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Wind turbine anomaly detection using surrogate models

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The reliable performance and asset health monitoring of wind turbines are becoming increasingly prominent for cost-effective operations. Surrogate models can play an indispensable role in developing advanced digital twin-based health monitoring technologies. This article investigates an application of a virtual representation of a wind turbine's normal operation for a computationally efficient, weakly supervised health monitoring approach. The adaptive neuro-fuzzy inference system with fuzzy c-means is proposed as a surrogate model of the NREL 5 MW offshore wind turbine, coupled with a Permanent Magnet Synchronous Generator. A set of anomaly modes are defined to assess the accuracy and effectiveness of Support Vector Machines for classifying extracted time and frequency domain features. The classification evaluation has been made by using different kernel functions for different operating conditions to deal with uncertainties in the system, such as the stochastic characteristics of wind speed, turbulence intensities, and power curve variations, including different sparsity levels in datasets.

The core idea deals with applying surrogate models in anomaly detection problems and addressing the main challenges of supervised and unsupervised approaches, where either a sufficiently large set of labeled sample data or unlabeled measured data are required [1]. Wind turbine anomalies may accrue in numerous ways, i.e., faults on blades, rotors, gearbox, and generators. These anomalies are not possible to be explicitly labeled for different operating conditions. Moreover, only unlabeled healthy data are usually available in realistic circumstances. Therefore, a weakly supervised method is studied in this paper, where a large amount of data from the normal operation with a small set of labeled data from abnormal operations are available for the proposed anomaly detection problem. For this purpose, a 5 MW offshore floating wind turbine is investigated by applying the Fatigue Aerodynamic Structure and Turbulence (FAST) software designed by the National Renewable Energy Laboratory (NREL), which can well unveil the wind turbine's nonlinear dynamics [2]. Subsequently, data-driven surrogate model is developed to approximate the nonlinear behavior of the wind turbine in various wind conditions in a healthy mode. Moreover, anomaly scenarios of pitch failure, PMSG abnormality, and yaw misalignment are created. The application of Support Vector Machines (SVMs) is investigated for the proposed classification problem and the health monitoring approach.

Condition indicators are needed for distinguishing a normal operation from a faulty operation. Choosing the appropriate condition indicators requires a good knowledge of the system, and some trial and error might be needed. A few features in both the time and frequency domains can be analyzed for the main outputs of the system, i.e., electrical power and rotational speed signals.

Figure 1 illustrates a workflow for developing the suggested digital twin-based condition monitoring approach. This workflow begins with data gathering that describes wind turbines in various healthy and faulty conditions and provides the model with measured data for anomaly detection and performance assessment. After creating a surrogate model that can mimic the healthy behavior of the system, it is required to extract features that can successfully identify appropriate condition indicators that are able to interpret normal and abnormal behavior. Then a classifier is needed to be trained to classify anomalies from what the surrogate model predicts for a healthy

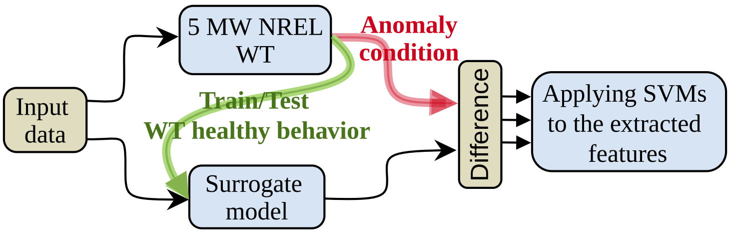

Figure 1: Proposed anomaly detection algorithm

state using a small set of labeled anomaly data. This process should be iterative, and the classifier should be updated in different operating conditions until achieving a robust and global performance.

As shown in Fig.2, the NREL offshore 5 MW baseline wind turbine with a variable blade-pitch-to-feather configuration is considered for developing the surrogate model. The operational control approach is developed based on power-production regulation and relies on the design of pitch and torque control systems.

The ANFIS model takes advantage of artificial neural networks and fuzzy logic in its structure to produce a realistic representation of the physical system. A hybrid learning algorithm of both the least-squares method and backpropagation learning is used to train the network and optimize the parameters of a fuzzy model capable of handling both quantitative and qualitative criteria. A nonlinear mapping of multiple inputs, i.e., wind speed, blade pitch angle, and generator torque into multiple outputs, i.e., rotor speed, mechanical power, and other FAST outputs, is carried out using Takagi–Sugeno inference model employing fuzzy if-then rules. In the fuzzification layer of the ANFIS structure, the Gaussian membership functions of the crisp inputs are created.

Moreover, the Transfer Learning (TL) in the deep neural networks approach can be applied to gain the under-

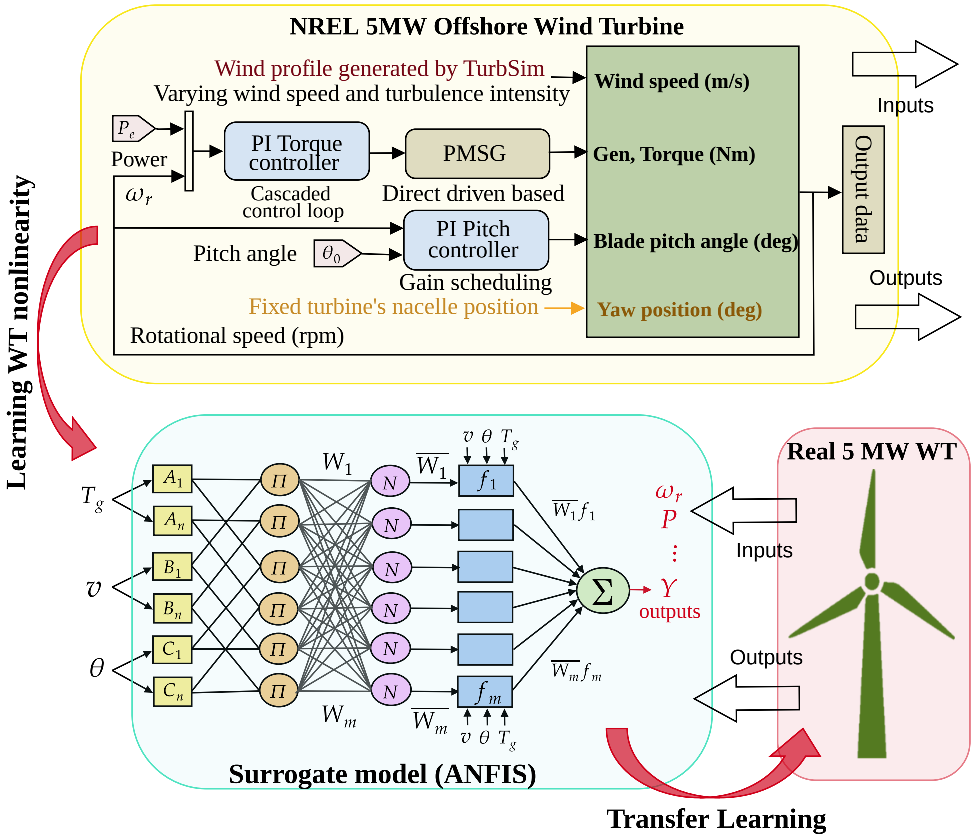

Figure 2: Using surrogate models in wind turbine anomaly detection.

lying nonlinearity of real wind turbines when labeling data is costly and time-consuming. Besides, TL can also be helpful as an adequate weight initialization strategy for the ANFIS model, specifically when the TL-ANFIS model can be adaptively modified as it concerns training a different wind turbine with continuously changing operational conditions. Adaptive TL not only helps provide good weight initialization but also employs the incoming data for effective learning between different task domains, i.e., fast transitions between pitch control to torque control regions.

The suggested health monitoring approach is developed and assessed in various working conditions with different sources of faultiness. Two control failures, i.e., blade pitch angle and nacelle yaw position error, are considered, affecting the rotational speed and causing electrical power degradation in full and partial load regions, respectively. The second type of data used for evaluating the proposed algorithm includes wind turbine operation in the transition zone, where all the anomalies are likely to accrue. At the same time, the control system performance degrades due to the frequent switching between pitch and torque control mechanisms.

The healthy prediction of the ANFIS model is fed into the weakly supervised health monitoring algorithm for two types of operating conditions using several time windows of 10 to 50 seconds. The first type represents the healthy and faulty operation of the wind turbine in partial and full load regions without considering the transition zone. The algorithm could successfully identify abnormal and faulty modes for at least 85% of samples. The lowest accuracy is achieved for the yaw misalignment detection in the transition zone. The highest is for pitch failure detection in the above-rated wind speed, which is given at around 98% accuracy. The results show that the proposed anomaly detection method is promising and can effectively improve health monitoring techniques.

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