Predictive Fault Diagnosis System for Intelligent and Robust Health Monitoring

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This paper describes work related to the *Predictive Fault Diagnosis System for Intelligent and Robust Health Monitoring*, which exists as a solution to complete failure detection, identification, and prognostics (FDI&P) in health monitoring applications. Several advanced FDI analytical redundancy techniques have been applied for such a purpose, with the most notable being a compound method comprised of optimal filtering, statistical analysis, and neuro-fuzzy algorithms that is able to detect and diagnose both known and unknown failures. Although this scheme has been proven to be quite successful for systems that can be well described in a state space representation, current research has shown the viability in extending the process to highly complex systems with considerable nonlinearities while still maintaining the FDI capabilities. This paper highlights the utility of these algorithms for determining failures in (1) a known reusable liquid rocket engine model and (2) an unknown input-output relation in a fluid flow testbed. Other research has focused on prognostic capabilities provided by a neural architecture enhanced with fuzzy logic using rule-based knowledge. An example of using data to construct fuzzy rules for determining the remaining useful life of components is provided to give insight into the process.

Nomenclature

\[\begin{align*}
FAM &= \text{fuzzy ARTMAP} \\
FDI &= \text{failure detection and identification} \\
FDI&P &= \text{failure detection, identification, and prognostics} \\
FFT &= \text{Fast Fourier Transform} \\
FPOV &= \text{fuel preburner oxidizer valve} \\
KF &= \text{Kalman filter} \\
MIMO &= \text{multiple input multiple output} \\
MR &= \text{mixture ratio} \\
NN &= \text{neural network} \\
OPOV &= \text{oxidizer preburner oxidizer valve}
\end{align*}\]

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Failure detection, identification, and prognostics (FDI&P) are concepts used to ensure the integrity and reliability of dynamic systems in the presence of malfunctions, actuator misbehaviors, sensor errors, and system uncertainties. For several dynamic systems, such as the components within reusable liquid rocket engines and associated test stand facilities at NASA Stennis Space Center, the early detection and analysis of failures can help avoid system shutdowns, breakdowns, or even catastrophic events. The ability to obtain a diagnosis for the cause of incorrect operation and to acquire a prognosis of an impending failure is a challenging effort that greatly enhances safety, improves operability, and reduces operational cost. Mission success potential is also improved by using prognostic information to conserve the remaining life of a failing component.

Traditional approaches are still sometimes used for the health monitoring of dynamic systems due to the simplicity they offer. Such approaches include hardware redundancy, red-lines, and scheduled maintenance. For example, hardware redundancy uses multiple independent sensors and actuators to perform the same task and thereby increase the probability that a failure in one instrument will not considerably degrade system performance. Although reducing the negative impact of a failure, a major disadvantage is that of the additional costs and space used for the redundant instruments. On the other hand, analytical redundancy techniques are based off of mathematical models, and can be implemented in digital logic, thus presenting considerable cost-savings. The main caveat here is that one must usually be provided with detailed enough models that are able to capture all relevant system modes and failures. Although there do exist mathematical models for reusable liquid rocket engines, they are only detailed enough to capture the main phenomena, not the full range of failure possibilities.

This study presents results of an analytical redundancy based approach consisting of a compound technique comprised of Kalman filters (KF), state propagators (SP), the state chi-square test (SCST), and fuzzy ARTMAP networks. Although this requires state space models for the filters, it is shown in this paper that the technique is versatile enough to be applied to complex and nonlinear systems. This is made possible through the use of on-line system identification (SI) to construct several transfer functions (TF) that describe single input single output (SISO) relations rather than resorting to the need to create a comprehensive multiple-input multiple-output (MIMO) system model. As such, rather than this KF-SP-SCST-ARTMAP method set to monitor all of the outputs of a system using complete models, several implementations of the algorithm run in parallel and monitor the various outputs individually. In this way, as long as the data are sufficiently rich, a proven analytical redundancy technique may be applied to a highly nonlinear and complex system such as a reusable liquid rocket engine.

This paper is organized as follows: Section II presents the solution setup consisting of two dynamic systems: (1) a simplified linear state space model of the Space Shuttle Main Engine (SSME) and (2) a fluid flow testbed. The state space model is simply used to discuss the traditional implementation of KF-SP-SCST-ARTMAP, whereas the testbed shows its application on a system for which we do not have a current model. Section III presents a brief description of this technique, and then shows the results of the algorithms on both the state space model and testbed. Section IV introduces current research related to providing prognostic statements, which when combined with the FDI engine, enables complete FDI&P. Finally, Section V concludes the paper and mentions future investigations.
where $F(k)$ is the state matrix, $G(k)$ the control matrix, and $H(k)$ the observation matrix. There are four states as defined by the vector $x(k)$. The control inputs, $u(k)$ are given as the fuel preburner oxidizer valve (FPOV) position, $\beta_{\text{FPOV}}$ and the oxidizer preburner oxidizer valve (OPOV) position, $\beta_{\text{OPOV}}$. The outputs, $z(k)$ represent the main combustion chamber’s pressure, $P_C$, and mixture ratio, $MR$. The vectors $c(k)$ and $d(k)$ represent additive failures to the actuators and sensors respectively (zero for nominal conditions). The system noise variance is modeled as a Gaussian vector $w_k \sim N(0,Q(k))$ and the measurement noise variance is also modeled as a Gaussian vector $v_k \sim N(0,R(k))$ for some matrices $Q(k)$ and $R(k)$. The state noise matrix, $\Gamma(k)$ is given by a $4 \times 4$ identity matrix. In the literature, input and response plots have been provided for this system\textsuperscript{10, 11}, and here Fig. 1 presents another possible control sequence, with Fig. 2 depicting the corresponding nominal response of the dynamic system.

![Figure 1. Arbitrary Input Control Sequence.](image1)

![Figure 2. Dynamic System Response.](image2)

There are different ways to categorize a failure as to validate the FDI algorithms for this system. Normally, they can be distinguished as soft or hard failures that may occur in the system, sensors, or actuators. Moreover, when occurring in the sensors and actuators, they can be modeled as either additive or multiplicative. As evident from Eq. (1), additive actuator and sensor failures are given by nonzero $c(k)$ and $d(k)$ vectors respectively. On the other hand, multiplicative failures manifest themselves as direct changes in the matrices themselves. For actuators, they are implemented by multiplying the column of $G(k)$ that corresponds to the particular failed actuator by a quantized scalar value termed $\alpha$. Following the same reasoning, to represent a failed sensor, the row of $H(k)$ associated with that sensor is also multiplied by an $\alpha$ term.

B. Prototype Testbed Model

In order to demonstrate the FDI algorithms of this paper, it was first necessary to use a testbed with components and measured variables that are similar to those in the reusable liquid rocket engines that are tested at NASA Stennis Space Center. Various prototype platforms have been constructed for such a purpose, and in this paper, the fluid flow testbed in Fig. 3 is presented as its easy adjustment of failure modes and control inputs facilitates a clear and concise explanation of the manner in which KF-SP-SCST-ARTMAP may be applied to complex systems.

In order to demonstrate the FDI algorithms of this paper, it is first necessary to identify the normal operation mode and control inputs (these can be arbitrarily defined since the testbed is being used as an example only). Here, we consider that valve 1 constitutes a control input which may vary from 100% open to only 25% open, and that any position within these bounds constitutes normal operation. On the other hand, normal operation occurs only when valve 2 is 100% open,
and when it is closed, we experience an undesirable increase in pressure upstream of the valve, as read by pressure sensor 1. We thus consider this partially closed valve as our failure mode for FDI. Figure 4 shows a pressure output during nominal operation for a control input sequence that progresses from valve 1 being 100%, 58%, 40%, and 25% open over a period of 2000 seconds. Note that the y-axis represents percentage open for the input, \( u(k) \), whereas it is an uncalibrated pressure for the output, \( y(k) \). From this figure, it is evident that the control sequence is essentially a discrete operation in which the valve is instantaneously moved from one position to the next. Although the pressure seems to behave proportionally to the valve position, the dynamic system responds at a slower rate while also exhibiting noise.

Now suppose that we do not have an analytically derived model for this input-output relation, and that we are simply given data. Using a recursive least squares (RLS) algorithm, system identification can be conducted to arrive at a transfer function for this purpose. It is assumed that we at least know the relation between the input and output may be given by a 2\(^{nd}\) order transfer function (1 numerator parameter and 3 denominator parameters). By running a standard RLS algorithm, Fig. 5 depicts the evolution of the estimated parameters of this transfer function, where it is noted that they converge to certain values. Then, using the actual control input, a linear simulation as shown in Fig. 6 is performed to indicate the response of this estimated dynamic system. Upon comparison with Fig. 4, the actual behavior is well accounted for with the only appreciable error being in the magnitude of the output. This can easily be corrected by appropriate scaling of the transfer function parameters. Moreover, as shown in Section III, a biased magnitude will have no impact on the KF-SP-SCST-ARTMAP algorithm’s ability to conduct FDI. Finally, this transfer function can be converted into state space form, and thereafter used as a filter model. A key point is that within the scope of the Predictive Fault Diagnosis System for Intelligent and Robust Health Monitoring, this parameter estimation occurs automatically during on-line operation. Moreover, sensors distributed throughout the system are used to feed data related to all other input-output relations that are of concern for FDI. The result is a vast collection of transfer functions, each of which is individually analyzed for possible anomalies or malfunctions.

![Figure 4. Normal Operation – Input and Output.](image)

![Figure 5. Estimated Transfer Function Parameters.](image)

![Figure 6. Simulated Transfer Function Response.](image)

III. Failure Detection and Identification Results

A. KF-SP-SCST-ARTMAP Combined Technique

The use of Kalman filtering, state propagators, the state chi-square test, and ARTMAP fuzzy neural networks is an analytical redundancy based solution that works well for all types of failures. This technique, as pioneered by C.F. Lin \(^5\), \(^6\), \(^7\) is based on using Kalman filters to generate optimal estimates, \( \hat{x}_k(k|k) \) of the system state \( x(k) \). In addition, state propagators generate estimates, \( \hat{x}_s(k) \) and are used as failure detection references since they are
based only on a priori system model information. Failure detection is carried out by checking the consistency between the estimates of the two filter types, which consists of computing the difference denoted by $\beta(k)$ and associated covariance, $B(k)$. A major problem associated with this approach is that the state propagator estimates are heavily influenced by initial errors and process noise of the system. As such, a pair of state propagators are periodically reset with Kalman filter data and alternatively used as detection references. Next, the state chi-square test detects changes in the statistics of the data by monitoring a chi-square distributed variable consisting of the KF and SP difference and associated covariance. When using the entire vectors for the difference and associated covariance, the test statistic reflects the overall effects of the states, and thus suffers from low sensitivity to failures impacting only a few components. As such, when applying a fault detection rule, for enhanced sensitivity each state $i$ is tested individually. The fault detection rule then consists of comparing the chi-square statistical variable with a threshold obtained from a chi-square distribution table given a chosen false alarm probability.

The patterns output from the SCST are then input to fuzzy ARTMAP (FAM) networks for rapidly detecting the failure, determining its location, time of occurrence, and severity level. The FAM uses supervised learning to create stable recognition categories of an optimal size while simultaneously maximizing predictive generalization and minimizing predictive error in an on-line setting. In this research, the FAM is simplified (SFAM) by removing several redundancies to result in improved computational characteristics while still retaining the classification abilities. The key point in the use of a NN in FDI schemes is that it can map the SCST output into a new space identifying features of the failures. The solution here contains two SFAM’s: SFAM-1 and SFAM-2. SFAM-1 forms a map between SCST patterns that arise due to failures into patterns describing the failure locations. The SFAM-2 network is trained on SCST data corresponding to different start times and magnitudes of failures.

B. Results on SSME State Space Model

The KF-SP-SCST-ARTMAP method has been tested on the state space model in Eq. (1) for rapidly detecting failures, determining location, assessing severity, and computing the time of occurrence. As an example, the results here are shown when tested for additive failures represented by non-zero values of the vectors $c(k)$ and $d(k)$. Before on-line operation of the algorithm, it is first necessary for proper ARTMAP training. For example, the ability to approximate failure intensity can be provided by an ARTMAP network that was trained with representative fault intensities for a particular sensor or actuator. During testing or on-line operation, the values used for training may not come up, but SFAM-2 will still estimate a reasonable value for the fault intensity. Given trained SFAM networks, the KF-SP-SCST-ARTMAP algorithm is then able to generate the appropriate diagnostic statements.

For the case of an additive failure in the second sensor occurring at the 5th second, Fig. 7 shows the output built upon the estimated states from the KF (in blue) compared to the output based upon the SP states (in green). It is readily evident that the failure is likely in the 2nd sensor due to the appreciable divergence of the KF output from the SP output (recall that the SP is not affected by failures). Figure 8 then contains the evolution of $\beta(k)$, which is the difference between the Kalman filter estimation states and those from the state propagator. Once a failure occurs, the value of $\beta(k)$ representing the fourth state results in the greatest deviation from a zero mean, meaning that it was most severely impacted by the failure. This makes sense given the knowledge that the observation matrix is formulated here such that the fourth state is equal to the second output (i.e. the fourth state is measured by the failed second sensor). It should be noted that although a sensor failure does not directly impact the dynamic system (unless feedback is used), the reason that all states show at least some slight divergence from nominal operation (evident since all $\beta(k)$ values are nonzero after the failure) is due to the fact that they are the estimated from the KF based on a faulty output and do not represent true values. Finally, Fig. 9 shows the SCST signals evolution for each state. The change in the SCST signal representing the fourth state is readily apparent, and is an order of magnitude larger than the other signals. These signals are then input into the ARTMAP networks, where statements are explicitly made indicating the intensity, location, and time of the failure. A properly trained SFAM-1 network is then able to trace the proper source to the second sensor, whereas the SFAM-2 network can determine the time of occurrence and severity. It should be noted that the process works equally well with actuator failures, and the failed actuators can also be located and diagnosed by the ARTMAP networks.

Figure 7. Estimated Output (Sensor Failure).

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C. Results on Prototype Testbed

A system failure was manually introduced into the testbed by gradually closing valve 2 to result in a linear pressure increase starting at 1000 seconds as shown in Fig. 10. The same input sequence as in Fig. 4 was maintained by the control valve. It is the ability of the KF-SP-SCST-ARTMAP algorithm to detect this failure since a certain control input no longer produces the associated output as was previously determined and quantified within a transfer function. The Kalman filter and state propagators use as models, the state space representation that was found by converting the estimated transfer function. In this case, the conversion yielded \( F(k), G(k), \) and \( H(k) \) matrices in controller canonical form with two states, one input, and one output. The Kalman filters estimate the states given a data stream that may vary, whereas the state propagators are based on \textit{a-priori} model information, and thus not affected by failures. Figure 11 then shows the output built upon the estimated states from the KF (in blue) compared to the output based upon the SP states (in green). Upon comparison with Fig. 10, although the magnitude is significantly off, the qualitative behavior due to the failure is captured. Figure 12 shows the estimated states for the two filters, where state 1 is zero during constant pressure, and acts as an impulse signal during pressure transitions, with the magnitude depending on the size of the transition. On the other hand, state 2 follows the same path as the output. This is due to the fact that the observation matrix found here is given by \([0 \ \nu]\) where \(\nu\) is a nonzero value.
The Kalman filter and state propagator data are then analyzed using the SCST algorithm which detects in a statistical sense if a failure has occurred. Before this is done, it is first important to make sure that the algorithm does not generate false alarms during nominal operation. As such, by running the simulation using actual input data without a failure, Fig. 13 shows the evolution of $\beta(k)$, which was previously defined to be the difference between the Kalman filter estimation states and those from the state propagator. Since the formulation of the filters requires some measurement and state noise, the results here are not constantly zero. However, it is readily apparent that the mean maintains a zero bias, and therefore with an appropriate threshold, no failure should be detected. Next, the valve failure resulting in an unforeseen pressure increase was introduced into the system. Figure 14 shows the evolution of $\beta(k)$, where a clear divergence occurs at 1000 seconds, such that the two no longer have a zero mean. Figure 15 includes the results of the SCST where it is evident that a change in the statistics has occurred. A failure associated with this input-output relation is then flagged, and ARTMAP networks are then able to determine the time of occurrence, severity, and location.

![Figure 13. $\beta(k)$ during Nominal Operation.](image1)

![Figure 14. $\beta(k)$ during Faulted Operation.](image2)

![Figure 15. SCST during Faulted Operation.](image3)

It is evident that despite the fact that we do not have a mathematical model derived from physical principles, by applying system identification on SISO relations inherent in our system, we may still use an analytical redundancy based technique for failure detection and identification. In fact, even though a detailed mathematical model of the testbed would be quite complex, we have shown that it is sufficient to use a simple 2nd order transfer function to detect a failure. This has implications with regard to the computational processing requirements for monitoring such systems. In particular, it is possible that the processing is faster when using the KF-SP-SCST-ARTMAP method in parallel for each SISO relation as compared to one implementation of the algorithm for all the inputs and outputs at once. This would make the SISO TF generation scheme a desirable path to take even when we do have complete models at our disposal. It is then left to quantify this possibility in future tests.

**IV. Prognostic Framework**

The prognostic framework presented in this paper discusses how a fuzzy neural network may be used for providing statements regarding the life of different components. By using data that in some way indicates the component health over long periods of time (i.e. recurrent system operations have been performed several times), and by analyzing long-term trends, statements can be made regarding remaining useful life (RUL). For example, certain structural components may repeatedly be subjected to tension and compression loading cycles below their material yield strength. It is then of interest to be able to predict possible future failures as well as the component’s remaining service life. This can be accomplished using vibration time signal features such as root mean square,
variance, skewness, and kurtosis. Once a relationship is found between these features and the number of loading cycles, a neural network enhanced with fuzzy logic may use on-line data to classify a monitored structure into a class that indicates the probability of future failures as well as its remaining useful life – thereby guaranteeing prognostic capabilities. Fuzzy logic aids in the classification process by providing membership functions for the inputs (the features extracted from sensors) and the output (the RUL class). Fuzzy rules must be imposed such that the appropriate input combinations are mapped into the output. These rules use knowledge that can be gained from the proper interpretation of large data sets representing long term component operation. Although the use of a neuro-fuzzy system for modeling the fatigue life of composite laminates has been previously explored, there is still much future work necessary for a full implementation of the method in prognostic systems.

As an example of the method, consider that a metallic cylindrical rod undergoes axial tension loading at a high temperature. The strain rate vs. time relationship is then shown in Fig. 16, where it is noted that this plot is fairly representative of many materials experiencing creep, or the permanent deformation under stresses. The mean and the variance are both provided, where it is noted that these features are computed for a single complete loading cycle, which itself consists of several samples of data. Initially, the strain rate is high, but slowly decreases as more cycles are performed due to strain hardening (primary region). Then, the strain rate reaches a constant value due to a balance between work strain hardening and annealing (secondary region). The variance is fairly low in this region as well. Then as cracks start to form and propagate, the material begins to weaken, and the strain rate once again begins to increase (tertiary region). This increase continues until the material finally undergoes a failure. Due to the large changes that are occurring in a relatively short period of time, the variance also increases substantially until failure.

A neuro-fuzzy algorithm for prognostics first requires the definition of membership functions for the input and output data. An example in the literature presents membership functions derived based on vibration features from a Carnallite surge tank pump. For the fatigue creep case considered here, the membership functions must be defined according to the structural lifetime depicted in Fig. 16. From this figure, a membership function for mean may take the form as in Fig. 17. Values at 0.5 occur during the middle period of the lifetime, values between 0.6 and 0.7 occur either during the initial or ending stage of the material’s life, and values greater than 0.8 occur during the ending cycles when failure is setting in. The fact that we are unable to differentiate between the initial and end lifetimes for strain values between 0.6 and 0.7 is actually a motivating factor for using fuzzy logic. In particular, fuzzy rules can be used for such disambiguation. Now consider the variance membership function given by Fig. 18. A variance at 0.2 indicates that we are either in the primary or secondary region of strain, but does not point towards one or the other conclusively. Once again, such disambiguation is handled with fuzzy rules. On the other hand, for a value greater than 0.2, it is fairly certain that we are in the tertiary stage. Finally, the output membership function of Fig. 19 defines the three main age classes that the structural specimen may be experiencing: primary, secondary, or tertiary stages.
The fuzzy inference system then requires rules imposed on the input and output functions. These rules are derived from the information and conclusions yielded by observation of Fig. 16. The rules here are as follows, where the names are taken from the membership plots:

1. Middle-High Mean + Middle Variance = Primary Stage
2. Middle Mean + Middle Variance = Secondary Stage
3. Middle-High Mean + High Variance = Tertiary Stage
4. High Mean + High Variance = Tertiary Stage

More rules could be defined with more combinations; however, these take into account what is experienced in Fig. 16. Note that rules 1 and 3 differentiate the scenario in which we have a mean between 0.6 and 0.7 (middle-high mean) but we do not know if we are in the primary or tertiary stage. Moreover, rules 1 and 2 differentiate the case in which the variance is 0.5, but we do not know if we are in the primary or secondary stages. Figure 20 shows the resulting fuzzy inference system with these rules and how they can conclude that a component with a mean of 0.58 and a variance of 0.29 is mostly in the tertiary stage (output = 0.732). A neural network is then able to use these fuzzy membership functions and rules to better classify a component into an appropriate RUL or future failure class. As was shown here, the fuzzy rules are necessary such that regions which may contain similar variances can be disambiguated using mean data, and vice versa. The output of the NN is a single prognostic statement indicating if the material may experience a future failure and its remaining useful life.

Figure 20. Fuzzy Inference System for Failure and RUL Prediction.

V. Conclusions

The Predictive Fault Diagnosis System for Intelligent and Robust Health Monitoring was shown to be an effective means for conducting FDI&P in health monitoring applications. The results of successfully conducting FDI using an approach consisting of optimal filtering, statistical analysis, and fuzzy ARTMAP networks was illustrated on two very different systems. The fact that such an analytical redundancy based approach works to identify a failure in a nonlinear and complex system as with the testbed presented in this paper shows the versatility of the technique. The other state space model system was simply used to better describe how the method works. It is concluded that for complex systems it is best to use several transfer functions, each monitoring different single-input single-output relations, rather than a comprehensive mathematical model that covers all inputs, states, and outputs. The FDI algorithms are then applied individually to each transfer function, and are able to run in parallel for FDI of the entire system. Also, the ability to generate predictive statements in this paper was illustrated using a neuro-fuzzy architecture in which fuzzy membership functions are used to classify inputs and outputs, and fuzzy rules provide the appropriate mapping. It is also expected that the accuracy of the resulting neuro-fuzzy system is then better than that of a neural network used alone\(^6\), and as such, would present a considerable step forward for attaining reliable prognostics.

Future research is geared towards an FDI&P engine with a library of algorithms utilizing both data-driven and analytical-redundancy approaches that can be applied to any dynamical system. This entails the need to combine the
KF-SP-SCST-ARTMAP method with other well-established analytical redundancy approaches, such that fault detection can be conducted in synergy. Also the ability to automatically implement a neural network to complement the analytical redundancy approaches is an area of future work as well. Finally, in the event that a variety of algorithms are made available in the FDI engine, the ability to autonomously determine which method is most appropriate given expert knowledge of the system is a future and necessary step for complete implementation.

References