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# Fault detection and isolation of a dual spool gas turbine engine using dynamic neural networks and multiple model approach

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In this paper, a fault detection and isolation (FDI) scheme for an aircraft jet engine is developed. The proposed FDI system is based on the multiple model approach and utilizes dynamic neural networks (DNNs) to accomplish this goal. Towards this end, multiple DNNs are constructed to learn the nonlinear dynamics of the aircraft jet engine. Each DNN corresponds to a specific operating mode of the healthy engine or the faulty condition of the jet engine. Using residuals obtained by comparing each network output with the measured jet engine output and by invoking a properly selected threshold for each network, reliable criteria are established for detecting and isolating faults in the jet engine components. The fault diagnosis task consists of determining the time as well as the location of a fault occurrence subject to presence of unmodeled dynamics, disturbances, and measurement noise. Simulation results presented demonstrate and illustrate the effectiveness of our proposed dynamic neural network-based FDI strategy.



## 1. Introduction

For aircraft jet engine fault diagnosis problem one utilizes knowledge of the measured variables taken along the engine's gas path to determine how the engine performance differs from its desired state. Changes in the engine speed, temperature, pressure, fuel flow, etc., provide the required information for identifying the engine system malfunctions. The overall goal of a jet engine diagnostic system is to correctly detect, isolate and identify the changes in the engine parameters. This will prevent heavy economic losses due to stopped or aborted flights as well as the cost associated with untimely and unnecessary replacement of components and parts.

Fault diagnosis algorithms are mainly divided into two categories, namely model-based and data-driven (computational intelligence-based) techniques. Both techniques have been extensively studied in the literature for health monitoring of aircraft jet engines. In model-based approaches, Kalman filters are quite popular [5,11,10]. Although, model-based techniques have advantages in terms of on-board implementation considerations, their reliability often decreases as the system nonlinear complexities and modeling uncertainties increase.

Data-driven approaches, such as those based on neural networks, mostly rely on real-time or collected historical data from the engine sensors and do not require a detailed mathematical model of the system. Neural networks are a promising tool for fault diagnosis due to their proven success in system identification and strong capability in learning nonlinear transformations that map a set of inputs to a set of outputs.

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Applications of neural networks in engine fault diagnosis have been widely presented in the literature. The authors in [17] have proposed a modular diagnostic system for a dual spool turbofan gas turbine. Multiple neural networks are proposed in [4] for fault diagnosis of a single shaft gas turbine. The author in [12] has further extended the multiple neural networks method to generate a cascade network to isolate component and sensor faults. The author in [3] has discussed the need to incorporate a neural network with other AI techniques to estimate the remaining useful life and incorporate prognosis capabilities of an engine. The authors in [14] have applied a probabilistic neural network (PNN) to diagnose faults on turbofan engines.

Dynamic multilayer perceptron or dynamic neural networks have recently been utilized for system identification problems due to their capabilities in modeling nonlinear dynamical systems. Such networks have a feedforward architecture and their dynamic properties are achieved by using dynamic neurons. Each neuron possesses dynamic characteristics that is achieved through a locally recurrent globally feedforward (LRGF) mechanism [16,2].

Recently, dynamic neural networks have been utilized for fault diagnosis of nonlinear systems. The authors in [15] have used a multilayer perceptron network that is embedded with dynamic neurons for fault detection and isolation (FDI) of thrusters in the formation flight of satellites. A dynamic neural network is constructed in [1] for accomplishing the fault detection task. This is followed up by a static neural classifier using the learning vector quantization (LVQ) scheme for the fault isolation task. The authors in [9] have applied the dynamic neural network that was developed in [16] for fault detection of aircraft jet engines.

In the present work a dynamic neural network-based multiple model strategy is proposed and developed as a novel approach for fault detection and isolation of aircraft jet engines. It will be shown that by using a bank of dynamic neural networks the problem of fault detection and isolation of a dual spool jet engine can be addressed quite effectively. For comparison of our developed methodology with another and an alternative dynamic neural network-based approach that tackles the similar problem and application, the reader can refer to our work in [9]. These details are not included here for sake of brevity.

The remainder of this paper is organized as follows. In Section 2, the dynamic neuron model and the proposed dynamic neural network structure are described. The overall model of the considered dual spool jet engine is presented in Section 3. In Section 4 the problem of fault diagnosis, that is the fault detection and isolation strategy is proposed and described in detail. Simulation results are presented in Section 5 followed by the conclusions in Section 6.

## 2. Dynamic neural network (DNN) architecture

Dynamic neural networks (DNNs) presented in [16,2] have great capabilities in learning the dynamics of complex nonlinear systems, where conventional static neural networks cannot yield an acceptable representation. Dynamic neural networks or dynamic multilayer perceptron networks (MLP) represents an extension of static neural networks by embedding discrete or continuous time dynamics to the neuron model. Such an extension enhances the capability of the resulting neural networks to approximate not only the static nonlinearities of the system but also its dynamic nonlinearities. The dynamic neuron model and the dynamic neural network architecture are described in detail in the following subsections.

### *2.1. Dynamic neuron model*

A dynamic neuron model is obtained by incorporating internal dynamics and by ensuring that the neuron's activity depend on its internal states. This can be achieved by augmenting an Infinite Impulse Response (IIR) filter within the standard static perceptron structure. Fig. 1 shows the structure of such a dynamic neuron model.

Three main modules are used in this structure. The first module is an adder, namely $x(k) = \mathbf{W}^{\mathbf{T}}\mathbf{u}(k) = \sum_{p=1}^{P} w_p u_p(k)$, where $\mathbf{W} = [w_1 w_2 \cdots w_p]^T$ denotes the input-weight vector, P denotes the number of inputs, and $\mathbf{u}(k) = [u_1(k) u_2(k) \cdots u_p(k)]^T$ denotes the input vector (T denotes the transpose operator). The output of the adder is passed through an IIR filter ($H(q^{-1})$) so that a dynamic mapping is then generated between the inputs and the output of the neuron. By utilizing an $n$th order IIR filter having the transfer function

$$H(q^{-1}) = \frac{b_0 + b_1 q^{-1} + \cdots + b_n q^{-n}}{1 + a_1 q^{-1} + \cdots + a_n q^{-n}} \tag{1}$$

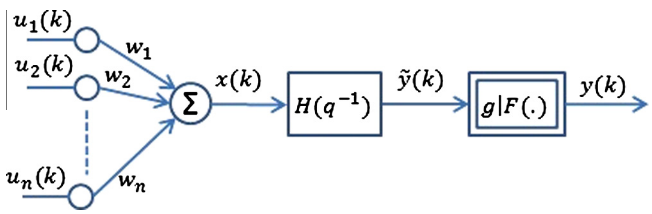


**Fig. 1.** A dynamic neuron having an internal IIR filter [2].