Spurious Symptom Reduction in Fault Monitoring using a Neural Network and Knowledge Base Hybrid System*

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Abstract

An approach to reduce number of spurious symptoms in aircraft engine fault monitoring is investigated. Two strategies were utilized. A set of rules designed to filter spurious symptoms was created. Then a neural network was designed to generate expectation value for each of the sensors monitored. The neural net was trained for a specific engine during normal operation. After capturing patterns for normal engine behavior in the neural net, an expectation value for the sensor is predicted. The success of this approach relies on generating better expectation values which in turn produce smaller variation from actual operating behavior and hence generate fewer spurious symptoms. Resulting hybrid system of neural networks and rule-based model demonstrates a drastic reduction of overall spurious symptoms.

1 Introduction

One of the challenges in airplane engine health monitoring is the fact that no two engines behave identically. Individual (serial number) engines may vary in behavior as much as 30%. If acceptable sensor deviation levels between expectation value and actual value are set at this level, recognition of valid symptoms is delayed or totally inhibited. Setting deviation values lower than 30% introduces spurious symptoms. Creating generic engine monitoring system is thus a difficult problem. An example is NASA's Faultfinder, an in-flight engine monitoring and diagnostic system [2]. The Faultfinder consists of three modules, an engine monitoring component called MONITAUR, followed by two diagnostic components: a rule based diagnostic system and a model based reasoning system shown in Fig.1. Using real engine data and an engine model for comparison, both spurious and real symptoms were generated by the MONITAUR module. These spurious symptoms resulted from the system's inablity to generate accurate expectation values from an internal engine model. As the spurious symptoms were passed on for diagnosis, the potential for erroneous diagnosis was increased.

The focus for the current work is to reduce spurious symptoms generated in MONITAUR. The first step in this task is to identify sources of spurious symptoms from results of healthy engine monitoring, generate rules which detect the spurious symptoms identified, and populate a knowledge base previously designed within MONITAUR to filter identified spurious symptoms.

The second step, and the thesis of this presentation, is to examine the feasibility of using a neural network and rule base hybrid as a "front end" and "back end" respectively to MONITAUR. The neural net front end, replacing the engine model, generates better expectation values than those generated by the engine simulation. The back end rule base (knowledge base) then filters out potential spurious symptoms.

2 Types of spurious symptoms

Before we discuss causes of spurious symptoms, we first describe five engine sensors, N_1, N_2, EPR, EGT, and FF. The N_1 and N_2 sensors measure the rotational speeds of the fan and high-pressure compressor, respectively. The fan and compressor generally rotate at different speeds because they are connected to different turbine stages. Fuel flow, FF, measures the rate at which the fuel is entering the engine. The EGT is the exhaust gas temperature.

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The EPR, engine pressure ratio, is a ratio of the air pressure at the exhaust divided by the air pressure at the engine inlet. In the MONITAUR module, each of the sensors listed are monitored for deviations in three attributes - absolute value, first derivative, and long term trend which is defined by an average slope of few seconds of time slices.

There are several sources of spurious symptoms.

- Model deficiencies produce poor expectation values which result in unacceptable deviations.
- Accurate modeling can produce nearly parallel expectation and actual curves with (short term) large deviations.
- Qualitative boundaries defined by MONITAUR can divide expectation and actual values.
- A lag factor between expectation and actual curves require a catch-up time factor.
- Sensor spikes and holes produce short term deviations.
- Sensor failure can apprear as a symptom.

Fig.2 whows a typical time-sensor value plot for a catch-up symptom.

3 Spurious symptom reduction by rule base and neural networks

Before an evaluation of techniques to reduce spurious symptoms could be attempted, a baseline of spurious symptoms had to be established. The approach used was to first examine healthy engine data. Ideally, monitoring a healthy engine should produce no symptoms. Data collection was confined to a single engine type since different manufacturer's engines manifested differing spurious symptoms. For the selected engine model, 9 data files of healthy engine data were used which had a total of 6900 data slices containing 35000 data points. A representative data subset was extracted for use as a baseline. This file was one of the 9 healthy engine files containing 115 data slices with two thrust lever advances followed by thrust lever retards.

The data was processed in batch mode by Faultfinder's MONITAUR module. In this procedure MONITAUR calls an engine simulation for generation of expectation values relevant to the current in-flight conditions. These values are compared by MONITAUR to the actual sensor data which was collected from the healthy engine during a flight. The baseline values obtained for spurious symptom generation are shown in Tables 1, 2, and 3.

3.1 Rule base spurious symptom reduction

The existing rule base from MONITAUR was populated with rules which would classify the symptom as spurious.

As the airplane sensor data is processed by MONITAUR, a set of symptoms are generated for each time slice. Before the symptoms are output from MONITAUR, the rule base is invoked to see if any symptoms are to be classified as spurious and need to be delayed.

When the representative baseline data set was processed with MONITAUR enhanced with the rule base filter, a reduction in spurious symptoms was achieved. A representative comparison of the results with the baseline by sensor is shown in Table 1.

	rule base	baseline
total # of spurious symptoms	35	256
# of time slices w/o symptoms	87	0
# of FF symptoms	4	97
# of N_1 symptoms	4	25
# of N_2 symptoms	9	31
# of EPR symptoms	3	11
# of EGT symptoms	15	92

Table 1: reduction of spurious symptoms by rule base. Total number of possible symptoms is 115.

To ensure that real symptoms were not being filtered by the rule base, a file of engine data containing a hung start fault was processed using this rule base. One symptom was delayed in recognition for two seconds, but none of the symptoms were removed or ignored by the rule base filter.

3.2 Spurious symptom reduction by neural networks

Second approach to reducing the number of spurious symptoms in healthy engine data is to create an adaptive engine model whose purpose is to produce better expectation values. The approach was to use a feed-forward neural networks to capture patterns of healthy engine behavior and generate an expected value for a given sensor. Since we have 5 sensors, we trained 5 separate neural networks for each sensor modeling. We also assume that each sensor output is correlated with others. In other words, the output of

EGT can be a function of $N_1, N_2, EPR, FF, \theta$, where θ represents throttle angle parameter, i.e.,

$$\begin{aligned} EGT &= f_1(N_1, N_2, EPR, FF, \theta), \\ FF &= f_2(N_1, N_2, EPR, EGT, \theta), \\ &\text{etc.} \end{aligned}$$

In addition to these input parameters altitude and air speed (MACH) information is available for in-flight test. Since our experiment was limited to a ground operation data we did not use the altitude and air speed information in this study.

In training a feed-forward network with backpropagation algorithm, we use the error function E,

$$E = \frac{1}{2}\sum_k (t_k - y_k)^2 + \lambda \sum_{i,j} w_{ij}^2,$$

where t_k and y_k are target value and actual network output of the kth output unit respectively, and λ is the regularization coefficient. Most of our simulations we use $\lambda = 10^{-5}$. The purpose of the penalty term in the above equation is to penalize large weight (w_{ij}) increase so that the trained neural net improves generalization capability [3]. Though we tried with different penalty terms and different network architectures with different learning methods such as recurrent network learning, we do not address network performances in this article.

To train the neural network off-line, we preprocessed each sensored data point (x) based on mean (M), standard deviation (σ), minimum ($\hat{x}_{min}$), and maximum ($\hat{x}_{max}$) for normalization x_n as following;

$$\hat{x} = (x - M)/\sigma, \quad \text{and,} \quad x_n = \frac{2\hat{x} - \hat{x}_{max} - \hat{x}_{min}}{\hat{x}_{max} - \hat{x}_{min}},$$

where $-1.0 \leq x_n \leq 1.0$. The $\hat{x}_{max}$ and $\hat{x}_{min}$ represent the maximum and the minimum of the $\hat{x}$ respectively. Fig.3 shows a typical result of network training by a training data file containing about 500 data points. Note that the model deficiencies are drastically reduced for EPR.

When the training is completed, the modified MONITAUR system is used to process the baseline data set. It is important to repeat that all the training sets and the baseline data must be generated from the same serial number engine. It is this engine's unique behavior that has been captured in the weight set during training. The results of processing the baseline test set of healthy engine data with expectation values generated by the neural network instead of the engine model is shown in Table 2.

	neural net	baseline
total # of spurious symptoms	96	256
# of time slices w/o symptoms	42	0
# of FF symptoms	51	97
# of N_1 symptoms	2	25
# of N_2 symptoms	8	31
# of EPR symptoms	2	11
# of EGT symptoms	33	92

Table 2: reduction of spurious symptoms by neural network.

Four healthy engine files from the same serial number engine were processed through MONITAUR with the neural network filter to cross validate the effect of the neural network. The neural net achieved at least a 40% reduction of spurious symptoms in the worst case. It should be noted that while a considerable reduction in spurious symptoms was achieved using the neural net, there were several instances in which the neural net did not perform as well as the engine model in predicting expectation value. In those instances spurious symptoms were generated by the neural net where none had been generated by the engine model. It is hypothesized that this condition was the result of incomplete training of the neural net and not necessarily a failure of the adaptive filter concept.

3.3 Spurious symptom reduction by a hybrid system

Once neural networks are trained, we apply networks as a "front end" to the MONITAUR module. Then we put the rule base as a "back end" to the module. A schematic is shown in Fig.4. Using the hybrid, the neural nets replace the engine model as a source of expectation values. This serves to reduce the number of spurious symptoms by generating better expectation values. Those spurious symptoms still generated were then filtered by the rule base. The ability to better filter the surviving spurious symptoms results from generation of better expectation values which makes the expectation curve more nearly coincide with the actual curve. Our analysis shows that the rules in the "nearly parallel" category are then more readily fired. The results of processing the baseline test set of healthy engine data with this hybrid is shown in Table 3.

	hybrid	baseline
total # of spurious symptoms	23	256
# of time slices w/o symptoms	96	0
# of FF symptoms	4	97
# of N_1 symptoms	0	25
# of N_2 symptoms	5	31
# of EPR symptoms	0	11
# of EGT symptoms	14	92

Table 3: reduction of spurious symptoms by neural net and rule base hybrid system.

4 Final remarks

A knowledge base of rules was constructed to filter known spurious symptoms and a neural network was developed to improve the expectation values used in the monitoring process. Both approaches were effective in reducing spurious symptoms individually. However, the best results were obtained using a hybrid system combining the neural net front end with the rule-based back in engine health monitoring.

This evaluation of strategies to reduce spurious symptoms should be discussed with the limitations of each approach in mind. Both approaches considered in this study are engine type dependent. The rule base constructed works for a specific manufacturer on a specific engine type. However the rule base filter is more generic than the neural net. The neural net should be trained for a specific serial number engine.

References

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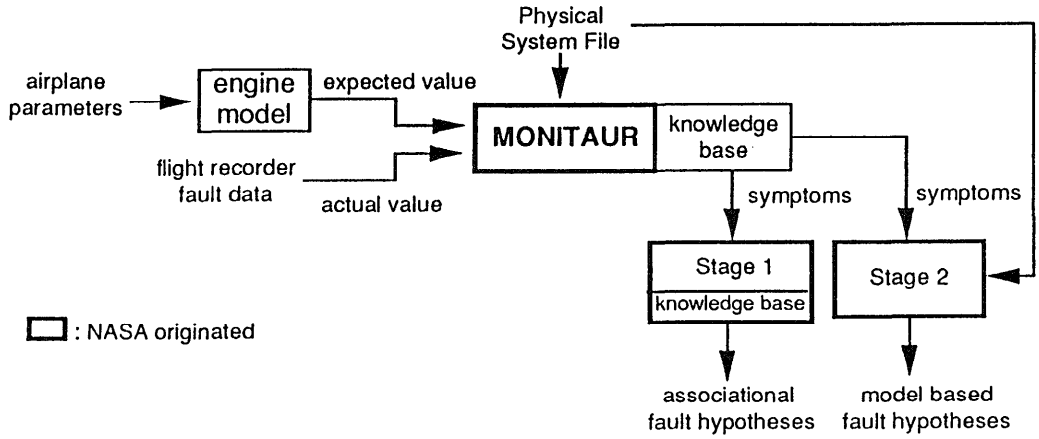

Fig.1. Engine Fault Monitoring in FAULTFINDER.

Symptoms generated by the comparison between expectation and actual values are passed to a rule based diagnostic system and to a model based diagnostic system.

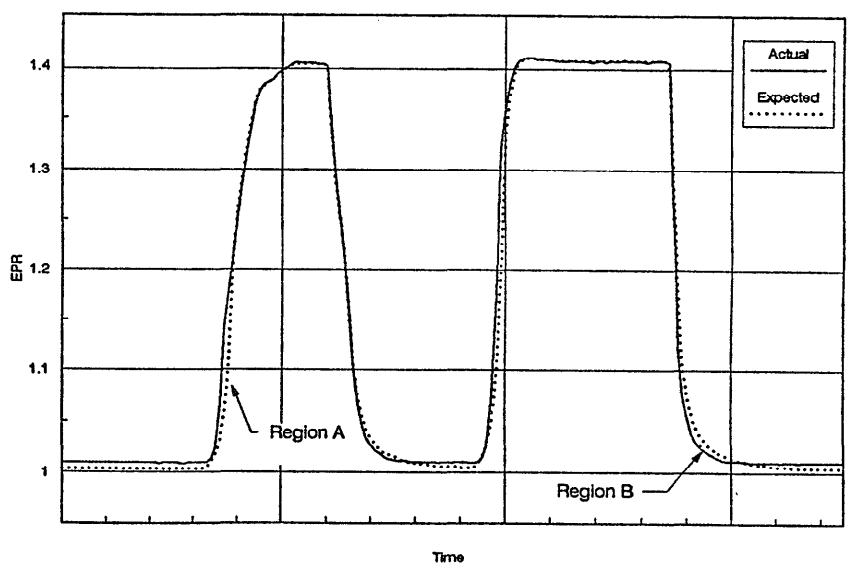

Fig. 2. Catch-Up Spurious Symptoms.

Typical time-sensor plot showing regions of spurious symptoms (A & B).

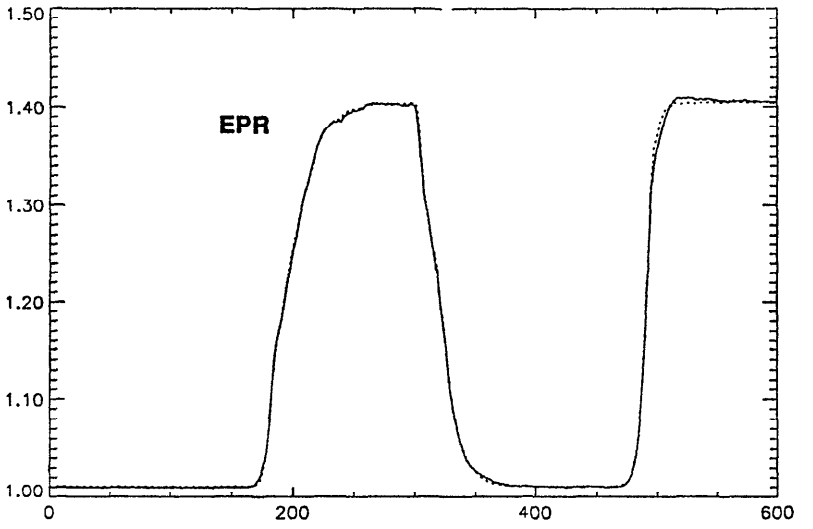

Fig.3. Actual and Neural Net Expectation Curves.

Regions of spurious symptoms are reduced as a result of better expectation.

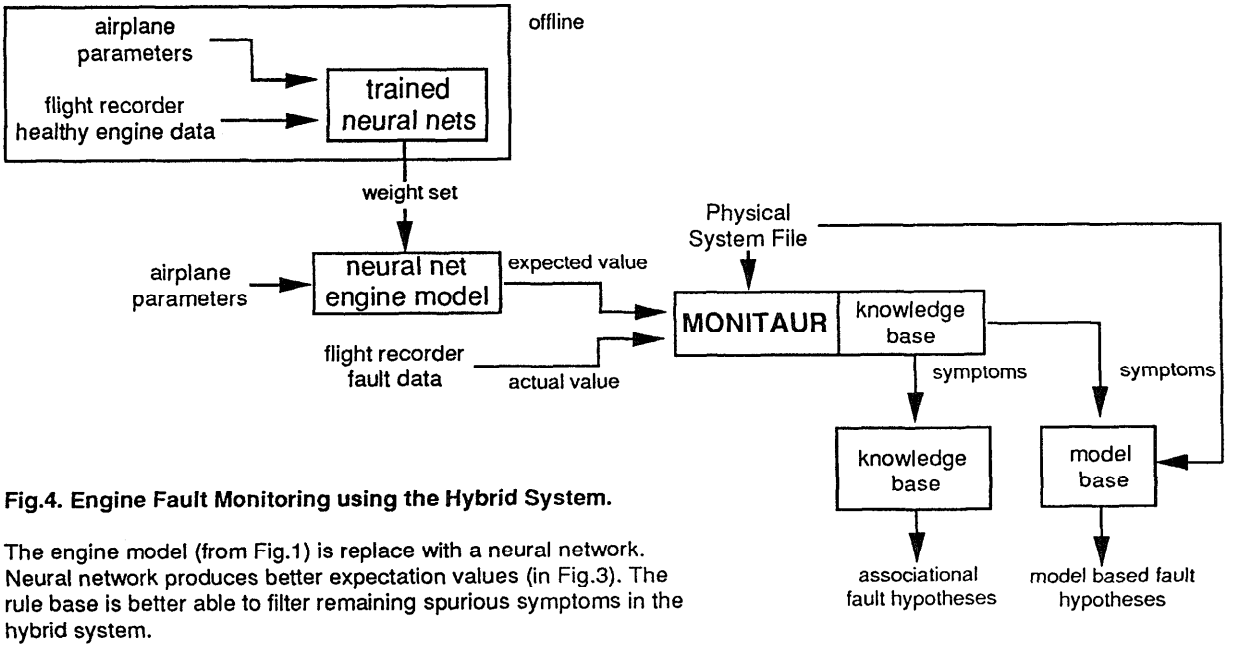

Fig.4. Engine Fault Monitoring using the Hybrid System.

The engine model (from Fig.1) is replace with a neural network. Neural network produces better expectation values (in Fig.3). The rule base is better able to filter remaining spurious symptoms in the hybrid system.