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Utilization of a Fuzzy Inference System to Prevent Measurement Uncertainties in Gas Turbine Engine Fault Diagnosis

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Abstract

In this study, a brand-new Takagi-Sugeno-Kang (TSK) fuzzy inference system-based performance-based defect detection and identification (FDI) method for turbofan gas turbine engines is suggested. We employ parameter correction to preprocess the raw measurement data in order to address the issue of changing ambient conditions, which can lessen the complexity of the FDI system. Additionally, the power level angle is configured as a scheduling parameter to lower the TSK-based FDI system's rule count. A component-level turbofan engine model is used to produce the data required for the design, training, and testing phases of the planned FDI strategy. The particle swarm optimization technique and the ridge regression method are used to optimise the antecedent and consequential parameters of the proposed TSK-based FDI system. Then, by fusing a unique fuzzy inference system with the TSK-based FDI system, a resilient structure against measurement biases is suggested. Through in-depth simulation tests, the first-order TSK-based FDI system's and the resilient FDI structure's performances are assessed. Comparative studies support the first-order TSK-based FDI system's advantage in terms of accuracy in fault isolation, identification, and detection. The successful rate index improves by 2% to 8% under rather severe measurement bias settings, demonstrating the robust structure's high resilience against measurement errors. Comprehensive case simulations have demonstrated accuracy against a wide range of bias values and computation time, proving that the suggested resilient structure has favourable online performance.

Introduction

An essential component of the advanced engine control system and health management system is the aero-engine Fault Detection and Identification (FDI) system. The engine's safety, maintenance expenses, and danger of disasters may all be decreased with a good FDI system. The FDI system uses changes in the gas-path parameters, such as speed, temperature, pressure, and flow rate, to assess how the engine performance deviates from the target condition. The model-based method and the data-driven method are two groups of algorithms that the FDI methods fall under. Due to its many benefits, including but not limited to, handling sensor noise and bias, minimal computing cost, and acceptable estimate accuracy for a linear issue, the Kalman filter (KF) is the typical and the most widely used model-based approach. It was initially effectively used to address the problem of assessing the health of an aero-engine in the late 1980s, which promotes the adoption of KF-based methods for managing aero-engine health. Based on a modified KF, Pratt & Whitney devised a diagnostic system they called the improved self-tuning onboard real-time model (eSTORM), and they used it with the PW6000 engine. Two things are the main downsides of the KF-based approach: (i) only a small degree of nonlinearity can be handled by issues using EKF-based approaches. Nonlinear diagnostic problem estimations are frequently skewed and insufficient. (ii) When the number of measurements is restricted, the KF-based method's performance is readily impacted by the "smearing" effect, which causes this algorithm to frequently ascribe a single defect to many components. In recent years, machine learning techniques, which can handle the nonlinearity of the gas turbine engine and has high computational speed, have become widely employed for gas turbine engine problem detection. Building residual generators and modelling the

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engine is a typical troubleshooting technique. The faults are then located and isolated using the residuals produced by the residual generator. Shahnazari suggested a fault isolation and detection technique in 2020 that relied on a bank of residual generators that were built utilising a bank of recurrent neural networks (RNN). He uses a bank of RNNs to identify and isolate single, multiple, and concurrent actuator and sensor problems in his research. In 2021, Djeddi suggested a robust diagnostic technique based on an adaptive neural fuzzy inference system (ANFIS) observer. To improve the detection's resilience, an adjustable threshold was utilised. Each component was represented using a distinct ANFIS in order to pinpoint the problems. On an MS5002B gas turbine, experiments were conducted to demonstrate the real-time capability. In order to track the usage of rotating equipment, Rahmoune et al. employed neural network dynamic nonlinear autoregressive with external exogenous input (NARX) to simulate a gas turbine. Another common technique that requires engine measurement data under anomalous situations is performance-based strategy.

The performance of component parts is frequently modelled using artificial neural networks (ANN). Convolution neural network (CNN), deep neural network (DNN), and partially interpretable CNN have all been studied in recent years for gas turbine performance-based defect diagnostics. Using this sort of technique, the mapping relationship between the quantifiable gas route characteristics and the intangible component health metrics is modelled. The hidden layers of the neural network's operation are not visible, making it a "black-box" model. The mapping between the characteristics and the faults lacks interpretability. An FDI system that is performance-based on the performance of a gas turbine engine must be robust against measurement errors. Measurement noises can be handled using the aforementioned algorithms. Measurement biases, which can easily lead to the incorrect interpretation of component failures, are challenging to cope with. Additionally, all of the aforementioned investigations of FL-based fault diagnostic techniques employed Mamdani FIS or zero-order TSK, which did not fully use the TSK FIS's potential. This paper suggests a strong FDI structure against measurement biases that consists of a "biased sensor isolation" component and a "fault diagnostic" part. This structure is made up of two parts: the first is a particular FIS with fuzzy complement in the rules, and the second is a bank of first-order TSK-based FDI system.

Conclusion

In this study, a twin-shaft turbofan gas turbine Fault Detection and Identification (FDI) system that is resistant to measurement biases is suggested. During the design phase, varying ambient and load conditions are also taken into account. The FDI system is created using a first-order Takagi-Sugeno-Kang (TSK)-type Fuzzy Inference System (FIS). By introducing errors, noises, or biases into the AGTF30 engine model, the data for design and testing are created. The FDI system's parameters are optimised using a hybrid of the particle swarm optimization technique and ridge regression.