrated within control system, can be utilized to determine the stability margin between current operating point and the surge line for “new and clean” component and provide the control system with this information. Combining this information with the knowledge of current degradation level of surge line, obtained by real-time model, adaptive and active model-based control strategies could be used for compressor stability management (Greitzer et al., 1992, Paduano and Epstein, 2000).

Emissions control

Emission of combustion system is usually managed by controlling fuel/air mixture. The challenge for this control concept is development of emission sensors for the harsh engine environment. Integration of simplified NOx prediction models with online dynamic models could offer cost effective approach to actively control the fuel/air ratio.

Combustion dynamics

To achieve low level of NOx (Nitrogen Oxides) emissions in gas turbines, combustor must operate at “lean” conditions where the fuel/air mixture is richer in air to allow for complete combustion of the fuel. As the fuel/air ratio approaches the lean blow-out limit, concentration of CO (Carbon Monoxide) in combustor increases. For specific range of fuel/air ratio and corresponding flame temperature, NOx and CO will result in low concentration. However, thermo-acoustic instabilities in these regimes are commonly observed and they must be addressed to secure optimal operation of combustion system.

To overcome problem associated with combustion instabilities usually passive techniques are employed. Those techniques include solutions such as increase of acoustic damping within the system or modification of combustor geometry to prevent excitation of unstable modes. These passive solutions generally require considerable development time, and they are limited to a specific system and operating range.

More flexible approach is to utilize active combustion instability management based on closed-loop control by monitoring the combustor pulsation in real-time (Morgans and Dowling, 2005). Model-based active combustion control can offer further enhancement of this concept by optimizing combustion pulsation and emission levels (Schneider et al., 2008).

SUMMARY

The various ***engine health-monitoring*** (EHM) systems of today provide a basic level of monitoring. Their capabilities are relatively limited and usually they are collection of separated, unrelated technologies. Information they provide is used mostly to initiate maintenance actions, but not for on-line decision making in real-time. While these traditional control and diagnostics techniques are reliable, they are not optimal, and new advanced techniques provide the promise to meet the challenging requirements of increased reliability, improved efficiency and extended operational life. Using an on-line real-time dynamic engine model to meet the challenging control and diagnostics requirements has emerged as the most viable approach. These models could provide unified framework for advanced model based control and diagnostics technologies.

Among the intended uses for such a model, is to enable real-time, on-line tracking of engine performance changes and engine parameter synthesis for fault detection and accommodation. Model tracking methodology offers a means to compensate engine to engine variations, and furthermore aligns the model to particular engine being monitored to insure accurate performance tracking while engine performance deteriorate with time.

Adaptive model based control with integrated model based diagnostics, isolation and accommodation has significant potential to contribute to operational improvement of gas turbine engines, due to ability to diagnose and adaptively manage degradation of engine components while taking into account engine-to-engine variation and current operating conditions. These model based control strategies include methods for optimization of operational limits such as compressor and combustor stability, turbine life and emissions. In addition life extending control can contribute towards reduction of operational costs, taking into consideration the impact on component life usage in ways that trade minor performance degradation, for significant component life extension.

Model based prognostic approach is also increasingly favoured due to capability to provide more accurate estimation of remaining useful life. This approach is naturally extensible to the physics of failure, and hence it has been considered to be a promising enhancement of the conventional prognostic technology. The potential payoffs of prognosis based asset management are increased component life entitlement, improved time in service, better asset utilization and lowered engine maintenance costs.

There are number of technical challenges that must be met in order to model based concepts become a standard practice for gas turbine engines. Development and implementation of online damage models is prerequisite for robust prognostic and damage prevention strategies. More accurate gas turbine models that capture the dynamics of interest are required to guide the development of both, diagnostic and control methods, and on the other hand, simplified dynamic models are needed to enhance the performance of the engine under adaptive control while maintaining stability and operability margins.

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