Chapter 3 – INTELLIGENT CONTROL AND HEALTH MONITORING

by

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ABSTRACT

Advanced model-based control architecture overcomes the limitations state-of-the-art engine control and provides the potential of virtual sensors, for example for thrust and stall margin. "Tracking filters" are used to adapt the control parameters to actual conditions and to individual engines. For health monitoring stand-alone monitoring units will be used for on-board analysis to determine the general engine health and detect and isolate sudden faults. Adaptive models open up the possibility of adapting the control logic to maintain desired performance in the presence of engine degradation or to accommodate any faults. Improved and new sensors are required to allow sensing at stations within the engine gas path that are currently not instrumented due in part to the harsh conditions including high operating temperatures and to allow additional monitoring of vibration, mass flows and energy properties, exhaust gas composition, and gas path debris. The environmental and performance requirements for these sensors are summarized.

3.1 INTRODUCTION

Ref. [3.1] provides an overall summary of the state-of-the-art of engine control and health monitoring which is reproduced here to provide the reader with background information. Typical aircraft engine control systems maintain fan speed or engine pressure ratio to regulate thrust which is not directly measurable. The control logic is generally based on a variant of a Proportional-Integral scheme combined with limit logic as shown in Figure 3.1. This limit logic consists of a series of *min select* and *max select* blocks, each of which selects a fuel flow rate command based on various physical limits, acceleration/deceleration schedules (maximum rotor speed rate-of-change as a function of rotor speed), and the current operating state (speed governor loops).

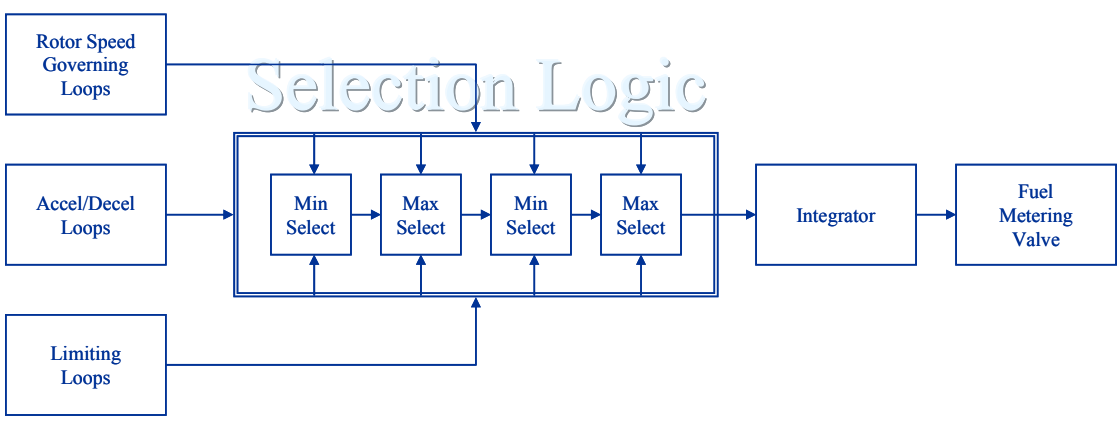

Figure 3.1: Block Diagram of Typical Engine Control Law Architecture.

The various on-wing health monitoring systems of today, which are a collection of separate, unrelated technologies, provide a basic level of monitoring. Their capabilities are relatively limited and the information they provide is used mostly to initiate maintenance actions, not for real-time decision-making. One instance where the information is used on wing is for sensor validation. The controller has some simple logic to perform basic limit or rate of change checks on engine sensors and actuators. In some cases, on-board engine models are used in conjunction with the controller's own sensor voting scheme to help determine which sensor is correct when redundant sensors disagree. The controller has the additional responsibility of checking whether a speed red-line has been exceeded, and reducing fuel flow when it has. Current engine vibration monitoring systems sample at a relatively low frequency – too low to capture much significant or useful information on the vibratory modes of the system. They check the vibration magnitude to determine that it is within a normal range. Magnitudes that are too high might indicate a bearing failure or engine imbalance, magnitudes that are too low might indicate a faulty sensor or seized engine. Lubrication system monitoring is performed using a magnetic chip detector to determine the existence of ferrous debris in oil. This is an indication of part wear. Life cycle counts are performed on-wing. Engine parts, especially those in the hot section, may experience a maximum number of severe thermal transients before they must be retired. Each time the engine goes through a start-up transient, the life cycle count for each of the critical components is incremented. This way, part life is tracked as a function of use to facilitate scheduled maintenance.

While these traditional control and diagnostic techniques are time-tested and reliable, advanced techniques provide the promise to meet the challenging requirements of improved fuel efficiency, increased durability and life, decreased life cycle costs, and improved operations. Using an on-board engine model to meet the challenging control and diagnostics requirements has emerged as the most viable approach. The continuing increase in computer processing capability has reached the point where the use of model based algorithms for diagnostics and control of aircraft engines has become practical. Previously the complexity of the thermodynamic cycle model has made their use impractical. Model based technologies offer the potential for creating intelligent propulsion systems – defined as self-diagnostic, self-prognostic, self-optimizing, mission adaptable and inherently robust – that far exceed current systems in performance, reliability and safety [3.1].

The concept of model-based control and diagnostics is shown in Figure 3.2. The engine model is driven with the measured engine inputs (shown here as control signals, u, but usually also includes environmental conditions) to obtain the predicted engine outputs $\hat{y}$. The predicted outputs are differenced with the measured engine sensor outputs, y, to form residuals, which can be used to diagnose engine health and adapt the model.

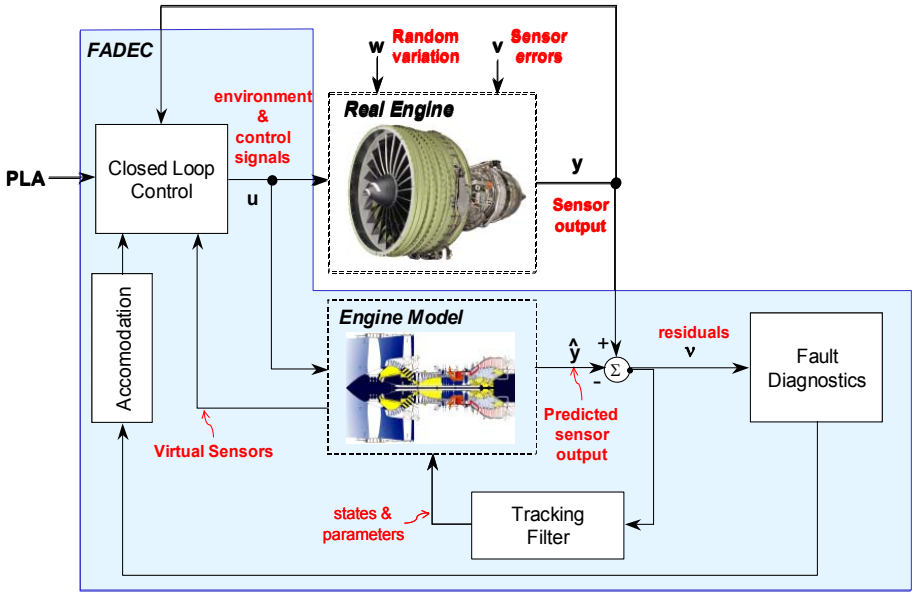

Figure 3.2: Model Based Control and Diagnostics Concept.

Historically the control architecture has relied on Single Input Single Output (SISO) feedback loops. Transition to model based control can occur in several ways. First, faults can be accommodated by changing the control laws, in a predetermined way, when a fault is detected. The changes are designed to, at a minimum, take the engine to a safe state, and preferably allow the engine to operate safely with best, although probably degraded, performance. Secondly, the model allows the loop to be closed on unmeasured values (e.g. thrust, stall margin) for which there is no sensor, i.e. virtual sensors. Finally, in its most advanced form, the model is used directly in the control enabling the control to automatically adjust as the model adapts to the mission, deterioration, faults, weather, etc. Here the control can be designed to maximize performance without excessive conservatism.

This chapter provides an overview of the progress and challenges in using model based approach to intelligent control and health monitoring of aircraft engines. The chapter is organized into three sections – model based control; on-board condition / health monitoring; and adaptive control. The chapter concludes with a summary of sensor needs to enable intelligent control and health monitoring. The focus of these technologies is on developing algorithms that are implemented in the FADEC (Full Authority Digital Engine Control) in the form of software without any hardware changes on the engine in terms of any additional control effectors/actuators.

3.2 MODEL-BASED CONTROL

The SISO control approach is simple and adequate for conventional engines where the main fuel is indeed the dominant actuator and the control requirements are not very stringent. However, it is inadequate for engines where there are multiple actuators with significant interaction between the actuators and the engine outputs to be controlled, e.g. a variable cycle engine or advanced commercial/military engines. A more advanced model-based Multi Input Multi Output (MIMO) control architecture shown in Figure 3.3 overcomes the limitations of the SISO architecture, where all available control actuators (e.g. main fuel, variable geometries, exhaust nozzle area, clearance control actuator) are manipulated in a coordinated manner to achieve multiple objectives like thrust and speed regulation, and limits on temperatures, pressures, stall margins, etc.

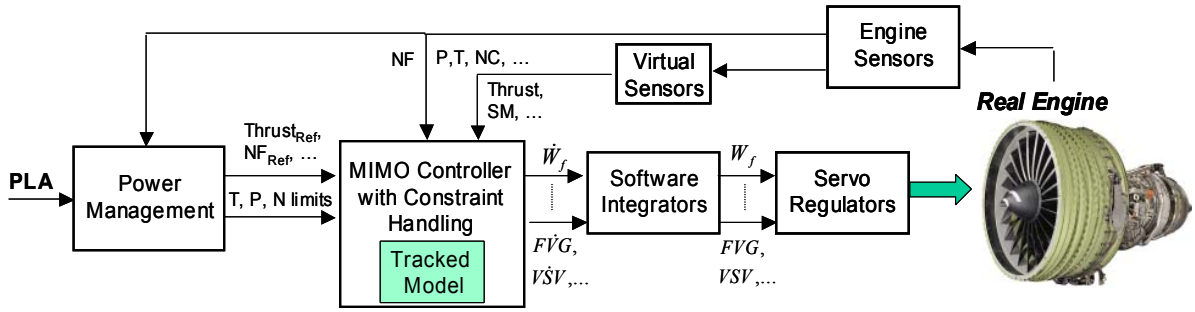

Figure 3.3: MIMO Control Architecture for Enhanced Control and Accommodation.

In such a model-based control structure, the model can provide outputs for which there is no sensor, i.e. virtual sensors. These virtual sensors provide the capability to directly control unmeasured variables such as thrust and stall margin. Additionally, the model outputs can be used for sensor fault accommodation, where model output (predicted sensor reading) temporally replaces a failed sensor, and virtual duplex redundancy, where the model output permanently replaces one sensor in a duplex pair. As confidence is gained with implementation of model-based control, it is envisioned that these virtual sensors can eventually eliminate the need for some of the sensors where the model output permanently replaces a simplex sensor or duplex pair.

One of the major challenges in implementation of model-based control is to have the model reflect the actual condition of the engine. Historically a single, fleet average model is used based on known or expected fleet average performance of a particular engine type. Use of this average model to predict individual engines within a fleet results in varying model errors, corresponding to how each engine deviates from the average. The resulting model error couples with normal flight variations in the input conditions to cause systematic error in the residuals, which limits the capability of the model to accurately predict the unmeasured variables. Also, when a fault occurs in the engine, if this fault is not appropriately reflected in the model, it can cause significant errors in estimation of the unmeasured variables. Thus, it is important to ensure that the model being used for control reflects the true condition of the engine. Typically a “tracking filter” is used to estimate model parameters related to deterioration causing the model to “track” the individual engine over time. Additionally the tracked parameters can be monitored to provide an indication of the health of the components of the engine, e.g. the level of deterioration (see On-board Condition Monitoring Section below). Typically abrupt faults are detected with the diagnostics algorithm and slowly changing health assessed by monitoring these tracked parameters.

Error reduction is accomplished by applying state and parameter estimation techniques to adapt model parameters to the individual engines. An appropriate set of model parameters must be identified which address the nature of the model mismatch and are also observable from the measured outputs. Because the engine model is nonlinear and the parameter estimation problem itself is nonlinear, an Extended Kalman Filter (EKF) formulation is typically chosen [3.2] [3.3]. Many variations of the EKF exist to meet varying performance and computational requirements. For example an iterated EKF (IEKF) is often used for remote services implementation on the ground and a linearized or suboptimal gain scheduled Kalman filter is used on-wing when computational constraints warrant. A general description of these techniques can be found in Gelb [3.4] or other texts on optimal estimation.

During transient operation of the engine, such as takeoff, an engine state estimator is employed along with the model parameter estimator so that the effects of engine states are accounted for and separated from the parameter

estimates. Engine states are typically the spool speeds and various metal temperatures. The resulting model parameter estimates for a particular engine at a particular time are used in that model to reduce the systematic errors in the residuals. For example Figure 3.4 shows the residuals over several Monte Carlo simulations (random deterioration) where the tracking filter is engaged midway through (25 sec).

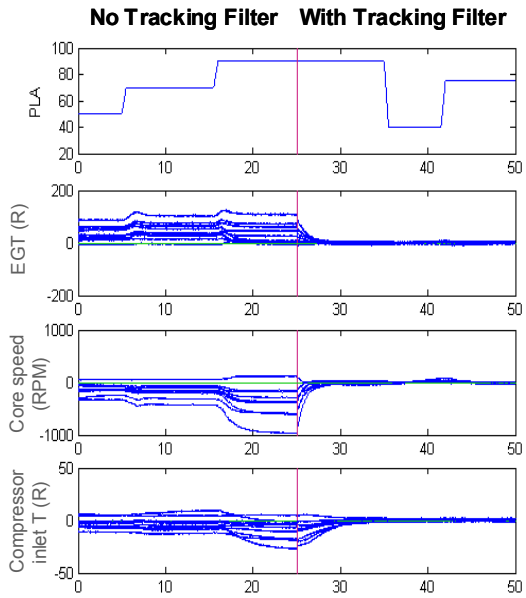

Figure 3.4: Monte Carlo Simulation of a Tracking Filter.

The parameter adaptation can be continuous or periodic but must be performed with sufficiently high bandwidth to keep the effects of normal deterioration out of the residuals, but low enough so that abnormally rapid shifts in performance are fully observed in the residuals.

The MIMO controller, with multiple available closed-loop control actuators, can be designed to meet the desired performance objectives (e.g. thrust) as well as optimize other important objectives like minimize specific fuel consumption (SFC) or minimize turbine temperature to enhance engine life, depending on the mission objectives. For instance, during take-off the controller can be designed to minimize turbine temperatures, while in cruise operation it can be designed to minimize SFC. The availability of model-based virtual sensors allows direct control to important un-sensed variables, e.g. thrust, stall margins, turbine temperatures. Also, the availability of a tracked engine model that is matched to a particular engine as it slowly deteriorates over time enables improved controls and performance optimization with reduced conservatism. Finally, the model-based MIMO control architecture also lends itself to automated fault accommodation, wherein the updated model reflects the specific component fault and forms the basis for an updated control action. Ref. [3.5] provides an excellent example application of model-based control to aircraft engines.

3.3 ON-BOARD CONDITION MONITORING

Engine Condition (or Health) Monitoring (ECM) systems comprise an on-board (or on-engine) and on-ground part. An example of the total on and off engine system as applied to the Trent 900/A380 program is depicted in the diagram in Figure 3.5, which shows the key data flow paths [3.6].

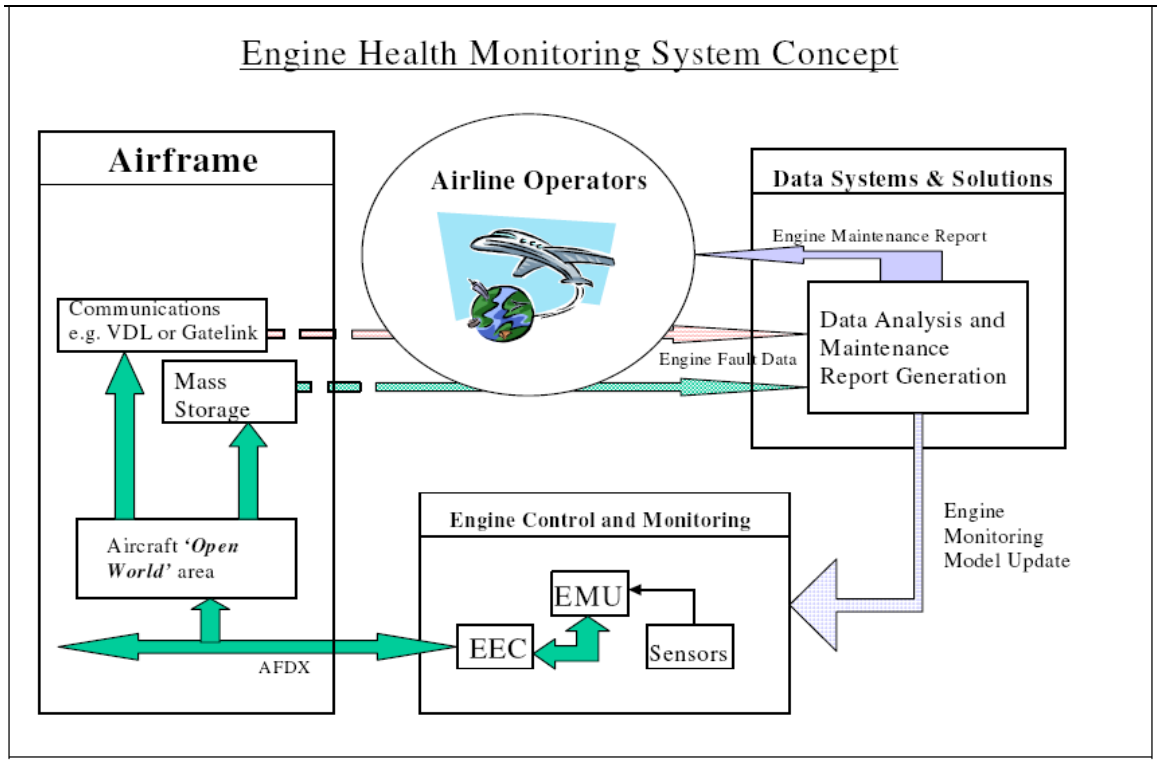

Figure 3.5: T900 Engine Condition Monitoring Concept.

The on-board part of the ECM system has been for a long time embedded in the Electronic Engine Control (EEC) unit of Full Authority Digital Engine Control (FADEC) system, or in some cases the Engine Monitoring Unit (EMU) was a standalone unit either engine or airframe mounted.

With increased performance and affordability of the on-board computer there is a recent trend, at least in large civil engines, to have a standalone, engine mounted EMU. Such an EMU has access to continuous data, powerful computing capability that provides on-board analysis, can process large volume of data which are impractical to transfer to the ground and can look also for transient effect and do this throughout the duration of the whole flight [3.6].

The reasons for having EMU separated from EEC and installed on engine are:

1) Different level of criticality, with FADEC having highest criticality level and requiring redundancy and software level A and EMU being mostly single channel with non-flight critical software level. Such a separation has positive impact on development cost of both EEC and EMU, MTBF (mean time between failure) of the control system is not compromised by "non-control" sensors, electronics and software of engine condition monitoring.

2) Different life cycle. Engine control unit shall be mature at engine certification; engine monitoring system has initial functionality and diagnostic algorithms evolve with experience from the engine operation.

3) Condition monitoring detection limits can adapt to an individual engine, account for the normal degradation and performance deviations, and therefore reduce false alarms. In keeping the EMU as an

integral part of the engine, the logistic problems that would arise when an engine is removed, replaced or otherwise separated from its health status 'memory' are avoided.

Example of ECM system structure for T900 is in Figure 3.6 [3.7]. The close proximity of the EMU and the associated monitoring sensors on the engine gives the capability to capture and process high bandwidth signals without the constraints of limited digital transmission rates, significant weight of cabling over long runs, and increased exposure to electrical radiation and lightning threats [3.6].

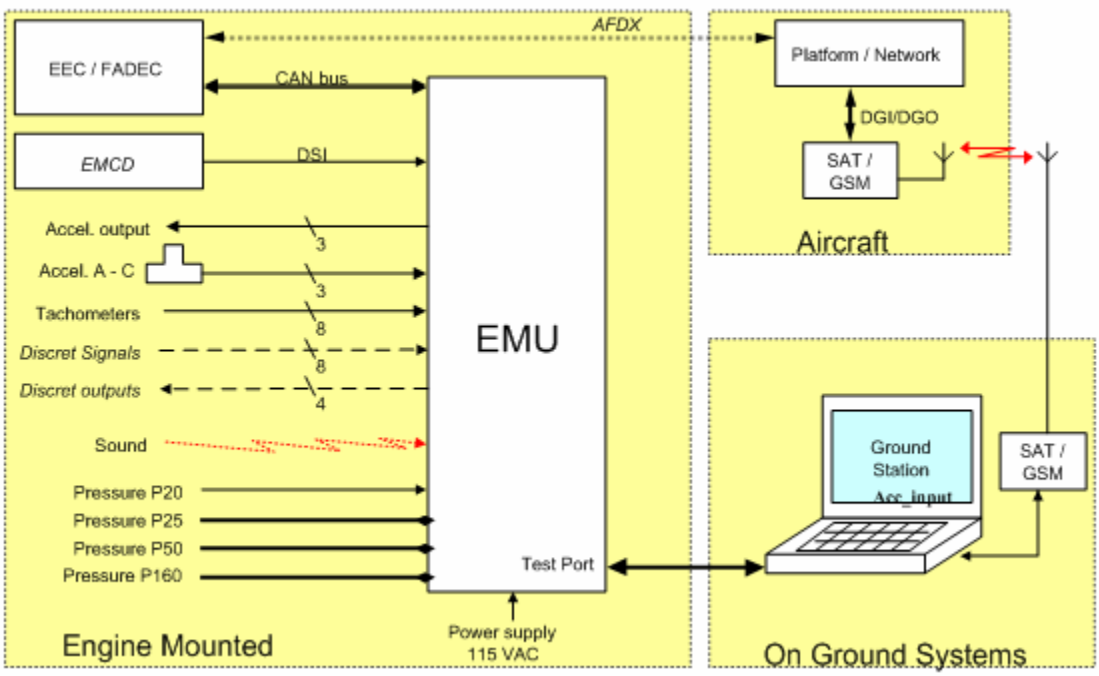

Figure 3.6: Structure of T900 Engine Condition Monitoring System.

The functions of the state of the art military prognostics and health management typically include fault detection and isolation, advanced diagnostic, predictive prognostics, useful life remaining and time to failure predictions, components life tracking, performance degradation trending, warranty/guarantee tracking, engine health reporting, aids in decision making, fault accommodation, information fusion and reasoners, information management to provide Right Information to Right People at Right Time.

The focus of this section is on on-board condition monitoring from the perspective of gas path performance diagnostics. Gas path performance diagnostics involves estimating the values of specific variables associated with the gas path components, or changes in these values that might indicate a fault. It is important to distinguish between the general health of the engine gas path components and sudden faults. The general health of the engine is equivalent to its level of degradation or effective age, and is the baseline from which changes are measured. In the gas path, the health condition of each component is defined by its efficiency and other parameters that change slowly. In general there are not enough engine sensors available to allow estimation of these *health parameters* in flight. Some diagnostic schemes relate faults to abrupt changes in the parameters associated with component health. Thus, on-line monitoring of unmeasurable variables is the basis for many fault detection and isolation approaches [3.8]. The information flow diagram in Figure 3.7 indicates

how damage and wear is related to degraded performance [3.9]. Many linear and nonlinear techniques have been applied to this problem, but without the addition of diagnostic sensors, the problem will remain. The estimation problem arises because the number of health parameters exceeds the number of measurements, which means that the problem is underdetermined and thus the health parameter shifts can not be uniquely determined [3.10]. The problem is further complicated by estimation errors due to model mismatch, noise and sensor bias. Sensor validation is an integral part of on-board condition monitoring.

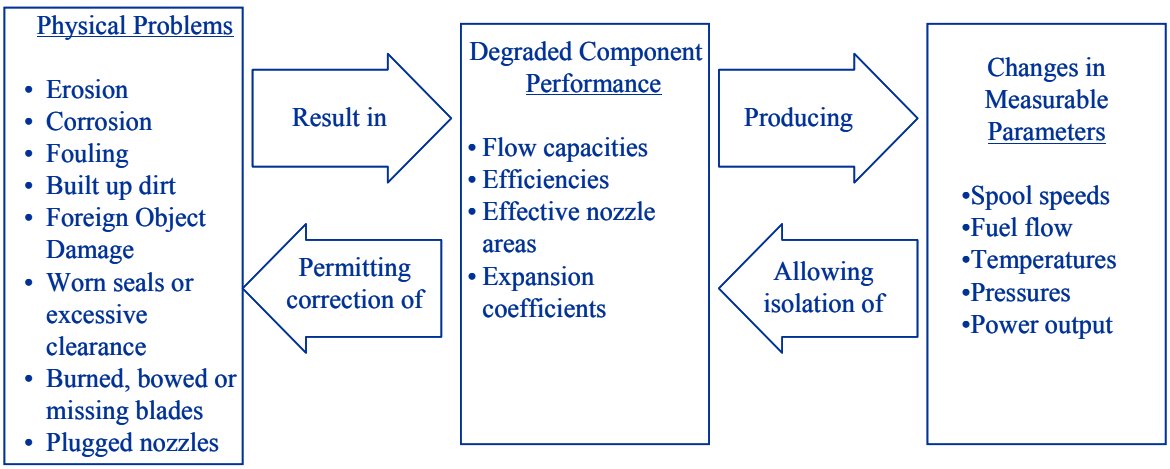

Figure 3.7: Diagram Indicating Information Flow for Turbine Engine Gas Path Diagnostics.

As discussed under the Model-Based Control section, the emerging approach to on-board condition monitoring is to use an on-board real-time model to estimate the health and fault status of the engine. When a fault occurs in the engine, a pattern, typically called the signature, occurs in the sensor residuals. The job of the diagnostics algorithm is to detect and identify unique signatures in the residuals (the difference between the sensed value and the model predicted value – see Figure 3.2). The presence of random (e.g. sensor noise) and systematic errors limits the sensitivity of fault detection, i.e. the size of the fault that can be detected.

The random sensor error cannot be eliminated but the systematic errors in the average model can be eliminated if an individual model is employed. This is done using the tracking filter approach discussed in the section above. Reducing the systematic error in the residuals (measured minus model predicted outputs) effectively increases the Signal to Noise Ratio (SNR) of the detection system, where the systematic error is part of the "noise". The increased SNR results in improved detection capability by allowing either greater fault sensitivity through smaller detection thresholds, or lower false alarm rates for existing thresholds.

Fault detection is structured around classical techniques in the signal processing field, e.g. multiple model hypothesis testing (MMHT). Other techniques such as fuzzy logic and neural networks can also be employed, alone or in combination, and their results fused [3.3]. Specifically, for the MMHT case, fault detection decisions result from Bayesian probability computations based on maximum likelihood considerations applied to the residuals, and from any a-priori reliability information available. The residuals represent information from multiple locations throughout the engine, and fusion of the information is accomplished through use of multi-variate likelihood functions.

Fault isolation is achieved by extending the above fault detection technique to a whole set of specific engine fault candidates through a multiple model hypothesis test structure [3.11]. Figure 3.8 illustrates the MMHT

algorithm with a one-dimensional (i.e. one sensor) example, where L_i is the likelihood of the residual, Δ, given fault i, S_i is the signature of fault i and $prob_i$ is the probability of fault i given the observed residual, Δ.

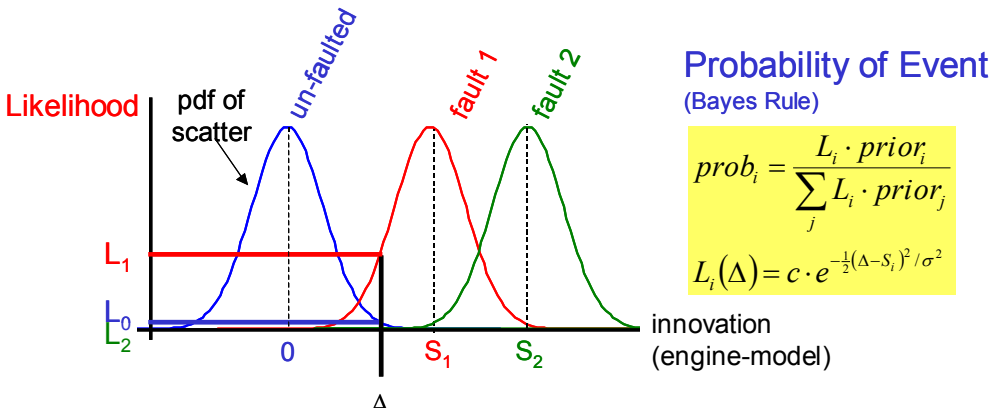

Figure 3.8: MMHT – 1-D Example.

Generally, this requires a model of the unfaulted engine, and one for *each* candidate engine fault to generate residuals for each candidate hypothesis (no fault, and each fault). The ensemble mean of the residuals for each fault model, when run on an unfaulted engine, define the physics based fault signature of each particular fault. Under steady state conditions, the individual fault signatures are constant offsets from the no fault signature, leading to a simplified implementation running just the unfaulted engine model. The residuals for the faulted models are formed by adding the precomputed signatures to the unfaulted residuals. Similar techniques exist to simplify the implementation when the assumption of steady state is not valid [3.11] although in practice the steady-state signatures are often applied transiently.

The personalization of each engine model provides estimates of model parameters that are directly related to the health (e.g. deterioration) of the individual engine components. This information is monitored over time to assess the condition of each component, and can be used to optimize work scope. Figure 3.9 shows an example of trending the tracked parameters for a typical commercial engine.

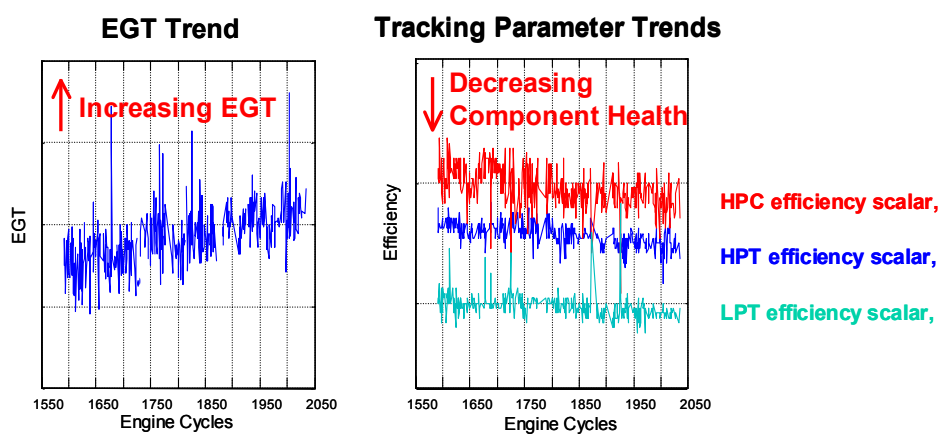

Figure 3.9: Example of Trending Tracked Parameters.

As discussed in Ref. [3.12], a gas path fault might consist of one or more of the following: sensor fault, actuator fault or component fault. The on-board condition monitoring system should not only be able to detect a fault, but also isolate the fault so that appropriate action might be taken. If the effect of the fault on engine operability and/or safety is small, no accommodation is required and maintenance can be scheduled appropriately. However if the fault has an appreciable effect, then accommodation can potentially avoid in-flight shut downs, stalls, excessive life consumption, etc. [3.13] [3.14]. The accommodation strategy is unique for each fault but typically grouped into three main categories, sensor faults, actuator faults and gas path component faults. In addition the strategy is dependent on the control architecture.

Sensor Fault Accommodation: Sensor accommodation is the easiest to accomplish. Once the fault is detected, feedback can be switched to a redundant sensor. This can be either a physically redundant sensor, as in the case of duplex or greater redundancy, or a virtual sensor generated by the on-board model through analytic redundancy. In some cases the virtual sensor may have less accuracy than the physical sensor and some accommodation will be required such as changing control laws and schedules.

Actuator Fault Accommodation: The specific action required to accommodate a failed actuator depends not only on which actuator has failed but also on the specific failure mode. For example, if a VGV (Variable Guide Vane) is failed full open, it may not be possible to run the engine above idle while maintaining operability. But if it fails to some other position, it may be possible to keep the engine running by modifying the engine operation (e.g. changing constraints and opening the bleed valve) – of course some compromise in performance will likely be required.

Gas Path Component Fault Accommodation: Gas path component fault accommodation is more involved than the other two categories. The components are typically large, complex systems, which may operate reasonably well in the presence of the fault, due to closed loop control. Control architecture changes would likely be required when accommodation is necessary. However, the highly nonlinear nature of the engine controller and the complexity of its implementation make the task non-trivial. In addition many diverse requirements exist; maintaining stall margins above certain limits, minimizing both peak temperatures and the time spent above a certain temperature, and obtaining short response times to changes in demand values – all of which must be met over a wide range of flight conditions and disturbance inputs.

Although the focus of this discussion has been on gas path diagnostics, an important part of engine condition monitoring is using vibration diagnostics to determine the structural health of the engine components [3.1]. Increases in vibration amplitude over time might indicate a change in rotor balance related to, for instance, a damaged fan blade or a bearing failure. The low sample rate of current vibration measurements essentially preclude using a real-time diagnostic tool, but many possibilities will be opened up when high frequency measurements become available along with on-board signal processing.

3.4 ADAPTIVE CONTROL

The traditional engine control logic consists of a fixed set of control gains developed using an average model of the engine. Having an on-board engine model which “adapts” to the condition of the engine, opens up the possibility of adapting the control logic to maintain desired performance in the presence of engine degradation or to accommodate any faults in a way such as to maintain optimal performance or trade-off performance with remaining useful on-wing life of the engine. An emerging technique for such an adaptive engine control is the Model Predictive Control (MPC) approach. MPC solves a constrained optimization problem online to obtain the “best” control action, based on a tracked engine model, constraints, and the desired optimization objective.

The ability to account for the constraints explicitly in the controller design is a key benefit of MPC in contrast with other control algorithms, and allows addressing key engine operability and safety constraints directly; e.g. speed and temperature limits, stall margin limits. Also, these constraints can be easily modified for increased/decreased conservatism, based on the operation mode or during a fault. Moreover, since MPC solves an optimization problem online, the optimization objective can be modified based on the operation mode; e.g. minimize fuel consumption during cruise, minimized turbine temperature for increased life, minimized emissions, etc.

Figure 3.10 shows the overall approach for MPC. At each time sample, the nonlinear engine model is linearized about the current operating point, and the resulting linear state-space model is used to formulate and solve a finite-horizon constrained optimization problem. In this way, we obtain the optimal control profile $u_k, \ldots, u_{k+n}$, while enforcing all input and output constraints over the horizon. However, only the first sample of this optimal control profile (i.e. u_k) is implemented, and the whole process is repeated at the next time sample with correspondingly shifted control/prediction horizons.

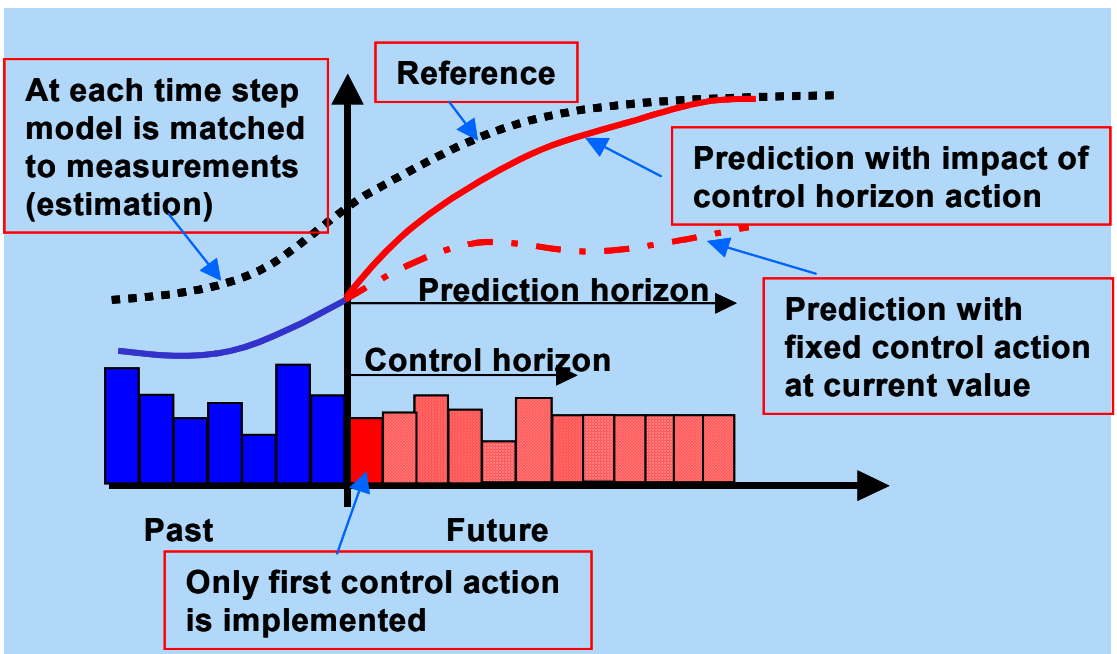

Figure 3.10: Example of Trending Tracked Parameters.

Figure 3.11 demonstrates the kind of performance improvements that a MPC based MIMO controller can provide over a traditional SISO engine control. The figure shows time responses for an engine controlled by a SISO controller (the current FADEC) and by a MPC, during an idle-takeoff transient. We zoom in on some key variables – exhaust temperature, turbine temperature, fuel flow – and notice substantial peak reductions in all of them, which translate into extended engine life. The improvement comes mainly from the fact that the current FADEC is in essence a SISO controller, which drives fuel flow ignoring the interaction between all actuators. The MPC, on the other hand, is multivariable and thus accounts for the interaction between multiple engine actuators and avoids the overshoot in fuel flow. The actuators used by the MPC are fuel flow, VSV, and bleed-valve. More details on applications of MPC to jet engines are available in the literature [3.1] [3.15].

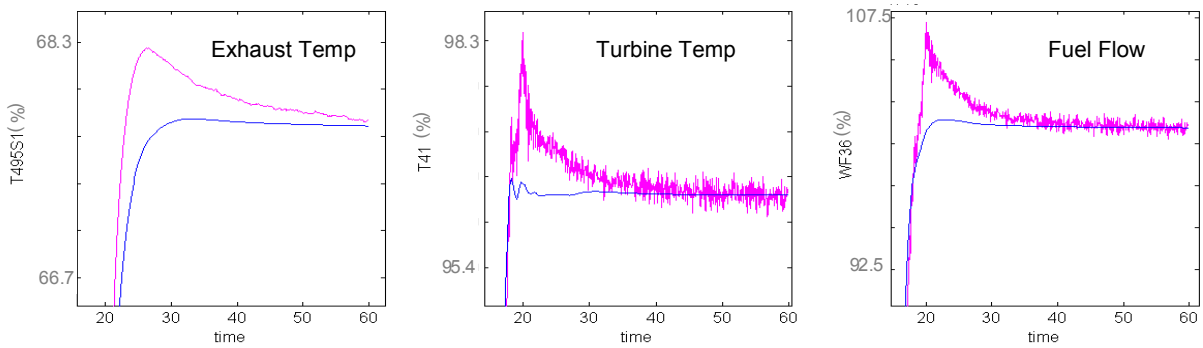

Figure 3.11: Improvements of MPC-MIMO Controller over SISO Controller for Idle-Takeoff Transient. Reduction in peak temperatures extends engine life. SISO actuator is fuel flow, MIMO actuators are fuel flow, VSV, and bleed-valve. Figure shows FADEC/SISO (magenta) vs. MPC/MIMO (blue).

3.5 CHALLENGES AND SENSOR NEEDS

Challenges exist in several areas in implementing the technologies described above. The models must be computationally efficient in order to run in real time without sacrificing accuracy. Sufficient model accuracy is critical in achieving performance enhancement. However, model error is difficult to quantify because it must be evaluated in close loop (i.e. with the tracking filter) which couples it with the choice of tracked parameters and their observability with the given sensor suite. This creates a sensor paradigm shift where sensors are chosen not only for direct control purposes but also for model accuracy, virtual sensors, etc. Equally important is the fault model or signature as it limits the sensitivity of fault detection. Finally the increased complexity brings certification and maintenance challenges. Any engine models used inside the control loops will need to be certified. The complexity of the models and adaptive nature of the tracking filter adds to the challenge. In addition the required model accuracy may necessitate a finer distinction of engine variants in the control software resulting in increased software complexity.

To fully exploit the benefits of model-based control and diagnostics, new sensors can be added. Sensors should be chosen not just for direct use as feedback in the controller but to improve model accuracy, reliability and enhance observability of virtual sensors. Ref. [3.16] provides an excellent summary of sensor needs for intelligent control and health monitoring of aircraft engines. As discussed in Ref. [3.16], structural health monitoring is an important aspect of engine condition monitoring, and there is a need for new and improved vibration and oil monitoring sensors. However, the focus of this chapter is on on-board condition monitoring using gas path information, so only the sensors that are needed for improved gas path diagnostics and engine control are discussed in the following. Since vibration monitoring can be used for indirect gas path diagnostics it will be included in the following discussions.

Typical gas path sensors consist of temperature, pressure and rotor speed measurements. Any improvements in the accuracy, uniformity and reliability of these gas path sensors will result in a direct improvement in the accuracy of performance diagnostics and model-based control technologies. Also, there are currently stations within the engine gas path that are not instrumented due in part to the harsh operating temperatures that exist at these locations. Measurements at these additional locations will further enhance the accuracy of gas path analysis techniques. In addition to conventional gas path pressure and temperature measurements, the ability to sense additional parameters would be beneficial in diagnosing engine performance faults and providing improved estimate of unmeasured variables such as thrust. For example gas path debris monitoring sensors for

monitoring and quantifying engine debris ingestion and discharge are desirable. Additional requirements for improved and new sensors are discussed in the following for vibration monitoring, measurement of air mass flow and fuel properties, and monitoring of exhaust gas composition.

Vibration Monitoring. The primary moving parts of turbine engines are the rotors and their shafts which spin at high speed within the engine case. The elements of these rotors, particularly the fan, compressor and turbine blades, are subject to wear and damage. Such wear and damage may unbalance rotor causing cyclic stress on the structure, engine bearings, engine parts and accessories. Engine vibration monitoring (EVM) systems monitor the level of vibration generated by such rotor unbalance.

The vibration measured by vibration transducers and afterwards processed by engine vibration monitoring unit contains additional diagnostic information about engine elements including bearings, transmissions, reduction gears, fan, compressor, afterburner and turbine and the availability of high speed digital signal processing made it practical to provide very sophisticated vibration analysis in on-board EVM systems.

Some examples of fan, compressor and turbine failures which may be detected by EVM system include [3.17]:

- Partial failure (loss) of turbine and/or compressor blades.
- Blade tip rubs and spacer ring frottage.
- Lockup of fan blade clappers (or mid-span shrouds) and general fan unbalance caused by foreign object damage.
- Shaft coupling misalignment and loosening of compressor stack retaining bolts.
- Blade locking plate misplacement.

Measurement of Mass Flow and Energy Properties. Sensors to estimate the flow through the fan duct and the nozzle will help generate better estimates of the thrust being produced by the engine – especially if there is any damage which results in degraded engine performance. The energy flow to engine can be calculated by multiplication of fuel mass flow and specific heating value of the delivered fuel. Such energy flow sensor can use separate measurement of fuel flow, temperature, density and heating value. The necessary calculation of energy flow can be performed in the EEC by the sensor performing local calculation of the energy flow. The challenge is in measurement of specific heating value for broad range of primary and emergency fuels with additives, contaminants and water that the fuel can contain.

Monitoring of Exhaust Gas Composition. Flames in gas turbine combustor and afterburner emit optical "signatures" that reflect chemistry of combustion process. The radiant emission energy from a combustor is collected by the optical viewing port and transmitted to the electro-optical sensors via the fiber optic cable. Compounds in combustion process emit distinct "lines" in photonic wavelength spectrum. Optical spectroscopy can identify chemical constituents in flame in visible, ultraviolet and infrared spectrum ranges. Technology of optical spectroscopy potentially could be applied to assess bad starts and propagation of flame into turbine, calculate temperature at combustor outlet/turbine inlet (avg. and hot spots), assess degradation due to fuel and inlet air contamination, real time emission monitoring and minimization (through potential development of an active emissions control system), and control instabilities/oscillations (by providing instability detection within an emissions control system).

The requirements/capabilities for the advanced sensors to enable different aspects of Intelligent Control and Health Monitoring for the various engine components are summarized in Table 3.1.

Table 3.1: Sensor Requirements for Intelligent Control and Health Monitoring

Component	Technology	Sensed Variable	Range/Requirements
Inlet	Stall margin management	Pressure	0 – 25 psi range; +-.25% accuracy; 500 Hz bandwidth
			Array of inlet static pressure sensors
Fan/Compressor	Thrust estimation	Flow	1.75% accuracy
Fan/Compressor	Thrust estimation	Torque	10.000 – 20,000 Nm, 10 Hz
Fan/Compressor	Vibration monitoring	Accelerometer	3%, 40 kHz, 1000g range
Combustor	Model predictive control and thrust	Fuel mass flow	± 0,1 % of actual value [kg/s] or [m3/s]
Combustor	Energy flow	Fuel properties	± 0,5 % of actual value [kJ/s]
		Fuel density	± 0,1 % [kg/m3]
Turbine	Clearance management	Clearance	2.5 mm range, accuracy 25 µm, 50 kHz bandwidth
			case-mounted installation
Turbine	Condition monitoring	Accelerometer	3%, 40 kHz, 1000g range
Turbine	Life management/temperature margin management	Temperature	T41, T4B, 5 degrees, 2 – 10 Hz, flow and blade temperature
Nozzle	Exhaust gas composition	NOx, Cox	1%

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