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MODELING, DIAGNOSTICS AND PROGNOSTICS OF A TWO-SPOOL TURBOFAN ENGINE

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14. ABSTRACT
Model-based diagnostic/prognostic techniques have the potential to predict, within reasonable bounds, the remaining useful life of critical system components. Due to the numerous uncertainties in the operation of a turbine engine and unavailability of accurate engine models, prognostics continue to pose a significant challenge. There is a need to develop an engine prognostic approach that can accommodate different damage modes, sensor failures, material properties, dynamic load histories and damage accumulation. Using an accurate physics-based model of the engine one can develop such a prognostic approach. We present a nonlinear dynamical model of a two-spool turbine engine developed from first principles. The simulation model has been implemented using MATLAB/Simulink. It is used with the Kalman Filter-based diagnostic technique previously discussed in literature to detect and isolate sensor faults. A literature review of the developments in the area of prognostics is also presented, along with the problems and challenges.

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Modeling, Diagnostics And Prognostics Of A Two-Spool Turbofan Engine

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Model-based diagnostic/prognostic techniques have the potential to predict, within reasonable bounds, the remaining useful life of critical system components. Due to the numerous uncertainties in the operation of a turbine engine and unavailability of accurate engine models, prognostics continue to pose a significant challenge. There is a need to develop an engine prognostic approach that can accommodate different damage modes, sensor failures, material properties, dynamic load histories and damage accumulation. Using an accurate physics-based model of the engine one can develop such a prognostic approach. We present a nonlinear dynamical model of a two-spool turbine engine developed from first principles. The simulation model has been implemented using MATLAB/Simulink. It is used with the Kalman Filter-based diagnostic technique previously discussed in literature to detect and isolate sensor faults. A literature review of the developments in the area of prognostics is also presented, along with the problems and challenges.

Nomenclature

Cp_3 = Specific Heat in Compressor J/kgK
Cp_4 = Specific Heat in Turbine J/kgK
C_{vol} = Combustor Volume m^3
C_v = Constant Volume Specific Heat J/kgK
η_{mech} = Mechanical Efficiency
γ = Specific Heat Ratio
I_L = Polar Moment of Inertia of Low Pressure Spool kgm^2
I_H = Polar Moment of Inertia of High Pressure Spool kgm^2
M = Mach Number
N_L = Low Pressure Spool Speed RPM
N_H = High Pressure Spool Speed RPM
P_2 = Pressure at LPC inlet Pa
P_{26} = Pressure at HPC inlet Pa
P_3 = Pressure at Combustor inlet Pa
P_4 = Pressure at HPT inlet Pa
P_{45} = Pressure at LPT inlet Pa
P_5 = Pressure at Nozzle inlet Pa
R = Universal Gas Constant
ρ_4 = Density of fluid in Combustor kg/m^3
T_2 = Temperature at LPC inlet K
T_{26} = Temperature at HPC inlet K
T_3 = Temperature at Combustor inlet K
T_4 = Temperature at HPT inlet K
T_{45} = Temperature at LPT inlet K

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T_5 = Temperature at Nozzle inlet K
W_2 = Mass flow rate through LPC kg/s
W_3 = Mass flow rate through HPC kg/s
W_4 = Mass flow rate through HPT kg/s
W_{45} = Mass flow rate through LPT kg/s
W_{noz} =Mass flow rate through Nozzle kg/s
Intercomponent Volumes
V_{26} = LPC - HPC m^3
V_3 = HPC - Combustor m^3
V_{45} = HPT - LPT m^3
V_6 = LPT - Nozzle m^3

I. Introduction

Aircraft engines constitute a complex system, requiring adequate monitoring to ensure flight safety and timely maintenance.[1] Conventional maintenance strategies (like corrective and preventive maintenance) are not adequate to fulfill the needs of expensive and high availability systems, such as the turbine engine.[2] Condition-based predictive maintenance is needed to assess the future health of engines, based on observed data and available knowledge about the system.

Diagnostics can be defined as an assessment about the current (and past) health of a system based on observed symptoms. Prognostics is the assessment of the future health of a system. Prognostic techniques can help provide early detection and isolation of precursor and/or incipient fault condition to a component failure, and can also help manage as well as predict the progression of various faults to component failure.[3] The prognostic module would also perform failure prognosis, which involves both forecasting of system degradation based on observed system condition (current diagnostic state and available operating data), and prediction of useful remaining life of the engine. Prognostic results are therefore used for making proactive decisions about preventive and/or evasive actions with the objectives of maximizing the service life of replaceable/serviceable components, minimizing operational risks, and reducing costs incurred during inefficient schedule-based preventive maintenance.[4]

The construction of a nonlinear dynamic simulation model of the engine is identified as an important first step for the development of prognostic techniques. The implementation and validation of well known diagnostic techniques on this simulation model is seen as the next step. Finally the data obtained from the diagnostic module for different failures would form the basis for implementing prognostic techniques.

The paper is organized as follows. Section 2 gives an extensive survey of literature for prognostic techniques. Section 3 addresses the development of a nonlinear dynamical model of the two spool turbine engine that has been based on the mathematical model available in Ref. 5. A reduced order linear model for the turbine is presented in Section 4 and this linear model is used to design a bank of Kalman filters for state estimation in Section 5. Section 6 presents some diagnostic results for certain sensor failures. Conclusions and future work are presented in Section 7.

II. Prognostics - Literature Review

The key stages in any prognostic process are:

- Detection and isolation (i.e., diagnostics)
- Prognosis (prediction of the course of a fault, and prediction of useful remaining life given the past and current system information)
- Decision making (about maintenance and mission planning)

Compared to diagnostics, the field of prognostics is relatively new, and hence there is less available technical literature. Most prognostic efforts are still in their infancy, and therefore results are not easily available in the public domain.

The fundamentals of prognostics, and the difficulties involved in predicting the remaining useful life, have been described by Engel et.al.[3] Emphasis was laid on the estimation and importance of accuracy and confidence in the prediction. Prognostics is described to be fundamentally different from a static, a priori estimate

of life expectancy (i.e., Mean time to failure, MTTF). The authors define prognostics as a remaining life estimation methodology that is condition-based and dynamic in both accuracy and uncertainty. Prognostics are shown to be more accurate as remaining life decreases. The paper also presents the variation of the prediction accuracy, precision and confidence with damage accumulation.

A generic prognostic and health management architecture for aerospace applications (for predicting the time to conditional or mechanical failure) was proposed by Roemer et.al.[6] The architecture emphasizes the integration of anomaly detection, diagnostic and prognostic reasoners through an integrated model of the entire system. Demonstration of the technical approaches proposed was done by implementing algorithms for:

- Detection of unhealthy surge control valve operation and performance degradation associated with an Auxiliary Power Unit (APU)
- Prediction of the time for the APU to reach an exhaust gas temperature limit (hot section lifing)
- Model-based prognostics for a Power Take Off shaft

Brotherton et.al have identified three different approaches for the development of prognostic techniques.[7] The first category includes approaches that develop physical models of the system based on component behavior and then validate it. The second category includes systems that follow a rule of thumb. This category includes artificial intelligence / rule-based expert systems / inference engines. The third category includes approaches that develop statistical models that 'learn' based on real system data (neural networks and data mining systems).

Various Artificial Intelligence (AI) techniques have been used by researchers to address the problem of prognostics. These techniques are categorized as data-driven prognostics, and are derived directly from system operating data. These data-driven approaches are based on statistical learning techniques, from the theory of pattern recognition. Examples include fuzzy pattern recognition and neural networks. In data-driven prognostics, the AI techniques are trained on features that progress through a failure (e.g., training a neural network by some vibration feature data). Once trained, the neural network architecture can be used to intelligently predict these same feature progressions for different test cases.

Wang et.al develop a dynamic wavelet neural network (DWNN) based prognostics algorithm, and suggested a method for its performance assessment.[8] The DWNN transformed sensor data to the time evolution of a fault pattern, and predicted the remaining useful life of a bearing. As with all neural networks techniques, the DWNN model had to be trained by using vibration signals of defective bearings with varying crack geometries. The model was then used to predict the crack evolution until failure occurred.

Roemer et.al have addressed the problem of prediction confidence levels.[9] A method was proposed to achieve the highest overall prediction confidence levels by finding the optimal combination of measured system data, data fusion algorithms and associated architecture. The main advantage of using neural networks is their ability to learn the faulty and normal operating signatures from actual test data and help with the reliable classification of faults in engines, without requiring detailed system models.[1] However, the efficacy of data-driven techniques is dependent on the quantity and quality of system operational data.

Model-based prognostic approaches make use of an explicit mathematical model of the system being monitored. These can be either physical or statistical models.[7] The advantage of model based techniques is the ability to incorporate physical understanding of the system being monitored.

A comprehensive engine bearing prognostic approach that utilizes available sensor information on-board the aircraft such as rotor speed, vibration, lube system information and aircraft maneuvers to calculate the remaining useful life for the engine bearings is presented by Orsagh et.al.[10] The algorithms developed utilized intelligent data fusion architectures to optimally combine sensor data, with probabilistic component models to achieve the best prognostic results. The authors proposed the use of model-based estimates when no diagnostic indicators are present and monitored engine features at later stages when failure indications are detectable.

Garga et.al describe a hybrid reasoning approach that is capable of integrating domain knowledge (in the form of rules), and test and operational data (sensor data) from the system, to assess the condition of the system being monitored.[11] This approach is illustrated with an industrial gearbox example. Two types of reasoning techniques are defined - implicit reasoning techniques (such as Artificial Neural Networks) that transform observed data into an assessment of the health of the system, and explicit reasoning techniques (such as rule-based expert systems) that encode explicit knowledge gained from maintenance personnel or system designers to allow interpretation of fault conditions based on the values of observed data. The limitations of each of these systems are also identified. The limitations of rule-based systems include: (a) inability

to handle both explicit and implicit knowledge simultaneously (combinatorial explosion); (b) consistency maintenance. The limitations of Neural Networks are: (a) hard to explain reasons why the network made specific decisions; (b) long time needed by the training techniques to converge. The authors suggest combining these two approaches to exploit their advantages and eliminate their disadvantages.

A prototype health monitoring and prognostic system for Gas Turbine Engines is discussed by Greitzer et.al.[12] The system comprises a set of sensors mounted on the turbine engine, a data acquisition system (for collecting and processing sensor signals) and microprocessors to process and analyze the information, and perform statistical prediction analyses. Artificial Neural Networks and rule-based algorithms are used for diagnostics purposes, while predictive trend analysis is used to predict future engine conditions. Prognostics is accomplished by trending results from the diagnostic module. Both short-term and long-term trends are computed using linear regression on the diagnostic values.

Kacprzynski et.al have developed a health monitoring scheme that can detect, classify and predict developing engine faults.[13] The development of an integrated prognostic and diagnostic framework is discussed. The prognostic module utilizes a physics-based, stochastic model. The generic prognostic and health management architecture emphasizes the integration of anomaly detection, diagnostic and prognostic techniques through an integrated model of the entire system. The diagnostic results are combined with past history information to train neural-network based algorithms for continuously updating projections on remaining useful life.

An integrated prognostic process was developed by Luo et.al, based on data collected from model-based simulations under nominal and degraded conditions.[2] The prognostic algorithm developed was demonstrated by conducting a simulation study on an automotive suspension system.

III. Two Spool Turbine Engine Simulation Model

A dynamic model of a two-spool turbofan engine was developed using the MATLAB simulation environment and its Simulink toolbox. The schematic configuration of the turbofan engine that was simulated is shown in Figure 1. The HP Compressor and HP Turbine are on one shaft (driven by the High Speed Rotor),

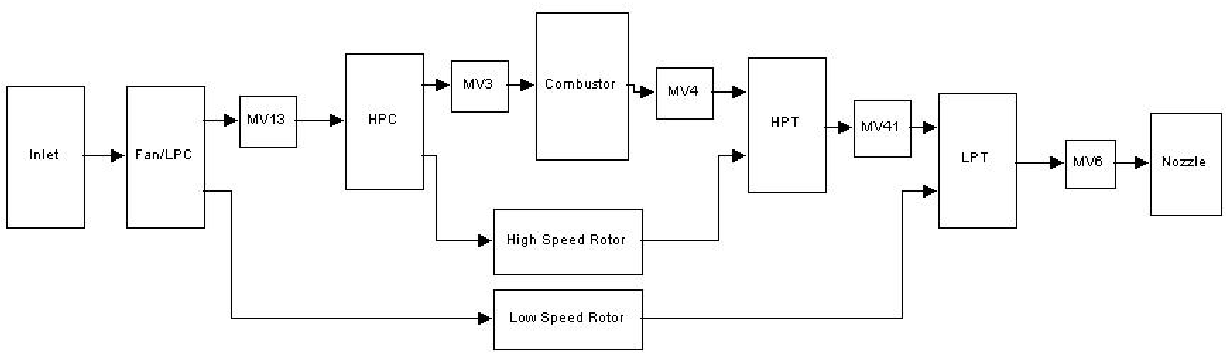

Figure 1. Schematic Configuration of the Two-Spool Turbofan Engine

while the LP Compressor (Fan) and LP Turbine are on the other shaft (driven by the Low Speed Rotor). Bleed effects (for air bleed from the compressor and turbine cooling air bleed) are not currently considered in the model.

The engine simulation model consists of the static elements - Inlet, Single stage fan (or LPC), High pressure compressor (HPC), Combustor, Low pressure turbine (LPT), High pressure turbine (HPT) and Main nozzle which are modeled as lumped parameter thermodynamic systems, represented by performance maps, constant coefficients, and thermo and aero-dynamic relationships and the dynamic elements which include the following: Intercomponent volumes, Low speed rotor and High speed rotor. In the model, the rotor dynamics (for the high speed and low speed rotors) is represented by the equation of conservation of angular momentum. The mixing volume dynamics are represented by the equations of conservation of mass and energy.

Based on the mathematical model and computational procedures for the various engine components as described in Ref 5, each component of the turbofan engine was developed using C-program based S-functions in Matlab/Simulink. Fan, Compressor and Turbine maps were used accordingly to model the fan, HPC, HPT

and LPT components. The dynamic elements were represented by the corresponding differential equations. For the turbofan engine model being developed, the 4 Mixing Volume components and 2 Rotor components resulted in a set of 8 nonlinear dynamical equations.
The 8 state variables include:

1. HPC Inlet Pressure (P_{26})
2. Combustor Inlet Pressure (P_3)
3. Combustor density (ρ_4)
4. HPT Inlet Temperature (T_4)
5. Low Pressure Spool Speed (N_L)
6. High Pressure Spool Speed (N_H)
7. LPT Inlet Pressure (P_{45})
8. Nozzle Inlet Pressure (P_6)

The dynamical equations for the various states are as follows:

$$\dot{P_{26}} = (1 + \frac{\gamma - 1}{2} M^2)^{\frac{1}{\gamma-1}} RT_{26} \frac{W_2 - W_3}{V_{26}} \tag{1}$$

$$\dot{P_3} = (1 + \frac{\gamma - 1}{2} M^2)^{\frac{1}{\gamma-1}} RT_3 \frac{W_3 - W_4 - u}{V_3} \tag{2}$$

$$\dot{\rho_4} = \frac{W_3 - W_4 + u}{C_{vol}} \tag{3}$$

$$\dot{T_4} = \frac{Cp_3 T_3 W_3 - Cp_4 T_4 W_4 + u\, LHV}{C_v T_4 C_{vol} \dot{\rho_4}} \tag{4}$$

$$\dot{N_L} = \frac{3600}{4\pi^2 N_L I_L} \left[W_{45} Cp_4 (T_45 - T_5) - \frac{W_2 Cp_3 (T_{26} - T_2)}{\eta_{mech}} \right] \tag{5}$$

$$\dot{N_H} = \frac{3600}{4\pi^2 N_H I_H} \left[W_4 Cp_4 (T_4 - T_45) - \frac{W_3 Cp_3 (T_3 - T_{26})}{\eta_{mech}} \right] \tag{6}$$

$$\dot{P_{45}} = (1 + \frac{\gamma - 1}{2} M^2)^{\frac{1}{\gamma-1}} RT_{45} \frac{W_4 - W_{45}}{V_{45}} \tag{7}$$

$$\dot{P_6} = (1 + \frac{\gamma - 1}{2} M^2)^{\frac{1}{\gamma-1}} RT_6 \frac{W_{45} - W_{noz}}{V_6} \tag{8}$$

The Simulink model of the turbine engine was created by arranging (stacking) the various engine computational modules in a configuration similar to that shown in the schematic configuration . In such a configuration, the exit gas condition of a component forms the inlet gas condition of the next component. These individual computational blocks were then interconnected to form the complete engine simulation model.
During simulation of the engine, the set of 8 nonlinear dynamical equations representing the dynamics of the turbine engine system is solved to determine the engine conditions during each time step, provided the initial operating point data for the engine components is specified.

IV. Linearization And Control

The Turbine Engine model was simulated in open loop with a constant value of fuel flow. It is assumed that the engine is being run in stationary conditions. The values of the various parameters were recorded when the three states N_L, N_H and T_4 reached approximate steady state values. These parameter values were used to linearize the nonlinear equations representing the low pressure spool speed, high pressure spool speed and turbine inlet temperature. The outputs measured include NL, NH and Overall Pressure Ratio(OPR). A fictitious output(F_y) involving a combination of the 3 states is considered in this paper to ensure observability

with every subset of 3 outputs. This is done so that the diagnostic technique involving the use of bank of Kalman filters can be applied to the model as an example. The reduced order linear system is given by

$$\dot{x} = Ax + Bu \quad x \in \Re^3 \quad u \in \Re \qquad (9)$$
$$y = Cx \quad y \in \Re^4$$

where $x = \begin{pmatrix} N_L & N_H & T_4 \end{pmatrix}$

$$A = \begin{pmatrix} 312.003 & 0 & -689.27 \\ 0 & 1872.4 & -6305 \\ 0 & 0 & -3.371 \end{pmatrix}$$
$$B = \begin{pmatrix} 0 \\ 0 \\ -5.91e7 \end{pmatrix}$$
$$C = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 3.74 \\ 1 & 1 & 3.74 \end{pmatrix}$$

A simple PID controller is implemented for the nonlinear system to regulate the high speed rotor speed $N_H$to a predefined setpoint.

V. Engine Sensor Fault Diagnostics Using Bank Of Kalman Filters

This section discusses the use of a bank of Kalman Filters for sensor fault diagnostics in Turbine Engine systems. This technique has been adopted from Ref 14 and the implementation of the same is described in the following subsection.
The Kalman Filter is an estimator for the linear-quadratic problem, which is the problem of estimating the instantaneous state of a linear dynamic system perturbed by white noise - by using measurements linearly related to the state but corrupted by white noise. To control a dynamic system, it is essential to know the entire state of the system. For applications where it is not always possible to measure every variable that needs to be controlled, the Kalman filter provides a means for inferring the missing information from indirect (and noisy) measurements.
With the Engine Simulation model that was developed, the model-based fault detection approach is implemented, which consists of a bank of Kalman filters that is used for sensor fault detection and isolation (FDI). Each Kalman filter is designed for detecting a specific sensor fault. In the event that a sensor fault does occur, all filters except the one using the correct hypothesis will produce large estimation errors, thereby isolating the sensor that has failed.

A. Sensor Fault Detection

The Kalman Filter problem requires the output variables of the plant and the control input commands for estimating the augmented state vector and the sensor measurements. A bank of 'm' Kalman filters (m is the number of outputs) is used to implement the sensor fault detection logic as shown in Figure 2. As mentioned, the control input and a subset of the sensor output measurements are fed to each of the m Kalman filters. The sensor that is not used by a particular filter is the one being monitored by that filter for fault detection (Example: the ith filter uses the sensor subset that excludes the ith sensor). Hence each filter estimates the augmented state vector using $(m-1)$ sensors. Therefore if sensor i is faulty, all filters will use a corrupted measurement, except for filter i. Filter i will thus be able to estimate the augmented state vector from fault-free sensor measurements, whereas the estimates of the remaining filters will be distorted by the fault in sensor i. Once the augmented state vector estimate is found, the sensor measurements can be estimated using the Kalman Filter system of equations.
For each filter, the residual vector is generated(Equation (10))

$$e^i = {y_e}^i - y \qquad (10)$$

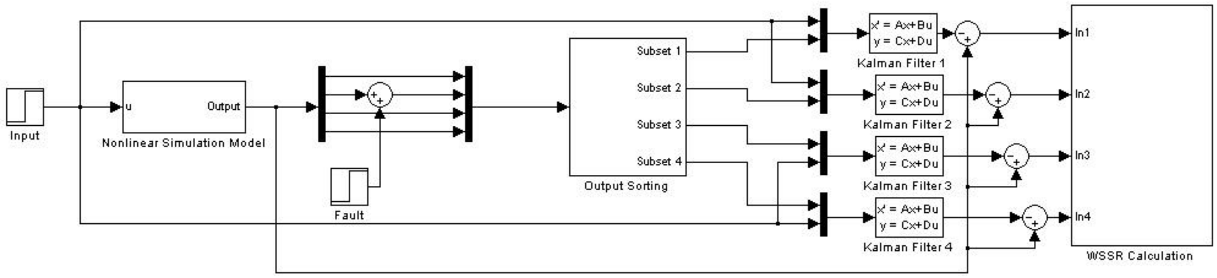

Figure 2. Sensor Fault Detection Using Bank of Kalman Filters

where:
y is the output of the plant
${y_e}^i$ is the output estimate of the Kalman filter i
The concept of Kalman Filters for Output estimation was extended to achieve Sensor Fault Detection and Isolation (FDI) for the engine simulation model. The method currently simulates a fault in a sensor by adding a step to the actual output generated by the simulation model. The Bank of Kalman Filters is used for detecting this fault that was deliberately introduced into the sensor measuring N_H. The inputs to each Kalman filter include the control input and a subset of the sensor output measurements. Hence the sensor subsets fed to the 4 Kalman filters are:
Sensor Subset y^1 contains measurements of N_H, OPR and F_y
Sensor Subset y^2 contains measurements of N_L, OPR and F_y
Sensor Subset y^3 contains measurements of N_L, N_H and F_y
Sensor Subset y^4 contains measurements of N_L, N_H and OPR
Hence each of the 4 Kalman Filters estimates the output using 3 sensor measurements (faulty) and the control input. In this case, since the sensor measurement 2 is faulty, all filters except for filter 2 will use a corrupted measurement. Filter 2 will thus be able to estimate the engine outputs from fault-free sensor measurements, whereas the output estimates of the remaining filters (i.e., filters 1, 3 and 4) will be distorted by the fault in sensor 2.

VI. Results

The bank of Kalman filters was implemented on the nonlinear dynamical model of the two spool turbofan engine with a fault in the high speed rotor measurement sensor.The fault is introduced as a step of magnitude 10000 at time=0.001 seconds. The weighted sum of squares residuals (WSSR) for each of the Kalman filters were calculated as

$$WSSR^i = V^i(e^i)^T(\sum)^{-1}e^i \tag{11}$$

where $\sum = diag(\sigma^2)$. The vector σ is the noise standard deviation and the scalar V^i is the weighting factor. The term e^i is the residual vector generated by taking the difference between the actual output(non-faulty) and the output of the i^{th} Kalman filter. The non-faulty output is assumed to be available from a model that runs simultaneously.

A. No Sensor Faults

The plots for the Kalman filter estimates are seen in Figures 3, 4, 5 and 6. The high speed and low speed rotor speeds are shown in Figure 7. (Note that the Kalman filter estimates are the perturbed values from the operating point around which the system has been linearized.)

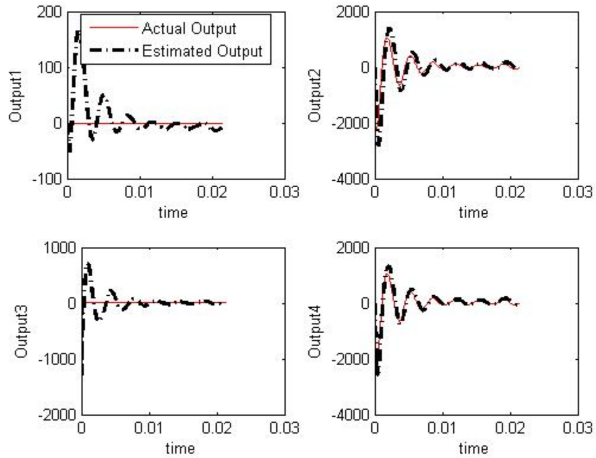

Figure 3. Kalman Filter 1 Output Estimates

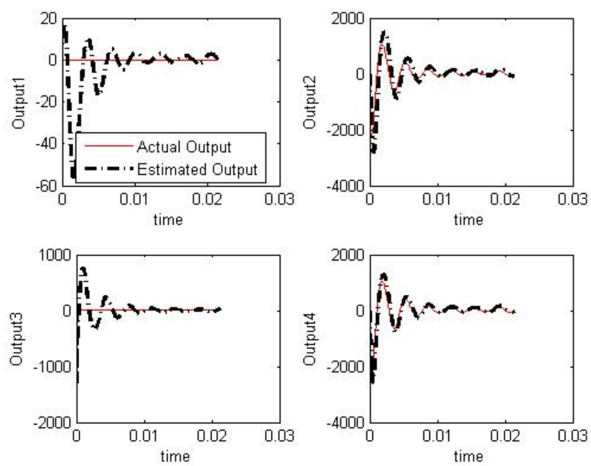

Figure 4. Kalman Filter 2 Output Estimates

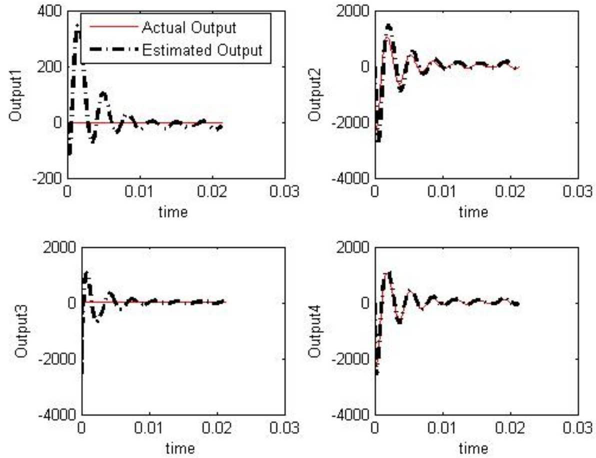

Figure 5. Kalman Filter 3 Output Estimates

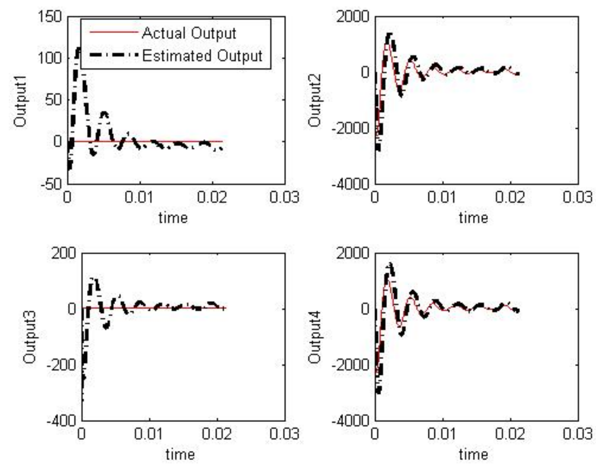

Figure 6. Kalman Filter 4 Output Estimates

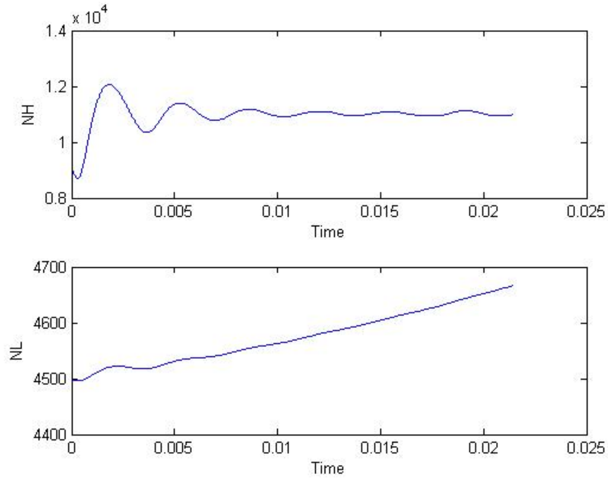

Figure 7. Rotor Speeds of the Engine Simulation

B. Fault in High Speed Rotor Measurement

The plots for the Kalman filter estimates are seen in Figures 8,9,10 and 11. The residual vectors and WSSR for the 4 Kalman filters are shown in Figures 12 and 13 respectively. We note that the estimates of the outputs from Kalman Filter 1,3 and 4 have higher error than Kalman Filter 2. WSSR plots for Kalman Filter 1,3 and 4 are also seen to be high whereas the WSSR for the Kalman Filter 2 goes to zero.

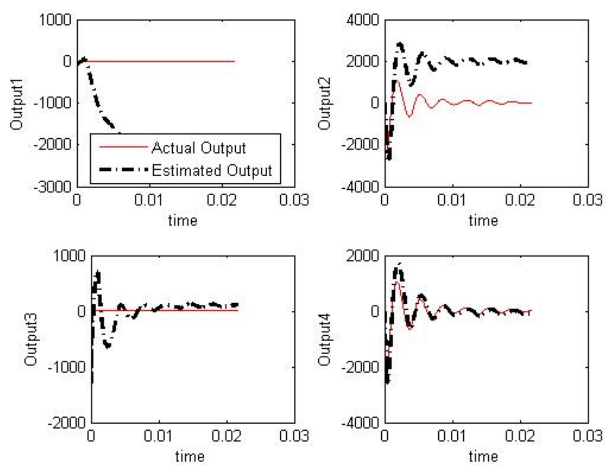

Figure 8. Kalman Filter 1 Output Estimates

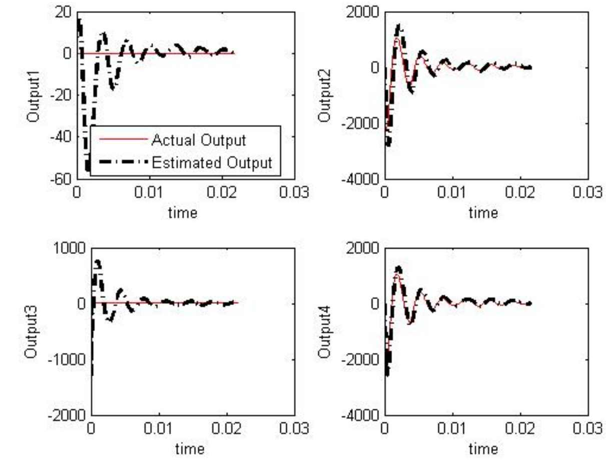

Figure 9. Kalman Filter 2 Output Estimates

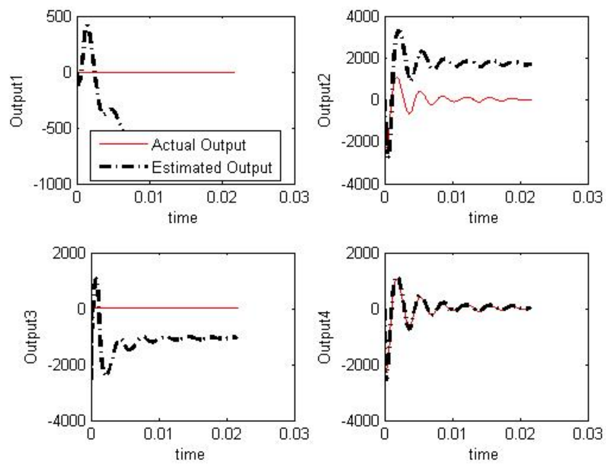

Figure 10. Kalman Filter 3 Output Estimates

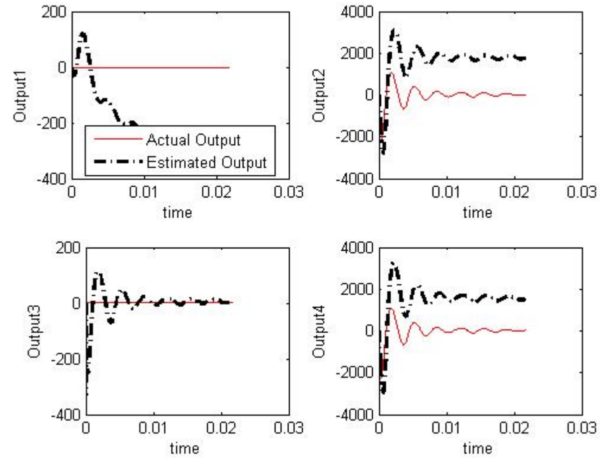

Figure 11. Kalman Filter 4 Output Estimates

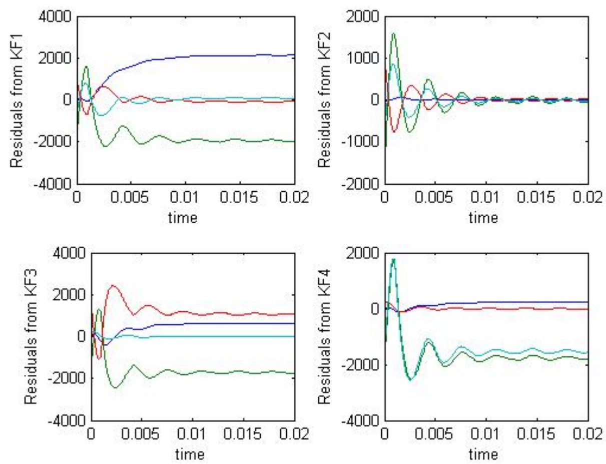

Figure 12. Residual Vectors for the 4 filters

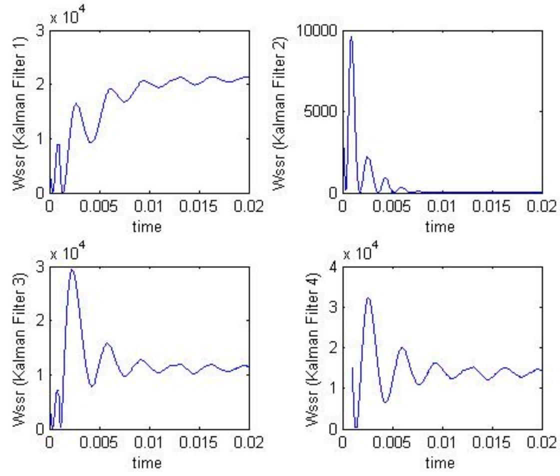

Figure 13. WSSR for the 4 filters

VII. Conclusions and Future Work

The main contribution of this paper is the development of a nonlinear dynamical model of a two spool turbine engine using MATLAB/Simulink environment. The model can be adapted to various engines by implementing appropriate component maps for the compressors and turbines. A PID controller is implemented to control the speed of the high speed rotor. The model, developed from first principles is linearized about an operating point and the linear model is used for the implementation of the Kalman filter based diagnostic technique that has been developed previously in literature for the isolation and detection of sensor faults. The paper also presented a survey of prognostic techniques for turbine engines. Future work includes the validation of the nonlinear engine model for different flight conditions, development of other diagnostic techniques that do not require observability from all outputs and implementation of a model-based prognostic technique that utilizes engine operating point data and the data obtained from the the diagnostic module.

References

[1]Tumer, I. Y. and Bajwa, A., "A survey of aircraft engine health monitoring systems," Joint Propulsion Conference, Los Angeles,CA, 1999.

[2]Luo, J., Namburu, M., Pattipati, K., Qiao, L., Kawamoto, M., and Chigusa, S., "Model-based Prognostic Techniques," IEEE AUTOTESTCON Conference, Anaheim, CA, September 2003.

[3]Engel, S. J., Gilmartin, B. J., Bongort, K., and Hess, A., "Prognostics, The Real Issues Involved with Predicting Life Remaining," IEEE Aerospace Conference Proceedings, 2000, pp. 457–469.

[4]Mathur, A., Cavanaugh, K., P.Willett, Galie, T., and Pattipati, K., "Reasoning and Modeling Systems in Diagnosis and Prognosis," SPIE Aerosense Conference on Component and Systems Diagnostics, Prognostics, and Health Management, Orlando, FL, April 2001.

[5]Walsh, P. P. and Fletcher, P., *Gas Turbine Performance*, Blackwell Science, 2nd ed., 2004.

[6]Roemer, M. J., Nwadiogbu, E., and Bloor, G., "Development of Diagnostic and Prognostic Technologies for Aerospace Health Management Applications," IEEE Aerospace Conference Proceedings, 2001, pp. 3139–3147.

[7]Brotherton, T., Janhns, G., Jacobs, J., and Wroblewski, D., "Prognosis of faults in gas turbine engines," Vol. 6, IEEE International Conference on Aerospace, 2000, pp. 163–171.

[8]Wang, P. and Vachtsevanos, G., "Fault Prognosis Using Dynamic Wavelet Neural Networks," Tech. Rep. SS-99-04, ISBN 1-57735-081-2, AAAI Spring Symposium, Palo Alto, CA, 1999.

[9]Roemer, M., Kacprzynski, G., and Orsagh, R., "Assessment of Data and Knowledge Fusion Strategies for Prognostics and Health Management," IEEE Aerospace Conference Proceedings, 2001, pp. 2979–2988.

[10]Orsagh, R., Roemer, M. J., Sheldon, J., and Klenke, C., "A Comprehensive Prognostics Approach for Predicting Gas Turbine Engine Bearing Life," 10th National Turbine Engine High Cycle Fatigue Conference, 2004.

[11]Garga, A. and et.al, "Hybrid reasoning for prognostic learning in CBM systems," IEEE Aerospace Conference, March 2001.

[12]Greitzer, F. and et.al, "Gas Turbine Engine Health Monitoring and Prognostics," SOLE '99 Symposium, Las Vegas, NV, September 1999.

[13]Roemer, M. and Kacprzynski, G., "Advanced Diagnostics and Prognostics for Gas Turbine Engine Risk Assessment," IGTI/ASME Turbo Expo, Germany, May 2000.

[14]Kobayashi, T. and Simon, D., "Application of a bank of Kalman filters for Aircraft Engine Fault Diagnostics," Tech. Rep. TM-2003-212526, NASA, 2003.

[15]Reed, J. and Afjeh, A., "Development of an Interactive Graphical Propulsion System Simulator," AIAA/ASME/SAE/ASEE Joint Propulsion Conference, Indianapolis, IN, 1994.

[16]Mattingly, J., *Elements of Gas Turbine Propulsion*, McGraw-Hill, 1996.

[17]Lietzau, K. and Kreiner, A., "Model Based Control Concepts For Jet Engines," ASME Paper, 2001.

[18]Merrill, W., "Sensor failure detection for jet engines using analytical redundancy," *Guidance, Control and Dynamics*, Vol. 8, No. 6, 1985, pp. 673–682.

[19]Merrill, W., DeLaat, J., and Bruton, W., "Advanced detection, isolation, and accommodation of sensor failures-A real-time evaluation," *Guidance, Control and Dynamics*, Vol. 11, No. 6, 1988, pp. 517–526.

[20]Merrill, W., DeLaat, J., and Abdelwahab, M., "Turbofan engine demonstration of sensor failure-detection," *Guidance, Control and Dynamics*, Vol. 14, No. 2, 1991, pp. 337–349.

[21]Wunnenberg, J. and Frank, P., "Sensor fault detection using Robust Observers," Joint Automatic Control Conference, 1987.

[22]Patton, R., "Robust Fault Detection using Eigenstructure Assignment," 30th IEEE CDC, United Kingdom, pp. 2242–2247.

[23]Patton, R. and Chen, J., "Robust fault detection of jet engine sensor systems using eigenstructure assignment," *Guidance, Control and Dynamics*, Vol. 15, No. 6, 1992, pp. 1491–1497.