A RAPID HELICOPTER DRIVE TRAIN FAULT DETECTION USING ADAPTIVE-NETWORK-BASED FUZZY METHOD

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Abstract: Nowadays, there are several methods to monitor the health of the mechanical systems through the vibration signals acquired during the running time of machines. One of the trends is to build systems that are capable of self learning and self diagnosis basing directly on the vibration signals. This paper discusses about a new application of the adaptive-network-based fuzzy logic method to detect the failures of the mechanical systems through their vibration signals.

1 INTRODUCTION

The helicopter maintenance is fulfilled by scheduled work cards. To improve the flight safety and also to reduce the operation and maintenance cost, a health and usage monitoring system (HUMS) is required to monitor the health of helicopters. The system uses the vibration signals from the drive train components and/or that from the cabin to analyze the current state of the helicopter. In case of fault detection, a warning will be triggered off to alert the maintenance service. If the system considers the detected fault is serious enough, the aircraft may be grounded for further checks.
Nowadays, the HUMSs use the indicators calculated from the vibration signals acquired after each flight to monitor the helicopter's health. The faults are detected through those indicators. One of the advantages of this method is the simplicity. In theory, the indicators are more representative than the vibration signals themselves and the abnormalities of the indicators' values will identify the faults incorporating to components. However, the real conditions are so complex so that to achieve to a certain level of precision, the number of indicators becomes large and several signal processing methods would be applied.
One of the trends to improve the performance of the system is to build systems that are capable of self diagnosis basing directly on the vibration signals. The inspiration of human intelligence such as the decision making and the learning processes of the nervous system leads to such methods as the neural networks and adaptive-network-based fuzzy inference system. In this paper, we present a new application of adaptive-network-based fuzzy inference system to detect faults by vibration data. The advantages of adaptive-network-based fuzzy inference system are the self learning, decision making and modeling capabilities for complex, non linear problems. By training the system with the vibration signals of mechanical systems in normal states, the system will be able to detect the cases that correspond to the mechanical failures without dealing with a great number of indicators.

In brief, the indicators are different features (e.g. 1/REV, 2/REV, RMS, etc.) from each set of time domain data. The analyses then are based on the evolution of each of those features to detect faults. By contrast, the adaptive-network-based fuzzy inference system detects and diagnoses faults by comparing the current data with healthy-identified data and/or with faulty-identified ones.

2 FAUTL DETECTION WITH ADAPTIVE-NETWORK-BASED FUZZY INFERENCE SYSTEM

The adaptive-network-based fuzzy inference system is a particular fuzzy inference system which bases on adaptive network-type algorithm. The membership function parameters that best allow the associate fuzzy inference system to track the input/output data are computed by an information learning procedure. The learning procedure uses the hybrid learning algorithm (backpropagation and gradient descent).

2.1 Fault detection overview

The fault detection is the first phase of the diagnosis process. In fact, the operators need at first range the general status of the helicopters to assure that the helicopters are to be in service or not.

In case that faults (crack, lost of torque, etc.) occur and propagate, the vibration data would be modified compared to the normal evolution of the signals from the drive train. These modifications represent faults. However, the lion share of vibration data correspond to the healthy state. Thus, if the analysis process may identify the healthy data without doing complex tasks, the analysis system would be faster and simpler.

The fault detection phase described below will classify the input vibration data as healthy or not by applying a test. The result of the test, a so-called health level, helps to automatically classify the data. If the data is classified as healthy, the module generates a report so that the helicopter may continue to operate. By contrast, if the data is classified as faulty, further analyses – diagnosis phase, will take place.

On the fault detection phase, see the diagram below (Figure 1).

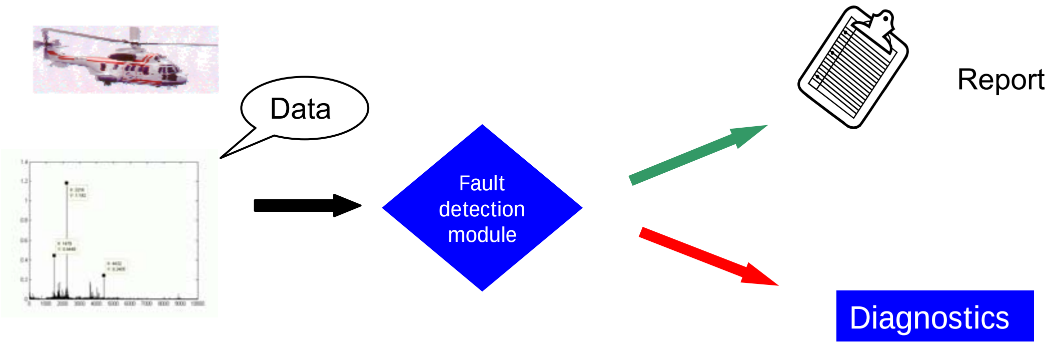

Fig.1: *Fault detection*

2.2 Adaptive-network-based fuzzy inference system for fault detection

The module learns from healthy-classified data and generates a set of parameters. These parameters will be used to test any other data. The result of the test classifies the health state of the helicopter at the moment associated with that set of data.

The algorithm includes 2 steps:

- Parameters set up
- Test and classify data.

<u>Step 1</u>: Parameters set up

The fault detection module includes indeed a set of parameters. To generate this set of parameters, we use the adaptive-network-based fuzzy inference system (ANFIS). To set up the system, a number of inputs and an output are assigned. By default, the output value is fixed as 1. As the inputs and output of the ANFIS are vectors of the same lengths, the output is a vector of 1. To classify the input, each output vector is represented by a value, which is assigned as the health level indicator of the data.

The characteristics of the chosen ANFIS (Figure 2):
- 2 input vectors
- 1 output vector
- Sugeno-type fuzzy inference system (5 layers)
- Membership functions: Bell-shaped functions, 5 membership functions per input.

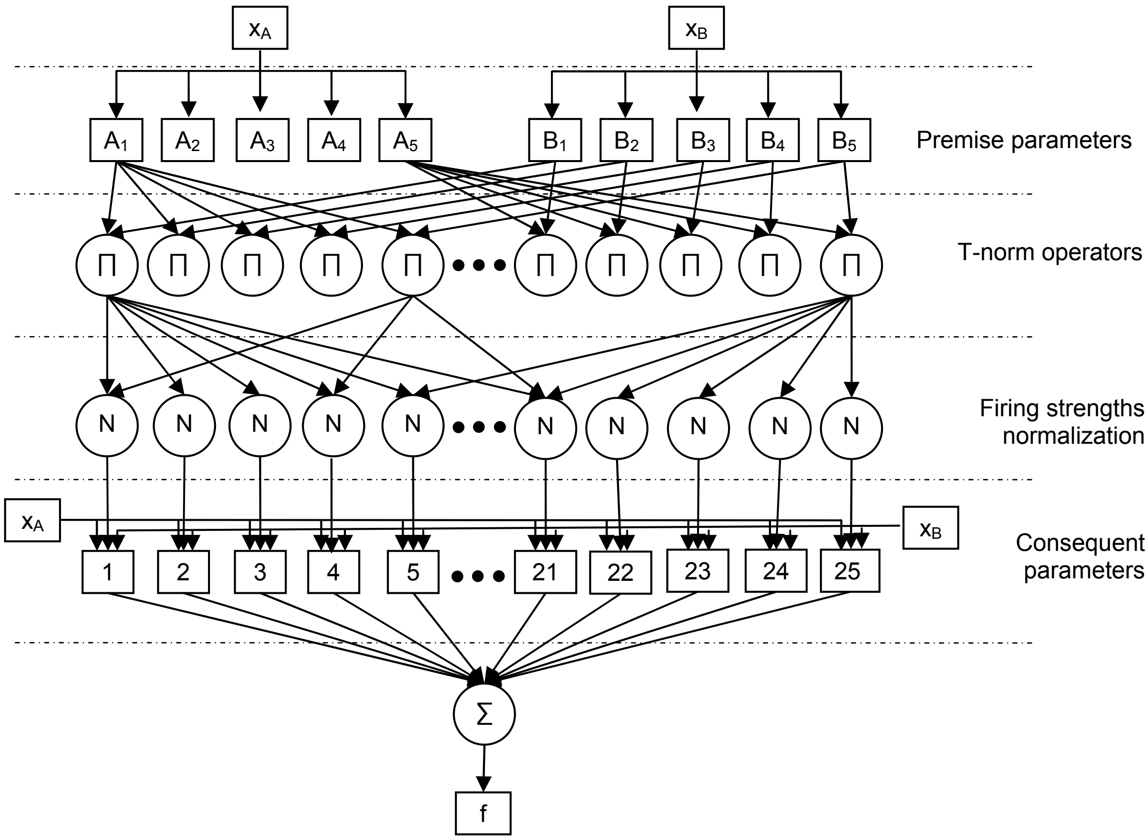

Figure 2: Adaptive-network-based fuzzy inference system (ANFIS) architecture

ANFIS architecture:
- Input vectors: two 1-by-n vectors, frequency domain values.
- Out put vectors: 1 vector of 1 by format, same size with the input vectors. In general, the output can be represented as:

$$output = \phi(parameters, input) \tag{1}$$

The fuzzy inference system has two inputs x_A, x_B and one final output f. The system's rule base contains 5 fuzzy if-then rules, type Takagi-Sugeno:

Rule i (i=1, 5): If x_A is A_i and x_B is B_i then output $f_i = c_{Ai}x_A + c_{Bi}x_B + r_i$ (2)

The membership values on the premise part are then combined to get the firing strength (or weight) w_i of each rule. In a general ANFIS structure, the "weights" are usually a product or "And" operator. These operators are referred to as triangular norm (T-norm) ones, which meet the requirements:

- boundary ($T(0,0) = 0$, $T(a,1) = T(1,a) = a$): impose the correct generation of the crisp sets.
- monotonicity ($T(a,b) \le T(c,d)$ if $a \le c$ and $b \le d$): a decrease (or increase) in the membership value in A or B cannot results in a increase (or decrease) in the membership value in A intersection B.
- commutativity ($T(a,b) = T(b,a)$): the operator is indifferent to the order of the fuzzy set to be combined.
- associativity ($T(a,T(b,c)) = T(T(a,b),c)$): the intersection of any number of sets in any order of pairwise groupings has the same results.

The qualified consequents of the rules are then aggregated to produce the final output:

$$f = \frac{\Sigma w_i f_i}{\Sigma w_i} = \Sigma \overline{w}_i f_i \tag{3}$$

The system has therefore 5 layers.

- Layer 1: Each node of the layer associates to a membership function.

$$O_i^1 = \mu_{A_i}(x) \tag{4}$$

where O_i^1 is the function associated to the node i of layer 1, x is the input and A_i is the linguistic label of the node. The membership function used in the module is the bell-shaped function:

$$\mu_{A_i}(x) = \frac{1}{1 + \left[\left(\frac{x - c_i}{a_i}\right)^2\right]^{b_i}} \tag{5}$$

The bell-shaped membership function (MF) that obtains the values in the interval (0,1] and one of the advantage of the function is its smoothness. The set $\{a_i, b_i, c_i\}$ is the parameters set of the function: when the values of the set vary, the form of the function varies respectively. Parameters of this layer are referred to as premise parameters which are updated by the gradient descent as the error rates propagate backward (hybrid learning algorithm).
The fault detection module uses 5 bell-shape functions for each input. The figure (4) below maps each element of the input to a membership value.

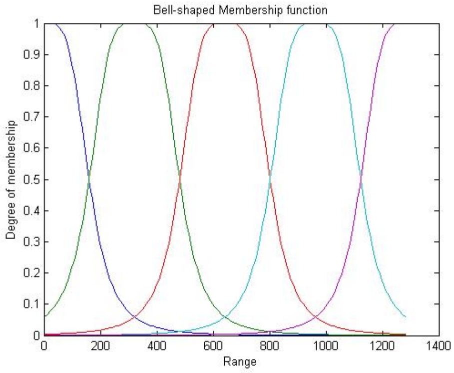

Figure 3: Bell-shaped membership functions: 5 for each input.

- Layer 2: Each node in the layer associates with a T-norm operator. For example, an operator may multiply the incoming signals and send the product out:

$$w_i = \mu_{A_i}(x_A) \times \mu_{B_i}(x_B) \tag{6}$$

Or an "AND" operator will generate the output from incoming signals as:

$$w_i = \min\left(\mu_{A_i}(x_A), \mu_{B_i}(x_B)\right) \tag{7}$$

- Layer 3: The layer will normalize the firing strengths (the "weights"): the i-th node determine the ratio of the firing strength of the rule i to the sum of all rules' firing strength:

$$\overline{w_i} = \frac{w_i}{\Sigma w_i} \tag{8}$$

- Layer 4: The i-th node of this layer associates to a node function O_i^4:

$$O_i^4 = \overline{w_i} f_i = \overline{w_i}\left(c_{Ai}x_A + c_{Bi}x_B + r_i\right) \tag{9}$$

where $\overline{w_i}$ are the outputs of layer 3 and $\{c_{A_i}, c_{B_i}, r_i\}$ is the parameters set. The parameters of this layer are referred as consequent parameters and are identified by the least square estimate in the forward pass of the hybrid learning algorithm.

- Layer 5: The layer determines the final output of the system as the summation of all incoming signals from layer 4.

$$O_i^5 = \sum_i \overline{w_i} f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \tag{10}$$

<u>Step 2</u>: Test and classify data

Once the parameters are set up, the faults detection module can analyze any flight data to detect faults. Each flight data will be represented by an output value, defined as "health level". As the module's parameters are adjusted by the above process so that the health level output will be close to 1 in case of healthy signal. The health level in fact is the energy of the output vector so that this indicator's behavior is linear: the low values correspond to healthy state of the helicopter and the high values correspond to faulty state (Figure 4).

The tests on classified helicopter data help to determine the threshold for the health level indicator. For the Super Puma, the threshold may be fixed for amber and for red type alarms for all machines.

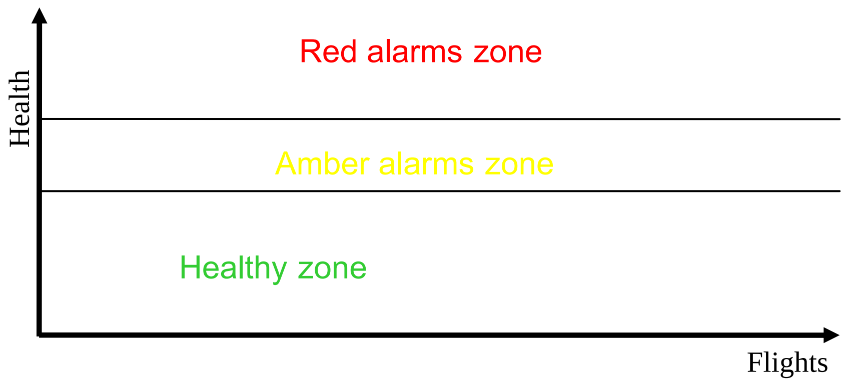

Figure 4: Health level and threshold.

3 MODEL VALIDATION

3.1 Choice of test data

The objective of the model is to detect the failures or faults appear in the vibration signals acquired during each flight. The validation of the model is based on a set of data from aircrafts that the information of fault detections and components replacements are determined. There are two categories: normal cases and fault detected cases. As the history of the aircraft is determined, we choose the vibration data near to the failure / components removal moments to test the output of the model to detect the failures. The data from the normal operational events are chosen as well to validate the model.

3.2 Model validation

The results from the test cases show a good detection capacity of the model: closer to the failure / component replacement events, the level of the output is higher than 1 – level defined for healthy states. The model is also capable to detect fault cases that the traditional indicators-based method ignores (only detected or reported by maintenance checks). In other words, the adaptive-network-based fuzzy inference system described in this paper may improve the performance of the fault detection for HUMS.

In the Table 1 below, we represent the performance of our fault detection module in comparison with the current monitoring system using the classical indicators. The chosen flight data are associates with the maintenance records on helicopters' state (in case of "No report", we assume that the helicopter was in good condition during the period where its data are available).

Case	State	Maintenance check	Flying hours	Fault detection Module	Current alarm level
1	Faulty	Hydraulic pump bearing play	968	yes	no
2	Faulty	Intermediate gear: lost of torque	86.03	yes	no
3	Faulty	Intermediate gear: lost of torque; Engine shaft: worn	372.8	yes	yes
4	Faulty	Intermediate gear: lost of torque	336.92	yes	no
5	Faulty	Intermediate gear: worn	78.52	yes	yes
6	Faulty	Intermediate gear: lost of torque	267.37	yes	yes
7	Faulty	Intermediate gear: slightly lost of torque	50.92	yes	yes
8	Faulty	Intermediate gear: lost of torque	194.47	yes	manual

9	Faulty	Intermediate gear: lost of torque	251.02	yes	yes
10	Faulty	Intermediate gear: lost of torque	336.88	yes	yes
11	Faulty	Intermediate gear: lost of torque	232.45	yes	yes
12	Faulty	Intermediate gear: lost of torque	77.43	yes	yes
13	Faulty	Intermediate gear: lost of torque	49.44	yes	no
14	Faulty	Intermediate gear: lost of torque	195.99	yes	yes
15	Faulty	Hydraulic pump bearing and shaft: worn and slightly break	36.53	yes	no
16	Healthy	Fault free report	877.78	no	n / a
17	Healthy	Fault free report	2019.85	no	n / a
18	No report	No fault report	1829.84	no	n / a
19	No report	No fault report	1608.58	yes	n / a
20	No report	No fault report	1479.9	no	yes
21	No report	No fault report	1093.09	no	n / a
22	No report	No fault report	218.5	no	n / a
23	No report	No fault report	148.74	no	n / a

Table 1: Fault detection performance

4 CONCLUSION

The fault detection using adaptive-network-based fuzzy inference system shows a better performance compared to classical method using indicators which are retrieved from vibration data of helicopters during the flights. By using the same process and only two flight data to set up the system, the method allows to detect faults on different types of helicopters. And the introduction of health level indicator helps to classify the normal and faulty states of helicopters without testing a large number of indicators.

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