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FULL LENGTH ARTICLE

Multi-mode diagnosis of a gas turbine engine using an adaptive neuro-fuzzy system

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Abstract Gas Turbine Engines (GTEs) are vastly used for generation of mechanical power in a wide range of applications from airplane propulsion systems to stationary power plants. The gas-path components of a GTE are exposed to harsh operating and ambient conditions, leading to several degradation mechanisms. Because GTE components are mostly inaccessible for direct measurements and their degradation levels must be inferred from the measurements of accessible parameters, it is a challenge to acquire reliable information on the degradation conditions of the parts in different fault modes. In this work, a data-driven fault detection and degradation estimation scheme is developed for GTE diagnostics based on an Adaptive Neuro-Fuzzy Inference System (ANFIS). To verify the performance and accuracy of the developed diagnostic framework on GTE data, an ensemble of measurable gas path parameters has been generated by a high-fidelity GTE model under (a) diverse ambient conditions and control settings, (b) every possible combination of degradation symptoms, and (c) a broad range of signal to noise ratios. The results prove the competency of the developed framework in fault diagnostics and reveal the sensitivity of diagnostic results to measurement noise for different degradation symptoms.

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1. Introduction

Components of Gas Turbine Engines (GTEs) operate in harsh environments that create different degradation mechanisms in the parts. The degradation mechanisms lead to growth of faults in various modes and result in deviation of the performance from that of the brand-new condition. In the compressor section, erosion of the blades and vanes and the fouling phenomena lead to loss of the isentropic efficiency and decrease of the mass flow capacity, given the shaft speed and

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Nomenclature

Symbols		W	mass flow
ANFIS	adaptive neuro-fuzzy inference system	$\overline{w}$	weight of fuzzy rules
ANN	artificial neural network	x	health state
APU	auxiliary power unit	y	performance parameter
$D(\cdot)$	diagnostic model	η	isentropic efficiency
e	diagnostic error	ρ	degradation symptom
EGT	exhaust gas temperature	σ	standard deviation of noise
GTE	gas turbine engine	ϕ	relative humidity
$G(\dot{s})$	measurement model	*Subscripts*	
N	shaft speed	A	actual value
NRMSE	normalized root mean squared error	am	ambient
P	pressure	C	compressor
PW	power	F	fuel
R	linear fuzzy rules	i	inlet
s	measurement signal	M	measured parameter
SNR	signal to noise ratio	o	outlet
T	temperature	T	turbine
u	control input		
v	ambient condition		

the pressure ratio.[1] In the turbine section, however, the mass flow capacity would increase, while the isentropic efficiency declines with degradation for a given pressure ratio and shaft speed.[2,3] It is a common practice to utilize the symptoms of the isentropic efficiency's decline and the mass flow capacity's change to quantify the degradation level in both compressors and turbines.[4,5] Degradation of the parts moves the operating match point of GTE subsystems away from the optimal criteria and results in deviation of gas path parameters from those of a healthy condition. At the same time, it leads to loss of the thermal efficiency and extra fuel consumption at the system level.[6] Deterioration of the GTE performance is not necessarily rooted in part degradation. When the ambient condition changes or the GTE is operated at off-design control settings, e.g., partial load, the performance of the GTE will deteriorate. Such deteriorations automatically reverse when the operating conditions return to on-design conditions 7. It is critical for a GTE diagnosis system to separate the deterioration causes and to isolate those attributable to degradation of the components but not off-design control settings.

Condition-based health management strategies tend to extract real-time health-related information from systems so that the required maintenance actions can be taken at the right time for the right part(s). GTE measurements of gas-path parameters contain valuable information on the health conditions of the parts; however, the number of operating parameters recorded with a GTE performance monitoring system is limited by the cost, maintenance, and other technical reasons. In many conventional GTEs used for power generation, measurements are limited to a few parameters such as power, shaft speed, EGT, and fuel flow. As a result, extraction of information from data analysis becomes challenging. At the same time, small variations of the measurements due to component faults can be masked by signal noise, if the measurement noise is relatively high. This calls for competent health monitoring and diagnostic techniques that manage to extract health information from limited measurements contaminated with noise.

There are two main approaches for fault diagnostics: system identification and pattern recognition.[8] In system identification where a measurement model for a system is required, the objective is to update internal fault-related parameters of the system model so that model outputs become consistent with measurements. It requires a reliable measurement model for the system that establishes functional relationships between internal health parameters and measurements.[9] Pattern recognition is a practical computational approach that can be applied effectively if an accurate measurement model is not available. Variations of the internal health parameters of gas turbines create distinct clusters in the multi-dimensional space of measurable operating data. The task of pattern recognition is to classify those clusters and attribute them to the corresponding faults.[10] Fig. 1 shows the process of GTE fault detection through pattern recognition in a multi-dimensional measurement data space, where x represents the health condition of the system and y, u and v refer to the performance parameters, control inputs and ambient conditions respectively. The dimensions are limited in this case to three for improved visualization. This is an effective approach for fault detection and isolation in GTEs with a limited number of measurable parameters. Mathematically, pattern recognition algorithms are mapping functions, which need a training process to set their internal parameters. After the training process, upon receiving a new set of measurements, the classification function maps the inputs to the corresponding classes of faults. Various classification techniques including fuzzy-logic,[11–13] probabilistic networks,[14,15] artificial neural networks,[16,17] support vector machines,[18] stochastic neuro-fuzzy inference systems,[19] and statistical-based approaches[20] have been utilized for GTE diagnosis by pattern recognition. In a comparative study, Bettocchi et al. showed that under measurement uncertainty, an

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