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Research Article

Aircraft Actuator Performance Analysis Based on Dynamic Neural Network

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Monitoring the condition of the aircraft actuators in various operating and environmental circumstances, this paper presents a method for measuring the surface roughness of aircraft actuators. The proposed method starts with the current and vibration signal as failure indicators and a dual-tree complex wavelet transformation (DTCWT) to generate the necessary features. Time-delay neural networks (TDNNs) have been developed for real-time performance monitoring to categorize problems and determine their severity. The simulation results show that the suggested method can accurately identify various faults.

1. Introduction

Health monitoring and predicting the severity of the fault, especially for critical applications, are essential for avoiding unwanted events and improving activity. Electromechanical actuators (EMAs) are becoming more popular in flight control surfaces as actuation devices. However, EMAs frequently operate under fluctuating operating conditions. The present work aims to create a dependable condition monitoring system that will allow EMA to maintain the general safety of new aircraft design. As a result, early detection of defects in the monitored process allows for critical preventive actions. The EMA surface turns out to be an unwanted vibration signal directly related to the location of the defective part [1]. However, it has been shown that the vibration signal may be related to other mechanical parts which may lead to a false alarm. So, to increase the diagnostic reliability of the proposed fault analysis technique, current can be used with vibration signals as an additional fault indicator, especially for critical applications [2]. The current sensor is still separated from power safety circuits, so it does not necessarily reflect other power system costs [3–5]. To extract valuable features, DTCWT is a suitable method for analyzing motor signals to provide features in the time-frequency domain under different speed and load conditions. DTCWT's work is to decompose the signal into a set of (detailed and approximate) subcomponents [6, 7].

The redundancy wavelet features should be removed for an accurate and reliable diagnosis system. A powerful feature reduction tool is needed to avoid redundancy that affects classification accuracy. Many diagnostic techniques have been developed, and they can be divided into groups according to the indication signals they use such as current, voltage, temperature, vibration, and sound. More than often, vibration signals are used for fault analysis. However, the vibration signal will be feeble at low speeds and may connect to other motor mechanical components. The current signal has been added as another problem indicator together with the vibration signal to improve diagnostic accuracy [8]. To avoid high dimensionality, both the principle component analysis (PCA) and linear discriminant analysis (LDA) were used [7]. However, PCA limitation is the ability to manage the dynamic behavior of data. Although LDA is a limited dimension reduction (class number-1), this will affect the best classification projection directions [9].

Recently, soft computing algorithms based on fault recognition are becoming more popular for various reasons such as using input and output data without model information or human experience [10–12]. Due to the ability to classify conditions, NN is commonly used among various pattern recognition tools to diagnose electrical machinery faults. Thus, the EMA's fault diagnosis technique is based on decomposing the variation mode (VMD) for extraction features than reducing the extracted features using PCA [13]. Optimization features feed to the probabilistic neural network (PNN) for fault classification; most industrial systems have nonlinear structures. They have considered the dynamic behavior of the electric EMA motor which was overlooked in previous techniques. Thus, dynamic neural networks (DNNs) for modeling nonlinear dynamic systems receive a lot of attention because of their capabilities. An effective modeling mapping should be performed where DNN output is based on the network's current and past inputs, outputs, or states. However, the conventional static NN cannot yield a degree [14]. Most contributions to the current work's field fault analysis of electrical machinery can be summed up as follows: building a test to see how the EMA motor would perform in various generalized (corrosion) variable and constant situations. Using current and vibration signals, mimicking vibration signals as a problem indicator has been defeated to provide a dependable diagnostic method. In addition, a dynamic TDNN algorithm that considers the dynamic behavior of electrical machines has been created. The majority of earlier work was focused on static NN for fault classification. The structure and content of the paper start with introductory material, and Section 2 summarizes the current methods used for fault diagnosis. Moreover, a feature extraction tool is introduced in Section 3. In Section 4, a description of a ground-breaking defect prediction method based on dynamic neural network architecture follows. Section 5 contains a discussion and comparison section. Lastly, Section 6 provides conclusions.

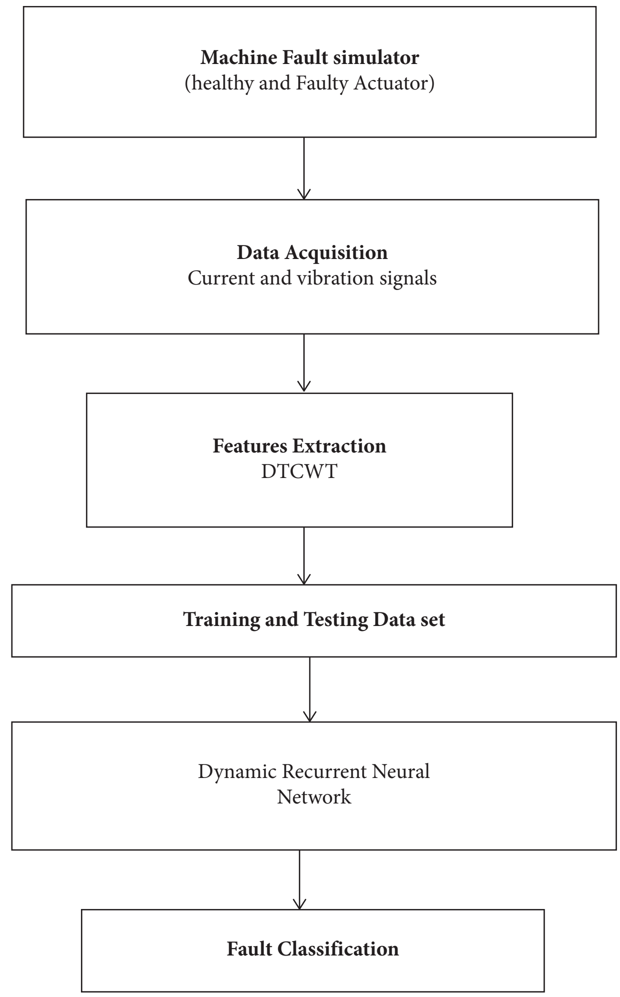


Figure 1: Proposed fault analysis technique.

2. Feature Extraction

The proposed fault analysis consists of three significant steps as shown in Figure 1. The EMA motor raw stator winding current and vibration signals are observed in healthy and faulty conditions with a total dataset size of 36, sampling rates of 300, and 15,000 samples per test. Then, using DTCWT, the time and frequency domain features are retrieved. By using wavelet window length 50, 300 features are obtained. Figure 2 illustrates the DTCW-reconstructed signal. One tree's low-pass (scaling) and high-pass filters are implemented as independent two-channel filter banks in DTCWT. Wavelet coefficients and scale coefficients can be employed to improve signal processing. Furthermore, the two trees' complex-valued scaling functions and wavelets are analytic. As a result, DTCWT has less shift variance and more directional selectivity for two-dimensional data than critically sampled DWT with simply a redundancy factor. DTCWT has substantially less redundancy than undecimated DWT [7]. The two discrete wavelets are $\psi h(t)$ and $\psi g(t)$, respectively, and by converting them to the complex domain, the double-tree complex wavelet is formed. The wavelet is as follows:

$$\psi(t) = \psi h\ (t) + i\psi g(t), \tag{1}$$

where $\psi h(t)$ is the real tree wavelet and $\psi g(t)$ represents the imaginary tree wavelet (both are real wavelets and I represent a complex unit). The real wavelet coefficients and scale coefficients for a real tree can be derived using wavelet transform theory from the inner product operation as follows:

$$\begin{aligned} \mathrm{cIJ}^{\mathrm{Re}} &= 2^{j/2} \sum_{-\infty}^{+\infty} x(t)\mathrm{yh}\left(2^{j} t - k\right)\mathrm{dt},\ j = 1, 2 \ldots, J, \\ \mathrm{cIJ}^{\mathrm{Re}} &= 2^{I/2} \sum_{-\infty}^{+\infty} x(t)\mathrm{yh}\,(2\wedge j\, t - k)\mathrm{d}t, \end{aligned} \tag{2}$$

where i is the scale factor and j is the most significant scale. Similarly, an imaginary tree's wavelet coefficients and scale coefficients are as follows:

$$\begin{aligned} \mathrm{dIJ}^{\mathrm{Im}} &= 2^{j/2} \int_{-\infty}^{+\infty} x(t)\psi g\,(2\mathrm{jt} - k)\mathrm{dt}, \quad j = 1, 2., J, \\ \mathrm{cIJ}^{\mathrm{Im}} &= 2^{I/2} \int_{-\infty}^{+\infty} x(t)\psi g\left(2^{j} t - k\right)\mathrm{d}t. \end{aligned} \tag{3}$$

The DTCWT's wavelet coefficients and scale coefficients can be calculated using the formula above as follows:

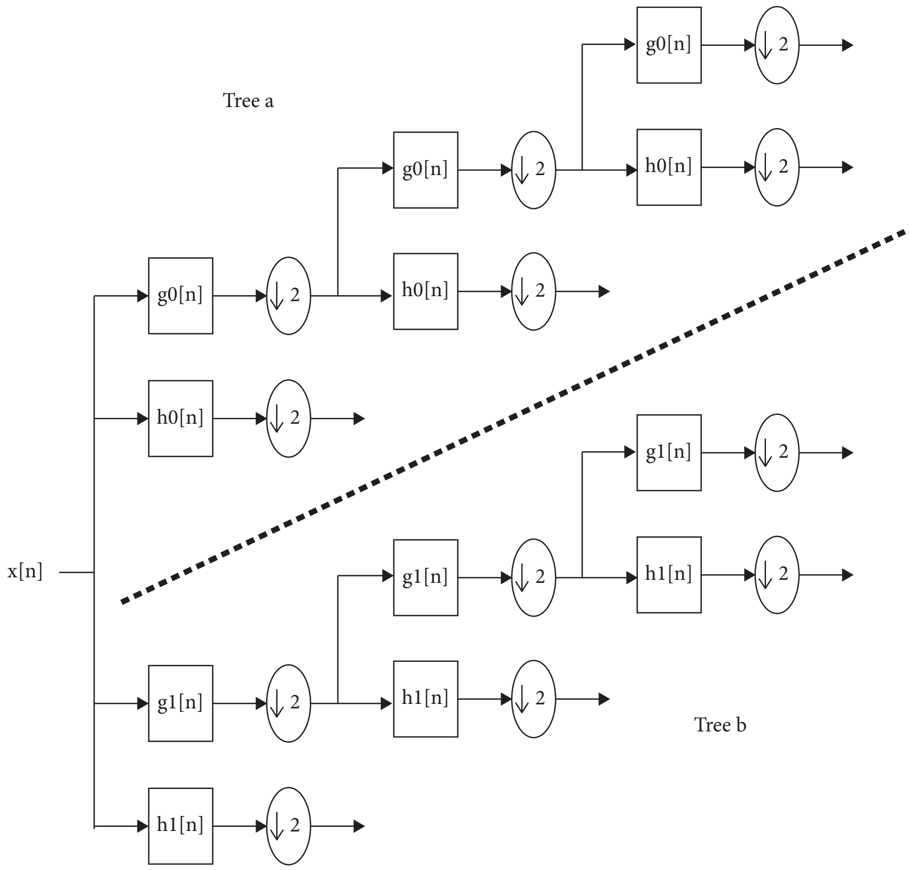


Figure 2: DTCWT structure.

$$\mathrm{d}J^{\phi}(k) = \mathrm{dIJ}^{\mathrm{Re}}(k) + i\mathrm{dIJ}^{\mathrm{Im}}(k), \; j = 1, 2, \ldots, J,$$
$$\mathrm{CJ}\wedge\phi\;(k) = \mathrm{cIJ}\wedge\mathrm{Re}\;(k) + \mathrm{CIJ}\wedge\mathrm{Im}\;(k). \quad (4)$$

The wavelet coefficients and scale coefficients after signal reconstruction are as follows:

$$C(J) = 2^{2J-1}\left[\sum_{k=-\infty}^{\infty} \mathrm{cIJ}^{\mathrm{Re}}(k)\psi h'\;(2t-k) + \sum_{k=-\infty}^{\infty} \mathrm{dIJ}^{\mathrm{Im}}(k)\psi g'\;(2t-k)\right],$$
$$x\wedge(t) = \sum_{J=1}^{J} \mathrm{d}j(t) + \mathrm{cJ}(t)\; j = 1, 2, , J. \quad (5)$$

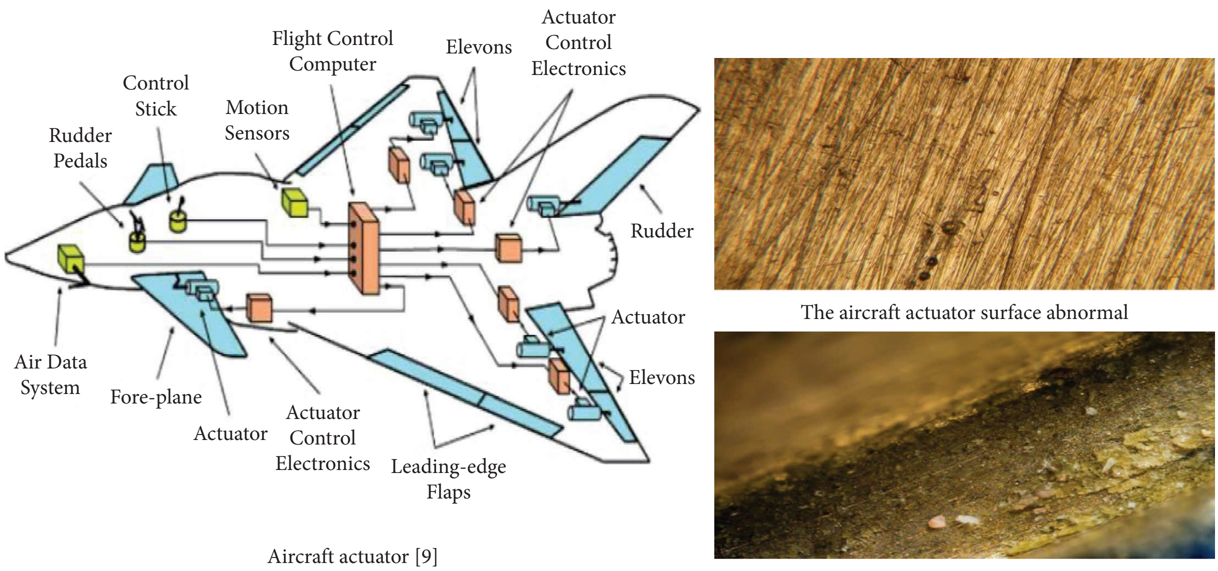
The components of the various frequency bands can be obtained by reproducing the wavelet and scale coefficients. Because $h(t)$ and $g(t)$ are a Hilbert transform pair, the double-tree complex wavelet has many positive characteristics including translation invariance frequency mixing suppression and two low-pass filter coefficients. We match the requirements for the following sample delay.

In the first level of decomposition, the interval of sample values coincides with the delay between the real and imaginary part filter banks. The second sampling yields a complementary link, meaning that the data sampled by the imaginary component are the same as the data not sampled. The actuator motor is simulated with the SimPower system toolbox using Matlab/Simulink environment.

The resultant features are used as input to TDNN that introduces the classification of faults and predicts their severity.

3. Level of Fault Severity Prediction

Most industrial systems are dynamic and nonlinear, and it appears ideal to use models that can describe the system's dynamics during fault identification to maximize operational reliability and optimize preventive maintenance. Furthermore, DNNs succeed in learning the dynamics of complex nonlinear systems, while traditional static NNs fail to provide and perform appropriate modeling representation and mapping.



Aircraft actuator [9]

Aircraft actuator surface at faulty condition [10]

Figure 3: Aircraft actuator surface with normal and corrosion defects.

Initially, the network input vector of the DNN is a moving window on the load time series, and it is trained using historical demand data. As time goes on, the NN weights are dynamically modified. It is typical to conclude that the networks will perform consistently well for the predicted demand trends once validated on the test data. The suggested technique in the current study has been tested with various applications [15–18] and does not require dynamic BP to compute the network gradient static MLP network. The TDNN, such as other neural networks, operates on multiple interconnected layers of perceptron and is implemented as a feed-forward neural network in which all neurons (at each layer) receive input from neuron outputs, where $x(t)$ and $y(t)$ are the input and output, respectively.

The system's operating conditions are needed to estimate the useful life of the EMA engine components (see Figure 3). It helps to analyze the information that indicates the system's behavior. The proposed feature reduction technique described above was prepared to eliminate any undesirable features of DWT from 12 to 4 for faster computing.

These features represent five TDNN network inputs and TDNN works with interconnected layers as a forward NN feed. We receive feedback from inputs at each layer neuron.

Table 1 demonstrates the capacity of the TDNN to diagnose rare conditions using training, testing, and validation data collection. The EMA engine was examined under variable speed and load conditions, and Figure 4 shows the performance of the current approach. The figure indicates that the length of misclassification periods is less than 0.7 s; thus, all misclassifications can be ignored [19, 20].

4. Results, Discussion, and Comparison

The present fault diagnostic technique compares with recently published works on artificial intelligent techniques, feature extraction, and dimensional reduction tools.

Vibration and current signals were recorded and shown in time and frequency domains to indicate normal and corrosion faults under various speed and load situations. The indirect way to evaluate the system's state is by collecting vibration and current signals and extracting useful features during simulation tests. A fault analysis based on time- and frequency-domain data is unreliable, especially when there is a large variety of fault severities and operational conditions. Liu [21] used PCA as an extraction technique and current diagnostic function and measured to extract useful data for the training and testing of the PNN. DWT of current signals was used with Welch's spectral density analysis in the experimental test to monitor EMA performance [22–25].

In addition, due to the nonlinear operating environment, it is challenging to accurately assess the operating condition by analysis in the time or frequency domains. Any pattern recognition system's first step is often feature extraction, and the most crucial step in pattern recognition is extracting the suitable feature set. Hence, every pattern classification system's effectiveness largely depends on the features selected to represent continuous-time waveforms.

DTCWT overcomes the shortcomings of other signal processing methods and can identify stationary and nonstationary signals, with the windowing of DTCW automatically adjusted for low and high frequencies.

In the current work, the EMA engine was tested under different load conditions at a constant speed, and the results show a mean accuracy of approximately 98.235, 97.30, and 95.46 percent. At the same time, the mean forecast fault accuracy under nonstationary rotation and constant load is 98.19, 96.36, and 97.63 percent. The overall classification accuracy is approximately 99 percent.

Table 1 displays the overall categorization accuracy. The performance of diagnostic accuracy is shown in Figure 4 where the y-axis shows how well current methods for

Table 1: Comparison of the current approach with related works.

Related works	Fault indicator	Features extraction	Fault classifier	Classification accuracy (%)
Camarena-Martinez et al. [26]	Stator current	Empirical mode decomposition	Static NN	90
Andrijauska et al. [27]	Stator current	DWT	Support vector machine	99
Zhang et al. [28]	Vibration signal	Empirical wavelet transform	Bistable stochastic resonance	97
Moloi and Yusuff [29]	Vibration signal	DWT	GA, NN	95
Current approach	Current and vibration signals	DTCWT	TDNN	99

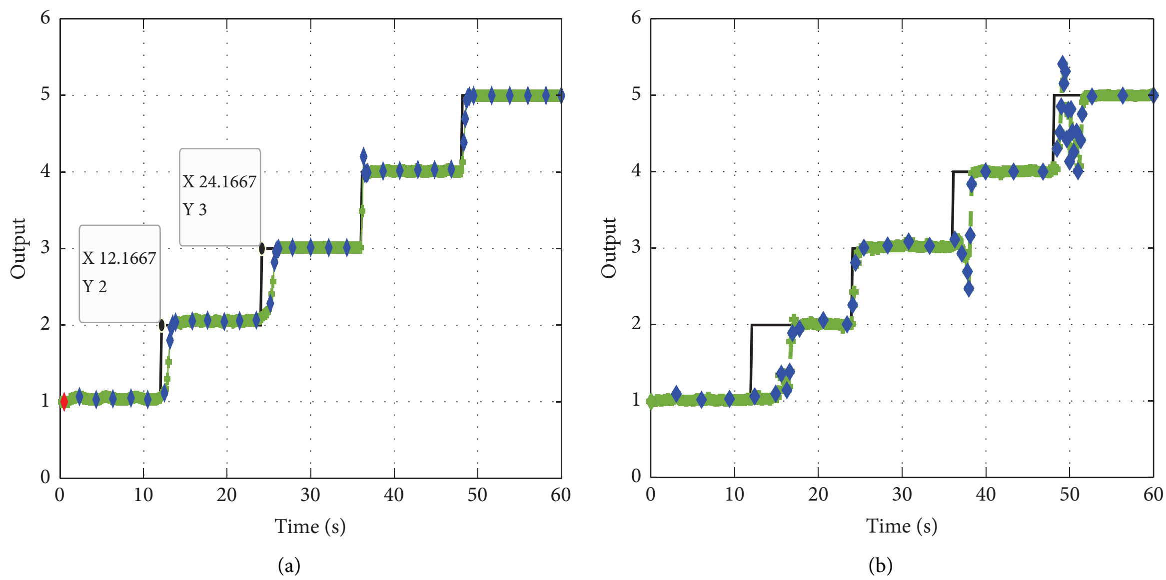


Figure 4: Prediction accuracy of corrosion fault at variable load and constant speed (1200 rpm). (a) Full load. (b) Half load. (c) No load.

diagnosing faults compare TDNN output to the target. Figure 4 illustrates misclassification; such times would not be apparent. Hence, all incorrect classifications can be regarded as random and disregarded.

The suggested defect detection technique is compared in Table 1 with the recently published research study based on feature extraction, soft computing techniques, and dimensionality reduction tools. Since the wavelet transform consists of many levels and provides information in both the time and frequency domains, it is more ideal for diagnostic purposes than for the fast Fourier transform and is superior to the short-time fast Fourier transform which has a constant window. The DTCWT technique helps determine the location and severity of defects. Most industrial systems are dynamic and nonlinear, and it is ideal to use models that can capture the dynamics of the system during fault identification. Therefore, providing a powerful tool for real-time analysis and process monitoring is essential. There are two types of NNs: static and dynamic. In static NNs, there are no delays or feedback because the output is calculated immediately from the input using feed-forward connections. However, in DNN, the output is based on the network's inputs, outputs, and states from the present and the past. Studies have demonstrated that adopting DNN can help increase the reliability of electric motor condition monitoring systems since they are often more active than static NN.

Underfitting will occur in the hidden layers of the NN when insufficient neurons are present. Underfitting occurs when there need to be more neurons in the hidden layers to identify the signals in a complex dataset accurately. Conversely, overfitting can happen when too many neurons are in the hidden layers. Overfitting happens when the NN can process so much data that the small amount of data in the training set is insufficient to train all neurons in the hidden layers properly.

DNNs have been used to diagnose faults successfully; they outperform their static counterparts and can learn the dynamics of complex nonlinear systems which the standard static NN cannot describe. An aircraft actuator is a dynamic system so the use of TDNN for fault diagnosis is more suitable compared with the static neural network that is implemented in most of the previous work [26–29].

Camarena-Martinez et al. [26] used empirical mode decomposition features under variable load conditions to train static NNs, and the overall fault classification accuracy is 90%. At the same time, Andrijauska et al. [27] and Zhang et al. [28] used current and vibration signals, respectively, as fault indicators and WT as feature extraction tools to train and test different soft computing techniques. Meanwhile, Moloi and Yusuff [29] used continuous DWT to train GA and NN under variable speed conditions.

5. Conclusions

The current work analyzes the aircraft's EMA performance using an intelligent approach. Generalized roughness (corrosion) is considered in this work. EMA was tested under constant, variable conditions during the simulation test engine. EMA engine stator current and vibration signals were collected as fault indications. Many defects are used to support the ability of the proposed technique. DTCWT is implemented as an efficient method to extract functions. However, to improve the fault classification accuracy, WT features alone cannot achieve the optimum characteristics. Then, these features are used in real time for the training and testing of TDNN.

The obtained results illustrate the ability of the proposed technique to classify unwanted defects with high accuracy under variable load and speed conditions by comparing them with the previous related work.

The application of these techniques has shown the capability of the presented technique for detecting and classifying faults under variable operating working conditions with high accuracy. Some of the features are redundant features that may affect diagnostic accuracy. So in future works, the dimensionality reduction approach should be used to improve the proposed diagnostic performance.

Data Availability

Data available on request.

Conflicts of Interest

The author declares that there are no conflicts of interest.

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