Global Power & Propulsion Society

Proceedings of the 1st Global Power and Propulsion Forum
GPPF 2017
Jan 16-18, 2017,Zurich, Switzerland
www.pps.global

GPPF-2017-129

MODEL-BASED COMPENSATION OF SENSOR FAILURE IN INDUSTRIAL GAS TURBINE

Dr. Vili Panov
Siemens Industrial Turbomachinery Ltd.
vili.panov@siemens.com
Lincoln, Lincolnshire, UK

Dr. Sepehr Maleki
University of Lincoln
smaleki@lincoln.ac.uk
Lincoln, Lincolnshire, UK

ABSTRACT

This study investigates application of analytical sensor redundancy to improve reliability of gas turbine control system. Analytical redundancy, which uses a reference engine model to provide redundant estimates of a measured engine variables, has been utilized as a basis for the proposed sensor fault detection and accommodation method.

Model-based compensation of measurement fault is usually resolved by introducing virtual engine sensors, which are obtained via accurate engine modelling. In this paper, a real-time dynamic gas turbine engine model is used in order to generate the redundant virtual measurements. The engine model accuracy directly determines the validity of the model-based approach for sensor fault diagnosis, and hence a model with auto-tuning capability is deployed as a reference for the gas turbine.

The proposed fault detection technique examines the residuals between the redundant channels. Once the discrepancy between the virtual and the sensor measurement exceeds the prescribed tolerance levels, the sensor fault diagnosis determines the state of the switching logic in the dual lane control configuration. The deployed logic is also used for reconfiguration of the auto-tuning process. When a sensor fault occurs, the estimation process is affected, and hence the tuning process must be adjusted to account for this deficiency.

Single and multiple sensor failures are simulated during the gas turbine transient manoeuvre to assess capability of the proposed model-based detection and accommodation method. Hard (large in-range) and soft sensor failures (small in-range or drift) are injected during the numerical simulation and results are presented.

INTRODUCTION

In general, two methods are available for incorporating sensor redundancy, namely physical and virtual redundancy. The first method involves adding multiple identical sensors to the control system, while the second method considers software or analytical redundancy.

Analytical redundancy requires a sensor model to determine when a failure occurs without any physical redundant sensors in the control system. On the other hand, hardware redundancy is more costly, less practical and less reliable. Consequently, many researchers have investigated analytical redundancy strategies.

Wallhagen and Arpasi [1] have proposed an analytical sensor redundancy technique that is obtained by means of tabulated synthesized variables for steady-state and acceleration conditions. Hrach, Arpasl, and Bruton [2] have used a real-time non-linear hybrid computer simulation of an engine, where sensor fault accommodation is achieved by replacement with averaged synthesized variables.

Ellis [3] has investigated analytical redundancy techniques using a non-linear digital simulation of a gas turbine engine. Wells and deSilva [4] have applied Bayeslan hypothesis testing for detection of engine sensor failures.

The fault indication and correction system developed by Spang and Corley [5] has deployed an extended Kalman filter approach to generate state estimates and residuals.

DeHoff and Hall [6] have developed a unified framework to achieve engine performance monitoring, trending, and sensor fault isolation and accommodation. Behbehani [7] has deployed the generalized likelihood ratio technique, which is a hypothesis based test with the time and type of failure unknown.

In order to detect and isolate the sensor faults, and subsequently to provide software redundancy, Delaat and Merrill [8, 9] have developed an analytical redundancy design for real-time implementation. Merrill has used a bank of Kalman filters for detection, isolation, and accommodation of sensor failures [10].

More recently, Kobayashi has explored a fault detection and isolation system that utilizes a bank of Kalman filters for aircraft engine sensor and actuator fault isolation in conjunction with the detection of component faults [11]. Later on, Kobayashi and Simon [12, 13] developed an enhanced system utilizing dual-channel sensor measurements for aircraft engine on-line diagnostics.

This paper develops an integrated framework for sensor fault diagnostics and performance monitoring. A performance tracking technique is used to produce accurate engine status for both, sensor fault accommodation and gas turbine monitoring [14].

SENSOR FAULT DIAGNOSIS

The sensor fault diagnosis methods are generally divided into three categories: model-based, knowledge-based and signal processing-based. In this paper, a model-based approach is considered. This approach requires a pre-established engine model to acquire the analytical channel. The gas turbine model is generated by using the engine component characteristics and thermodynamic equations. Model-based methods avoid the problems of knowledge based maintenance and high robustness requirements of the measurement data. These methods, can be used to diagnose new sensor failures with no need of historical data or a priori knowledge.

To determine an anomalous sensor signature, the implemented technique compares the redundant measurement channels. Two typical residuals are examined by the detection logic, namely: *cross-check* and *analytical*.

In case of triplex redundancy, which consists of two physical and one virtual sensor, duplicate channels (y_j^I, y_j^{II}) are sensor measurements from the gas turbine, and y_j^{mdl} is the corresponding output from the engine model. The cross-check residual in this case is obtained by:

$$r_j^{CC} = \frac{\left|y_j^I - y_j^{II}\right|}{\sigma_j}, \qquad (1)$$

where, σ_j is the standard deviations of the jth sensor measurement uncertainty. This dual-channel residual for each available sensor set is compared against a corresponding threshold τ_j^{CCR}. If this residual does not exceed the prescribed threshold, the redundant measurements on both channels are acceptable. In case that residual is above threshold value, i.e.:

$$r_j^{CC} > \tau_j^{CCR} \qquad (2)$$

at least one channel is faulty. The cross-check residual can only determine whether at least one channel of the dual-channel sensor is faulty, but cannot determine which channel is faulty. To address this shortcoming, usually an analytical residual is introduced as an additional sensor fault indicator. Analytical residuals are defined as follows:

$$r_j^k = \frac{\left|y_j^k - y_j^{mdl}\right|}{\sigma_j}, \qquad k = \mathrm{I, II} \qquad (3)$$

In case of duplex redundancy, which consists of one hardware and one analytical sensor, only analytical residual can be used for sensor diagnosis. The analytical residual computed for measurement channel is compared against two thresholds, namely, $\tau_j^{\min}$ and $\tau_j^{\max}$. If an analytical residual exceeds a first threshold $\tau_j^{\min}$, this indicates the existence of soft failure, and if the residual exceeds the second threshold, $\tau_j^{\max}$, a hard sensor failure is diagnosed.

Threshold selection

Threshold selection for sensor fault classification directly affects the results of fault diagnosis. Therefore, a rational selection of the thresholds is necessary to achieve a reliable sensor fault diagnosis scheme. The engine outputs measured by sensors can be expressed as follows:

$$y_j^k = y_j^{mdl} + \Delta y_j + \nu_j. \qquad (4)$$

The parameters y_j^{mdl} and Δy_j, represent engine sensor model output and the modelling errors respectively. The parameter ν_j is a zero-mean, normally distributed white noise that corrupts the measurements ($\nu_j \sim N\left(0, \sigma_j^2\right)$).

The threshold of the analytical residual is determined by the measurement noise and modelling errors. Hence, analytical residual can be expressed with the following relation [15]:

$$r_j^k = \frac{\left|y_j^k - y_j^{mdl}\right|}{\sigma_j} \le \left|\frac{\Delta y_j}{\sigma_j}\right| + \left|\frac{\nu_j}{\sigma_j}\right| \qquad (5)$$

Considering that the random variables in $\left|\frac{\nu_j}{\sigma_j}\right|$, following a normal distribution, the minimum and maximum thresholds, $\tau_j^{\min}$ and $\tau_j^{\max}$, can be calculated as follows:

$$\tau_j^{\min} = \left|\frac{\Delta y_j}{\sigma_j}\right| + 2 \text{ for the } 2\sigma \text{ rule} \qquad (6)$$

$$\tau_j^{\max} = \left|\frac{\Delta y_j}{\sigma_j}\right| + 3 \text{ for the } 3\sigma \text{ rule} \qquad (7)$$

Assuming that parameters ν_j^I and ν_j^{II} are independent and normally distributed with zero mean, the probability density function for the dual-channel random residual $\Delta\nu_j = \nu_j^I - \nu_j^{II}$ is given as [15]:

$$f\left(\Delta\nu_j\right)=\int_{-\infty}^{+\infty} f(\nu_j^I)\cdot f(\nu_j^I-\Delta\nu_j)d\nu_j^I=\frac{1}{2\sqrt{\pi}\sigma_j}e^{\left(-\frac{\Delta\nu_j^2}{4\sigma_j^2}\right)} \quad (8)$$

In order to keep misdiagnoses to a minimum (a confidence level with the probability of 99.7% for diagnoses), the threshold for the dual-channel cross-check random residual $r_j=\Delta\nu_j=\sigma_j\sim N(0,2)$ is set as:

$\tau_j^{CCR}=4.5$ for the 3σ rule (9)

DUAL LANE CONTROL

Dual lane redundancy is often introduced into the gas turbine control systems to improve reliability of the measurement chains. In a dual lane configuration, both lanes simultaneously measure the engine parameters and compare the measurements to enable sensor health monitoring. One lane is considered to be in the control mode while the other is in the back-up mode. Once an instrument fault is confirmed, lane switching is initiated.

The total duration of fault confirmation and lane switching must not exceed a certain critical time. The reason for this is a trade-off between the accurate fault confirmation and the successful switching process. The probability of accurate fault confirmation increases with the time while the successful switching or fault accommodation probability decreases. Hence, the lane switching logic must be carried out considering this trade-off.

Figures, Fig. 1. and Fig. 2., show the use of on-line engine modelling in condition monitoring of dual lane control system and lane-to-lane switching logic. Fig. 1. shows double redundancy case, which is achieved with one hardware and one software sensor. Fig. 2. depicts triple redundancy where in the case of a double sensor fault in both lanes, the gas turbine control can be carried out with use of virtual sensor.

Dual redundancy

The objective of on-line diagnosis for sensors is to detect and isolate faults as early as possible. Fig. 1. represents the structure of the an on-line system composed of the Real-Time engine Model (RTM) and the lane switching logic. An engine model is used as an analytical second channel for the gas turbine application.

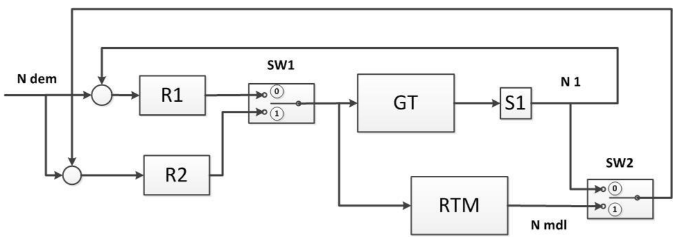

Fig. 1. Dual lane control with dual sensor redundancy

When discrepancy between virtual and sensor measurement exceeds prescribed tolerance levels, the sensor fault diagnosis logic determines state of switching logic in dual lane configuration. In this configuration when soft failure of sensor is indicated, lane logic will select lane with conservative control settings. In case that sensor hard failure is detected, the faulty sensor signal is replaced by the virtual measurement.

Triple redundancy

In this configuration the real-time model provides the analytical third channel against which the duel channel measurements are compared (Fig. 2.). Considering the measurement noise and modelling errors, sensor dual channel threshold and analytic threshold are determined and used in the proposed logic. When the difference among triplex channels exceeds certain tolerance levels, the logic determines the new lane switching configuration.

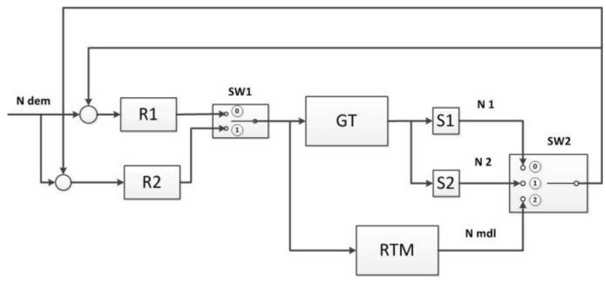

Fig. 2. Dual lane control with triple sensor redundancy

The devised logic indicates that a sensor fault is isolated when the dual channel residual of particular measurement exceeds the threshold, and also, this measurement's analytical residual exceeds the threshold in either one or both channels. If the analytical residual exceeds its respective threshold only in one channel, the corresponding channel is identified as faulty. Subsequently, the identified fault is classified as soft or hard. If the threshold violation occurs in both channels, depending on the classification of detected faults, lane switching logic determines the new configuration of the active control loop. When both channels of this measurement are diagnosed with a hard failure, the faulty sensor signal used for control system is replaced by the respective virtual measurement.

VIRTUAL INSTRUMENTATION

The real-time dynamic gas turbine engine model with auto-tuning capability is deployed as a reference model of the gas turbine engine [16]. This configuration has a dual purpose. Firstly, it serves as a model-based performance tracking system, and secondly, it is used for generation of redundant virtual measurements (Fig.3.).

Several practical aspects are considered during development of the proposed system. This includes measurement and modelling accuracy, and also complexity of the implemented algorithms. Implementation of detection algorithms can easily exhaust the computational capability. For time constants, comparable to the transient engine response, a fast decision requiring gross changes in engine / instrumentation characteristics must be made in real-time with a relatively small amount of information. The proposed integrated framework for sensor fault accommodation and performance tracking allows required real-time execution.

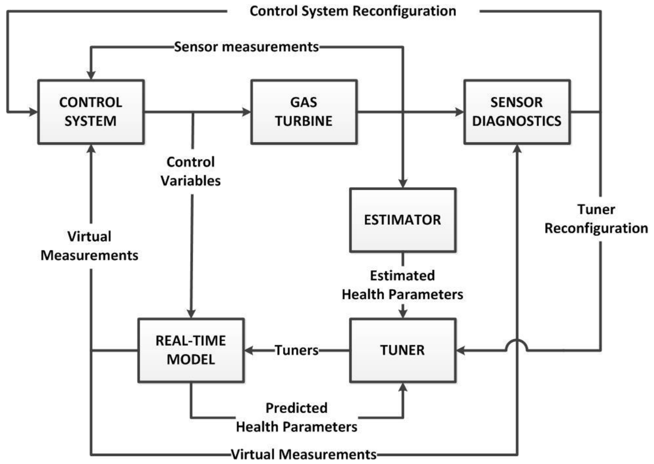

Fig.3. Model-based performance tracking with integrated sensor fault accommodation

Developing a model detailed enough for accurate diagnostics and isolation throughout the operating engine range technically is a formidable challenge. Commonly three different approaches are used: I) Parameter synthesis approach that normally does not include explicit engine dynamics and hence contributes to less accurate modelling. II) Pseudo-linear modelling approach that separates steady-state from the dynamic models, and these models could be modified independently. III) A simplified component based modelling technique that employs detailed nonlinear engine models. The final approach relates naturally to the physics of the actual engine and therefore it is used for the generation of a reference engine model in this paper.

Engine model

The engine model is developed using a generic toolbox for dynamic simulation of gas turbines [17].

The detailed dynamic model can be mathematically described by a set of nonlinear differential equations:

$$\dot{x} = f_x(x, h, u, \upsilon) \tag{10}$$

where, the distributed aero-thermodynamic, mechanical and electrical processes are lumped into a state coordinate vector x. For n state variables, n sets of the equation must be solved. Controls, u, operating conditions, υ, and health parameters, h, are quantities that can be obtained through measurements or algebraic manipulation.

Measurements are taken on various quantities in the engine. These sensed parameters are related to the states, inputs and parameters according to the general algebraic expression:

$$y = g_y(x, h, u, \upsilon) \tag{11}$$

where, general vector y consists of measurable and non-measurable parameters. Above equations (10) and (11) are general enough to provide a starting point to define the fault detection problem with respect to the control design and state estimation process.

Once when an accurate model is developed for the generic baseline, the engine model must be expanded to include data representing the deteriorated engine. These effects include various efficiency changes, area changes, pressure drops, as well as flow changes and disturbances due to bleed effects. Typically, the two quantities, capacity and efficiency are used to model the changes of component operations resulting in a decreased energy conversion efficiency or component flow characteristics.

The health parameters considered by the deployed model are: efficiency and capacity in the compressor and compressor turbine, and efficiency of the combustor and power turbine:

$$h^T = \left[\eta^h_{comp}, \Gamma^h_{comp}, \eta^h_{ct}, \Gamma^h_{ct}, \eta^h_{pt}, \eta^h_{comb}\right] \tag{12}$$

The selected set of health parameters can be estimated using available measurements from engine instrumentation and they are chosen to reflect a “complete” set of component performance parameters [18].

Auto-tuning process

The model accuracy directly determines the validity of the analytical approach for sensor fault diagnosis. The model must be sufficiently accurate and operate in real time. These requirements make general gas turbine models ineffective due to not-accounting for individual engine characteristics and environmental conditions.

Since the general gas turbine model represents a “nominal” engine, it must be tuned to the performance of a real engine. Therefore, the model is tuned such that it aligns to the actual engine being monitored using a model-based tracking approach.

Performance tracking is achieved in two steps. The gas turbine health parameters are estimated by a performance estimation tool [18], and subsequently are introduced into the real-time dynamic model via a tuner [16].

The health parameters z estimated from the sensor measurements are compared with the smoothed estimates of the health variables $\hat{z}$. The resulting vector is then used for generation of model tuners ξ and correction of the state variables x:

$$\dot{\hat{\xi}} = f_\xi\left(\hat{\xi}, \hat{h}\right) + K(z - \hat{z}), \tag{13}$$

where, function K represents the Kalman tuner gain and vector $\hat{\xi}$ consists of the estimated tuning parameters.

Therefore, the gas turbine dynamic model that incorporates the tuner takes the following form:

$$\dot{\hat{x}} = f_x\left(\hat{x}, \hat{h}, u, \upsilon, \hat{\xi}\right) \tag{14}$$

$$\hat{y} = g_y\left(\hat{x}, \hat{h}, u, \upsilon, \hat{\xi}\right) \tag{15}$$

where, vectors $\hat{x}$ and $\hat{h}$ represent the corrected state variables and predicted health parameters, respectively.

Continuous time invariant model of the tuning process in implemented structure is represented with linear model in the following form:

$$\dot{\xi}(t) = \Phi\xi(t) + \Psi h(t) + w \tag{16}$$

where, state and input transition models are described with diagonal matrices Φ and Ψ respectively. The tuner states are represented with tuned health vector:

$$\xi^T = \left[\eta^{\xi}_{comp}, \Gamma^{\xi}_{comp}, \eta^{\xi}_{ct}, \Gamma^{\xi}_{ct}, \eta^{\xi}_{pt}, \eta^{\xi}_{comb}\right] \qquad (17)$$

The state transition matrices Φ and Ψ correspond to the tuner states and predicted health parameters respectively, and they satisfy the following conditions:

$$\Psi = \mathrm{I} - \Phi \text{ and } 0 \le \Phi \le \mathrm{I}. \qquad (18)$$

Measurements model in the implemented tuner is represented with the following equation:

$$z(t) = H\xi(t) + v \qquad (19)$$

where, v is the measurement noise and $H = \mathrm{I}$ is the measurement sensitivity matrix, that considers the estimated health parameters as the tuning model states.

When a sensor fault occurs, the estimation process is also affected, and hence the tuning process must be adjusted to account for this deficiency. This correction is introduced into the tuning process via the transition matrix Φ and the gain matrix K:

$$\Phi = diag(\phi_{\eta_{COMP}}, \phi_{\Gamma_{COMP}}, \phi_{\eta_{CT}}, \phi_{\Gamma_{CT}}, \phi_{\eta_{PT}}, \phi_{\eta_{COMB}}) \qquad (20)$$

$$\mathrm{K} = diag\left(\kappa_{\eta_{COMP}}, \kappa_{\Gamma_{COMP}}, \kappa_{\eta_{CT}}, \kappa_{\Gamma_{CT}}, \kappa_{\eta_{PT}}, \kappa_{\eta_{COMB}}\right) \qquad (21)$$

Number of adjusted elements in the transition and gain matrix depends on the isolated sensor set. As an example, transition matrices for two failure cases are given below. In case of a CDP (Compressor Delivery Pressure) measurement fault, only estimation of PT (Power Turbine) efficiency is not effected and hence the transition and tuner gain matrix structure takes following form:

$$\Phi = diag(0,0,0,0,\phi_{\eta_{PT}},0) \qquad (22)$$

$$\mathrm{K} = diag\left(0,0,0,0,\kappa_{\eta_{PT}},0\right) \qquad (23)$$

On the other hand, in case of an exhaust thermocouple fault, for devised estimation method [18], only the estimated PT efficiency is affected, and therefore the structure of the transition and gain matrix are as follows:

$$\Phi = diag(\phi_{\eta_{COMP}}, \phi_{\Gamma_{COMP}}, \phi_{\eta_{CT}}, \phi_{\Gamma_{CT}}, 0, \phi_{\eta_{COMB}}) \qquad (24)$$

$$\mathrm{K} = diag\left(\kappa_{\eta_{COMP}}, \kappa_{\Gamma_{COMP}}, \kappa_{\eta_{CT}}, \kappa_{\Gamma_{CT}}, 0, \kappa_{\eta_{COMB}}\right) \qquad (25)$$

Correction of the state transition and Kalman gain matrix for compensation of sensor faults in a generalized form can be expressed as:

$$\Phi = \Phi_0 \cdot \prod \Omega_i^{comp} \text{ and } \mathrm{K} = \mathrm{K}_0 \cdot \prod \Omega_i^{comp} \qquad (26)$$

where, Φ_0 and K_0 correspond to healthy measurement set, when no sensor faults are present.

The correction process is based on the compensation matrices: (27)

$$\Omega_i^{comp} = diag\left(\omega^{comp}_{\eta_{COMP},i}, \omega^{comp}_{\Gamma_{COMP},i}, \omega^{comp}_{\eta_{CT},i}, \omega^{comp}_{\Gamma_{CT},i}, \omega^{comp}_{\eta_{PT},i}, \omega^{comp}_{\eta_{COMB},i}\right)$$

where, each compensation matrix represents influence of particular sensor. Correction factors in the compensation matrix are defined as follows:

$$\omega^{comp}_{l,i} = 1 \quad \text{for} \quad r_j^k \le \tau_j^{\min} \qquad (28.1.)$$

$$\omega^{comp}_{l,i} = \frac{\tau_j^{\max} - r_j^k}{\tau_j^{\max} - \tau_j^{\min}} \text{ for } \tau_j^{\min} < r_j^k < \tau_j^{\max} \qquad (28.2.)$$

$$\omega^{comp}_{l,i} = 0 \quad \text{for} \quad \tau_j^{\max} \le r_j^k \qquad (28.3.)$$

Correction factors are determined based on the threshold values used in the sensor fault diagnosis process. In the case that a sensor failure is not detected ($r_j^k \le \tau_j^{\min}$), estimation process is not affected and tuning of the model is fully preserved. When sensor fault probability increases, correction of tuning parameters takes place until sensor diagnostic residual parameters fall within the allowed band $\tau_j^{\min} < r_j^k < \tau_j^{\max}$. Beyond this point, for parameter being outside the allowed band ($\tau_j^{\max} \le r_j^k$), estimation process is compromised, and only unaffected health parameters can be tuned.

Sensor model

The sensor models that are considered in this paper include: thermocouples, speed probes and pressure transducers. It is assumed that measurements are taken with transducers whose output can be modelled as follows:

$$Z_m = Z + g_Z(Z,u) + v \qquad (29)$$

where $v(t)$ is a zero-mean random process. The measurement function $g_Z(Z,u)$, represents systematic errors in the measurements which could include bias offsets, scale factor effects, radial flow effects (e.g. pressure gradients), and cross coupling (e.g. temperature effects on scale factor).

A Generic model for a typical engine measurement instrumentation is described as a first-order system with dead time delay:

$$Z = \frac{Ge^{-C_D s}}{1 + C_L s} \qquad (30)$$

where, C_L is lag time constant, and C_D is the dead time constant. This generic formulation is used to model shaft speed sensor.

Temperature sensors are generally low bandwidth devices that filter high frequency, local temperature variations. The model for the sensor data can be represented by:

$$T_m = T + b + v \qquad (31)$$

where, $v(t)$ is a zero-mean random noise, which is assumed to be white and with normal probability distribution $v = N(0,r)$. The bias term, b, is treated as a long-term calibration drift.

Pressure sensors can exhibit a far more complex behaviour due to vibration effects, radial flow distribution shifts, wake effects, temperature changes, etc. The proposed pressure transducer model is described as follows:

$$P_m = P(1 + kT) + b + v \qquad (32)$$

NUMERICAL SIMULATION

Fault detection, isolation and accommodation

The proposed method is evaluated in a software-in-the-loop environment to prove its practicality as an alternative to the hardware sensor redundancy. The developed algorithm detects, isolates, and accommodates sensor failures in an industrial gas turbine control system. The method incorporates control system reconfiguration logic and is general enough to be applied to different engine configurations.

The method consists of sensor failure detection and isolation logic and the accommodation procedure. Two classes of sensor failures, namely hard and soft, are evaluated using numerical simulation. Hard failures are out-of-range or large bias errors that occur instantaneously in the sensed values. Soft failures are small biases or drift errors that accumulate relatively slowly with time.

The hard failure detection and isolation logic performs a straightforward threshold check on selected sensors residuals. Threshold values are determined from sensor and process noise values as well as sensor range consideration. If a residual value is greater that the threshold, hard failure detection and isolation follow immediately. Where hard failures can be detected almost instantly, soft failures are reliably detected only after some finite amount of time. This time to detect is a function of threshold level, which determines detection reliability, model accuracy, and logic complexity.

Two modes of operation, normal and failure mode are simulated. During the normal mode, when no sensor failures are present, the accommodation tuner considers full set of estimated health parameters, which are derived using all available measurements. In a failure situation, where one or more of the sensors have failed and depending on the type of sensor failure, accommodation tuner selects appropriate measurement subset.

A threefold process takes place once the failure has occurred. Firstly, the failure is detected. Once a failure is known to have occurred, the specific faulty sensor must be isolated. Finally, when isolation has occurred, the failure is compensated by reconfiguring dual lane control logic and accommodation tuner. This threefold procedure takes place for both, hard and soft failures.

Simulation results

A real-time dynamic model of industrial twin-shaft engine is developed and utilized as the numerical test bed for assessment of the proposed detection and accommodation system. Two engine models are used, where one simulates the “real” engine and second represents an on-line engine model with the sensor fault detection and isolation system. Noise and biases of the engine instrumentation are implemented in the model representing a “real” engine to introduce model-plant mismatch.

The capability of the devised system to detect, diagnose and recover a faulty sensor is assessed. Degraded and failed sensors are simulated, and system responses are evaluated. A sensor fault is injected into one or more channels at a time, whereas the health condition of the engine is set to the nominal health. Combined sensor and component faults [19], are not considered in this study. Two types of sensor faults are simulated: the step fault and the drift fault. In the presence of a sensor bias, the closed-loop system is trimmed at a full load operating condition. From full load steady-state condition, transient manoeuvre consisting of block load rejection with subsequent block load acceptance is simulated. Sensor faults are injected in the steady state between two transient manoeuvres.

The deployed fault diagnosis system utilises “sensor” measurements from “real” engine, and the output from the on-line engine model as the analytical channel. Through the comparison of redundant channels, the system diagnoses two types of faults in sensors.

The developed system based on a real-time on-line model can be used under the steady state and transient operation. The sensor fault detection and accommodation scheme is evaluated under a transient operating condition using several test cases. The developed system conducts fault diagnosis and isolation and additionally activates the reconfiguration logic. Reconfiguration logic selects the appropriate controller by means of a switching mechanism.

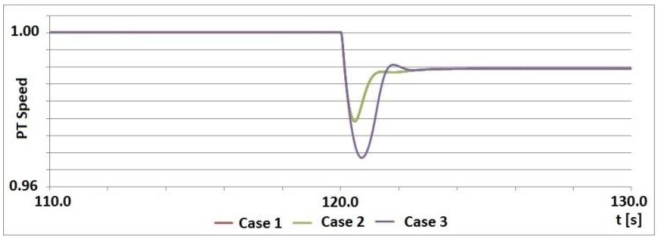

Fig.4. Power turbine speed profile for block load acceptance

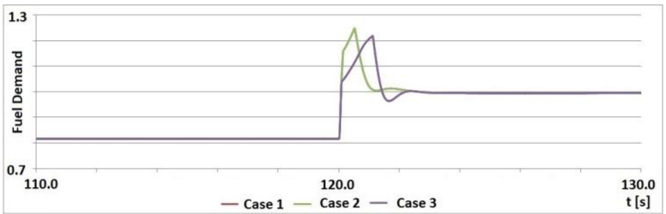

Fig.5. Fuel demand for block load acceptance – Conventional and model-based CDP limit

The engine operational parameter (power turbine speed) and control system variable (fuel demand) are shown in Fig.4. and Fig.5. Engine response to reconfiguration of control logic is presented in Fig.4. Three different cases are compered and two distinctive responses are observed. The first two cases correspond to the conventional compressor delivery pressure (CDP) limiter and second response (Case 3) to the model-based controller with conservative regulator settings. Accompanying plots of control system response (fuel demand), are given in plot Fig.5.

The diagnostic capability of the fault diagnosis system had been assessed using normal operation as a benchmark. In the normal mode, when no sensor failure is present, the accommodation tuner considers full set of estimated health parameters, and reconfiguration of control system is not initiated.

In the case when sensor faults are simulated, gas turbine measurements are compared with analytical measurements and physical values (gas pressure and temperature) from the engine model at measurement stations. To demonstrate reconfiguration of accommodation tuner, health indices:

$$I_\Gamma = 100\times\frac{\Gamma^\xi-\Gamma^h}{\Gamma^h};\ I_\eta = 100\times\frac{\eta^\xi-\eta^h}{\eta^h} \qquad (33)$$

for the considered engine components are presented. Health indices represent the percentage change in component characteristics due to component faults or gradual degradation. Two health indices are defined for any component and they correspond to the capacity and the efficiency index. Sensor fault detection and isolation process is also captured by depicting correction factors in compensation matrix, which are based on measurement residuals and are used for adjustment of accommodation tuner and reconfiguration of control logic.

Progressive Texh fault – drift error

The soft sensor failure is considered by simulating drift error in exhaust temperature measurement (T_{exh}). Simultaneous multiple sensor failures are rear events and simultaneous fault in redundant exhaust thermocouples was simulated just for the sake of simplicity (Fig.6.).

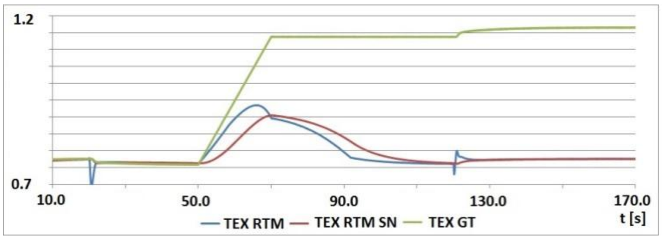

Fig.6. Exhaust gas temperature for RTM, virtual sensor and average GT sensor measurement

Once a soft failure is detected and isolated, the accommodation tuner is reconfigured by correction factors to compensate for the drift error in temperature measurements (Fig.7.).

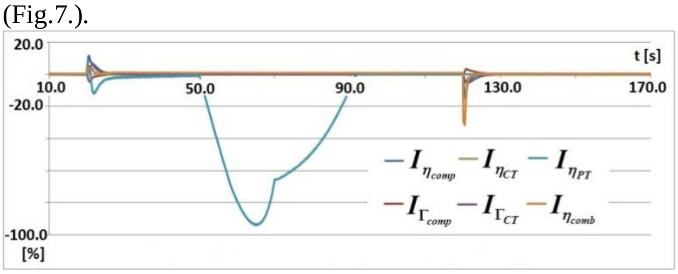

Fig.7. Tuning of the RTM - Health indices

In case of exhaust thermocouples fault, only the estimated power turbine efficiency is affected, and hence the correction factor $\omega_{\eta_{PT}}$ is adjusted. Initial PT efficiency underestimation is corrected once when sensor soft failure is detected. At the end of the process when a large bias error is detected, failed sensor is isolated and removed from further considerations (Fig. 8.).

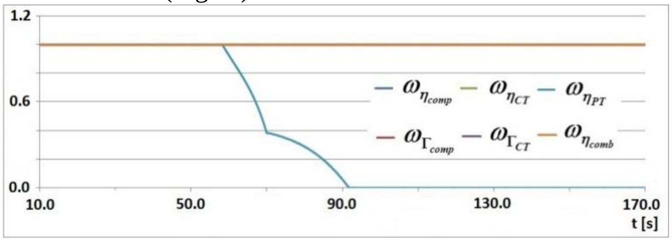

Fig.8. Compensation matrix correction factors

Combined abrupt CDP and Texh fault

Ability of the devised system to compensate multiple sensor faults is assessed by simulating combined abrupt compressor delivery pressure and exhaust temperature measurement fault.

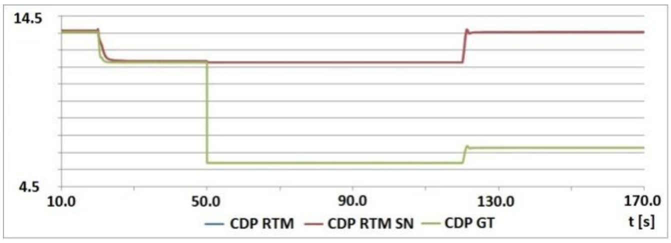

Fig.9. Compressor delivery pressure for RTM, virtual sensor and GT sensor measurement

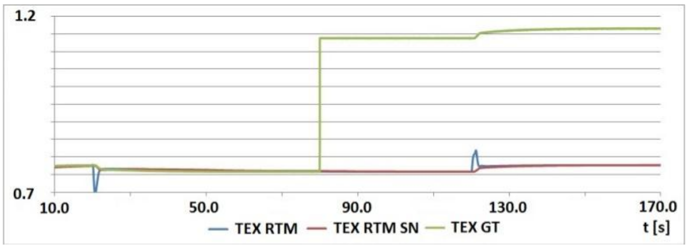

Fig.10. Exhaust gas temperature for RTM, virtual sensor and average GT sensor measurement

Comparisons of analytical and “measured” values for compressor delivery pressure and exhaust temperature are shown in figures Fig. 9. and Fig. 10. respectively. Implemented sensor fault tolerant control successfully recognizes when a particular fault occurs and initiates a reconfiguration.

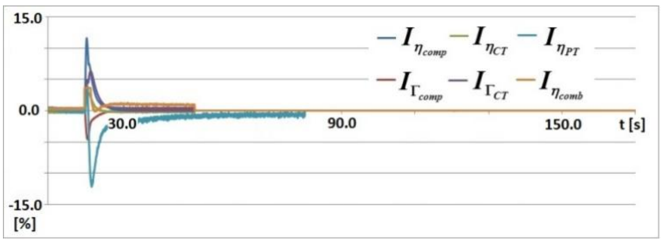

Fig.11. Tuning of the RTM - Health indices

In the case of a hard failure, straightforward residual check provides successful detection, isolation and compensation of the sensor fault. This test case simulates a large negative abrupt bias error for the CDP measurements

(Fig.9.). Based on the threshold violations occurring from the measurements, faulty sensor is isolated, and control reconfiguration is initiated (Fig.12.). System tuning and compensation process are depicted in Fig.11. and Fig.12.

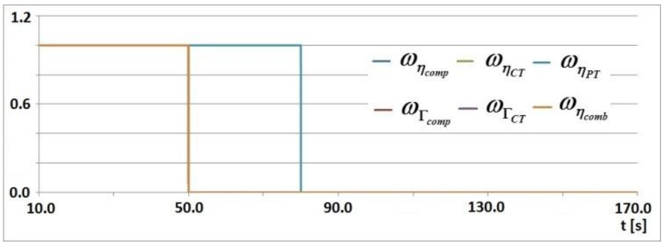

Fig.12. Compensation matrix correction factors

Large abrupt negative bias error in CDP measurement (Fig.9.) is accompanied with a subsequent large positive bias error in the exhaust temperature measurements (Fig.10.). This subsequent event is followed with isolation of these faulty measurements (Fig.12.), adjustment of accommodation tuner (Fig.11.) and reconfiguration of the control logic.

CONCLUSIONS

Current reliability requirements and more adverse sensor environments are pushing the engine controls designers towards analytical redundancy rather than hardware redundancy solutions. Hardware redundancy results in more costly, heavier, less practical, and less reliable systems than various analytical redundancy strategies. On the other hand, modelling is the key issue in the success or failure of analytical redundancy techniques. Various types of engine models are used in the industry, and each has its advantages and disadvantages.

The sensor fault detection system developed from a dynamic real-time model described in this paper is used for on-line diagnosis of gas turbine engine sensor failures. Moreover, the paper proposes a self-contained sensor diagnostic, isolation and accommodation system for utilization on industrial gas turbine engines. This aspect of fault detection and isolation is particularly important because of the significant improvements in the gas turbine availability and reliability, which results from ability to diagnose engine operational deficiencies before severe failure.

A generic baseline model of the twin-shaft engine was deployed to develop necessary software capability and to demonstrate the analytical and numerical procedures involved in this method. Proposed system consists of following elements: fault detection, isolation and accommodation subsystem; reconfiguration logic; and corresponding controllers in dual lane configuration. Fault detection and isolation system initiates reconfiguration of control system. These adaptable actions can react to the occurrence of sensor faults on-line, in an attempt to maintain the overall gas turbine system stability and performance.

Numerical simulation of gas turbine with performance tracking filter has conclusively shown the feasibility of devised method based on analytical redundancy to diagnose, isolate and accommodate hard and soft sensor failures. The results were very encouraging but validation work remains to be done on the full scale engine test.

NOMENCLATURE

Variables

Γ capacity [$K^{0.5}$/Pa kg/s]	$\boldsymbol{Z}$ measurement
η efficiency [ ]	$\boldsymbol{P}$ pressure [Pa]
$\boldsymbol{I}$ health indices	**T** temperature [K]
h predicted health vector	$\boldsymbol{H}$ sensitivity matrix
z estimated health vector	$\boldsymbol{\Psi}$ transition matrix
ξ tuned health vector	$\boldsymbol{\Phi}$ transition matrix
$\boldsymbol{t}$ time	$\boldsymbol{K}$ gain matrix
$\boldsymbol{r}$ residual	$\boldsymbol{\Omega}$ compensation matrix
τ threshold	$\boldsymbol{C_L}$ lag time constant
ω correction factor	$\boldsymbol{C_D}$ dead time constant

Abbreviations

RTM real-time model	**PT** power turbine
GT gas turbine	**R** regulator
CDP compressor pressure	**S** sensor
Texh exhaust temperature	**SW** switch

REFERENCES

[1] Wallhagen, R. E., and Arpasi, D. J., "Self-Teaching Digital-Computer Program for Fail-Operational Control of a Turbojet Engine in a Sea-Level Test Stand", NASA: TM X-3043, 1974.

[2] Hrach, P. J., Arpasi, D. J., and Bruton, W. M., "Design and Evaluation of a Sensor Fail-Operational Control System for a Digitally Controlled Turbofan Engine", NASA: TM X-3260, 1975.

[3] Ellis, S. H., "Self-Correcting Control for a Turbofan Engine", Proceedings of 3rd International Symposium on Air Breathing Engines, West Germany, March 7-12, 1976, pp. 171-186.

[4] Wells, W. R., and deSilva, C. W., "Failure State Detection of Aircraft Engine Output Sensors", Proceedings of Joint Automatic Control Conference, San Francisco, CA, 24 June, 1977, Vol. 2, pp. 1493-1497.

[5] Spang, H. A., and Corley, R. C., "Failure detection and correction for turbofan engine", Proceedings of Joint Automatic Control Conference, San Francisco, CA, USA, 22–24 June, 1977.

[6] DeHoff, R. L., and Hall, Jr. W. E., "Advanced Fault Detection and Isolation Methods for Aircraft Turbine Engines", ONR-CR-215-245-1, Feb. 1978.

[7] Behbehani, K., "Sensor Failure and Mu1tivar1able Control for Air Breathing Propulsion Systems", NASA CR-159791, 1980.

[8] Delaat, J. C., Merrill, W. C., "Advanced Detection Isolation and Accommodation of Sensor Failure in Turbofan Engine, Real-Time Microcomputer Implementation", NASA-90-2925, 1990.

[9] Delaat, J. C., and Merrill, W. C., "A Real-Time Implementation of an Advanced Sensor Failure Detection, Isolation, and Accommodation Algorithm", NASA: TM-83553, 1983.

[10] Merrill, W., “Sensor Failure Detection for Jet Engines Using Analytical Redundancy”, NASA: TM-83695, 1984.

[11] Kobayashi, T., “Aircraft Engine Sensor / Actuator / Component Fault Diagnosis Using a Bank of Kalman Filters", NASA: CR-2003-212298, 2003.

[12] Kobayashi, T., Simon, D. L., "Evaluation of an Enhanced Bank of Kalman Filters for In-Flight Aircraft Engine Sensor Fault Diagnostics", Proceedings of Turbo Expo 2004, Vienna, Austria, 14–17 June, 2004.
[13] Kobayashi, T., Simon, D. L., "Aircraft Engine On-Line Diagnostics through Dual-Channel Sensor Measurements: Development of a Baseline System", Proceedings of ASME Turbo Expo 2008 Gas Turbine Congress and Exposition, Berlin, Germany, 9–13 June, 2008.
[14] Panov, V., "Model-based control and diagnostic techniques for operational improvement of gas turbine engines", Proceedings of 10th European Turbomachinery Conference, Lappeenranta, Finland, 15-19 April, 2013.
[15] Lu, F., Huang, J., Xing, Y., "Fault Diagnostics for Turbo-Shaft Engine Sensor Based on a Simplified On-Board Model", Sensor 2012, 2012, Vol. 12, pp. 11061 – 11076.
[16] Panov, V., "Auto-tuning of real-time dynamic gas turbine models", ASME Paper No: GT2014-25606, 2014.
[17] Panov, V., "GasTurboLib – Simulink library for gas turbine engine modelling", ASME Paper No: GT2009-59389, 2009.
[18] Panov, V., "Estimation of health parameters in industrial gas turbine", Patent application: WO2015117791A1, 2015.
[19] Panov, V., "Gas turbine performance diagnostics and fault isolation based on multidimensional complex health vector space", ETC2015-0051, 11th European Turbomachinery Conference, Madrid, Spain, 23-27 March, 2015.