NEURO-FUZZY SURVEILLANCE FOR INDUSTRIAL PROCESS FAULT DETECTION

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Abstract. *In the last decade considerable research efforts have been spent to seek for systematic approaches to Fault Diagnosis (FD) in dynamical systems The problem of fault detection consists in detecting faults in a physical system by monitoring its inputs and outputs This paper presents a methodology to monitor and diagnose machine faults in complex industrial processes using neuro-fuzzy methodology.*
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Introduction

The main goal of an FD system is the monitoring of the plant during its normal working conditions so as to detect the occurrence of failures (fault detection), recognize the location (fault isolation) and the time evolution (fault identification) of the failures. In the model-based approach to FD, this goal is achieved by comparing the actual system's behaviour with the corresponding expected behaviour derived via its mathematical model. Usually, the output of a fault detection algorithm is a set of variables sensitive to the occurrence of a failure (residuals). Namely, when a failure occurs, a fault signature affects the residuals. Then, the information from the signatures is processed to identify the size and the location of the fault. The adoption of effective fault diagnosis techniques is becoming critical to ensure higher levels of safety and reliability in automated plants and autonomous systems. Process control is an efficient means of improving the operation of a process, the productivity of the plant, and the quality of the products.

The system architecture

Components, machines and processes fail in varying ways depending upon their constituent materials, operating conditions, etc. Failure modes are typically monitored by a sensor suite which is intended, for failure analysis purpose, to capture those failure symptoms that are characteristics of a particular failure mode. Let's take for example the case of a typical industrial process failure (sensors, actuators, components). Typical failure modes may include leaks, sensor failures, corrosion, debris, etc. which is characteristic of a process failures as well as a variety of vibration induced faults that are affecting mechanical and electro-mechanical process elements [1]. The low-bandwidth process faults such as temperature, pressure, leaks, etc may be treated with a fuzzy rule base set as an expert system while high bandwidth (see Figure 1) faults such as vibrations, current spikes, etc are better diagnosed via a feature extractor/neural network classifier topology

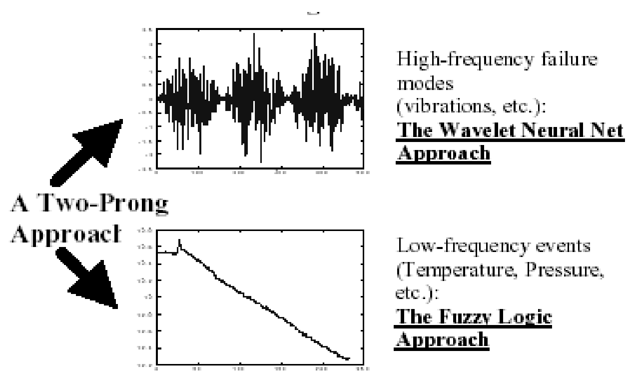


Figure 1. The two-prong approach of the diagnostic module.

The pre-processing and feature extraction unit takes raw sampled data from a plant and converts it to a form suitable for the fuzzy logic.

It incorporates filtering of noise from raw data and extraction of features from the filtered data. Feature extraction intends to extricate the most important characteristics from the filtered data such as slopes, levels relevant frequencies, etc (see Figure 2.)

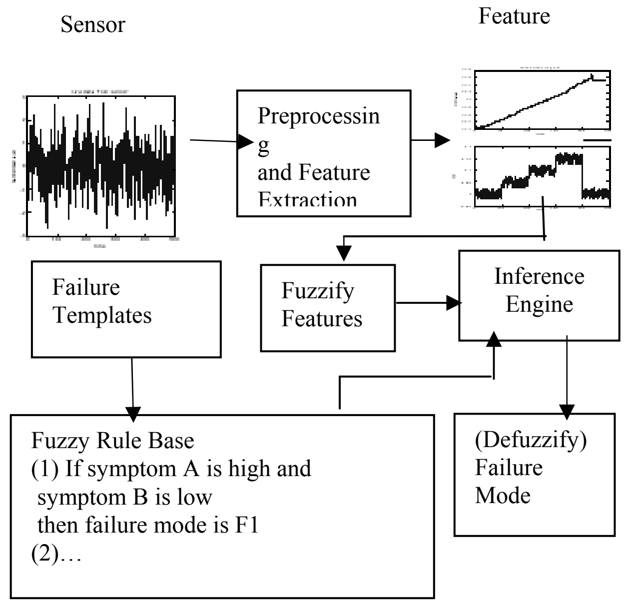


Figure 2. Fuzzy diagnostic system layout with feature extraction.

The basic diagnostic architecture is generic and applicable to a wide variety of industrial processes. A fuzzy logic approach is used to determine if a failure (or impending failure) has occurred and to assign a degree of certainty to this declaration. Figure 3 depicts the essential elements of the diagnostic process [2].

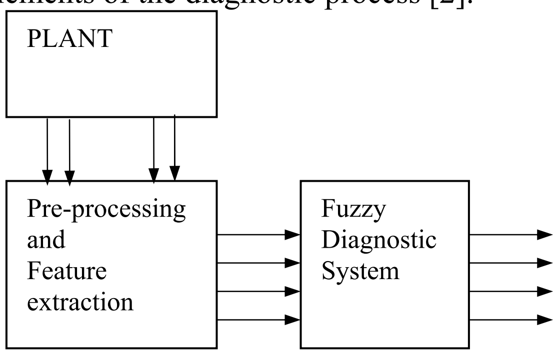


Figure 3. The fuzzy logic and evidence theory.

Process faults may be treated with a fuzzy rule base set as an expert system while high bandwidth faults are better diagnosed via a feature extractor/neural network classifier topology. This approach is adopted below in addressing typical machinery failures.

The fuzzification block converts features to degrees of membership in a linguistic label set such as low, high, etc. the fuzzy rule base is constructed from symptoms that indicate a potential failure mode. Figure 5 describe two typical rules.

An example of this kind of rules could be:

If the temperature is low in Recipient 1 and the pressure is low then the failure mode is Recipient 1 heating element is damaged.

If the slope of Recipient's water level is negative low and the slope of Recipient's pressure is negative low then the failure mode is Recipient 1 leaking.

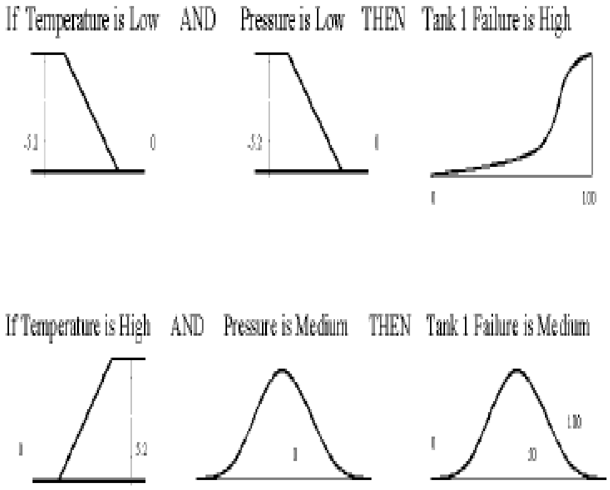


Figure 5. A graphical representation of a fuzzy rulebase.

The fuzzy rule base can be developed directly from user experience, simulated models, or experimental data. Fuzzy outputs are aggregated (maximum method) through the fuzzy inference engine to determine a degree of fulfillment for each rule corresponding to each failure mode. The last step defuzzifies the resulting output, using the centroid method, to a number between 0 and 100 (figure 6).

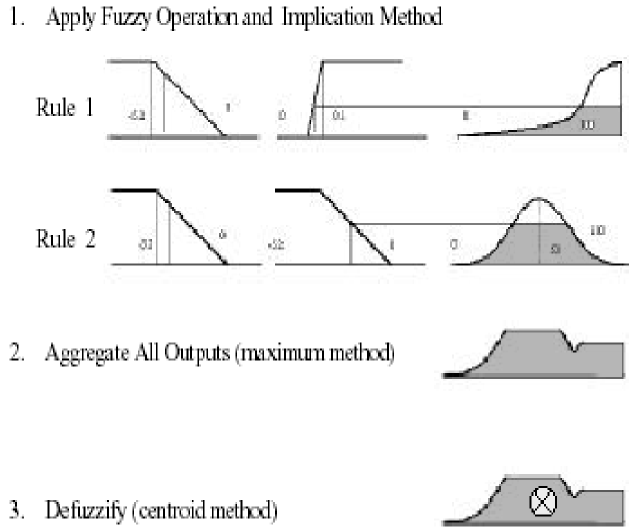


Figure 6. Graphical Inference and Defuzzification.

This is finally compared to a threshold to determine whether or not a failure mode should be reported [3].

High band failure detection and identification

The Wavelet Neural Network (WNN) belongs to a new class of neural networks with such unique capabilities as multi-resolution and localization in addressing classification problems. For fault diagnosis, the WNN serves as a classifier so as to classify the occurring faults (see Figure 7).

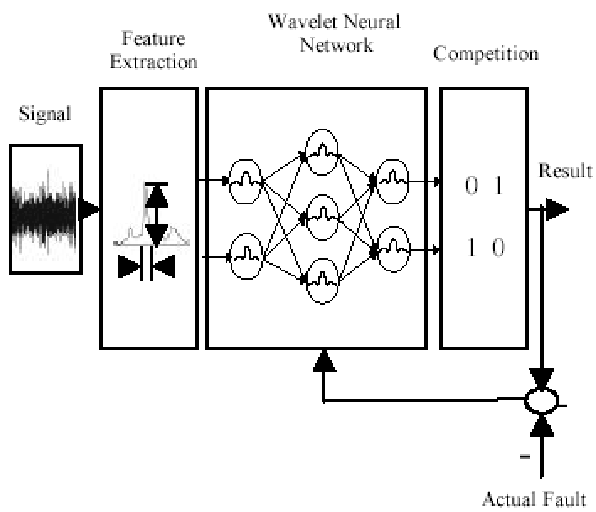


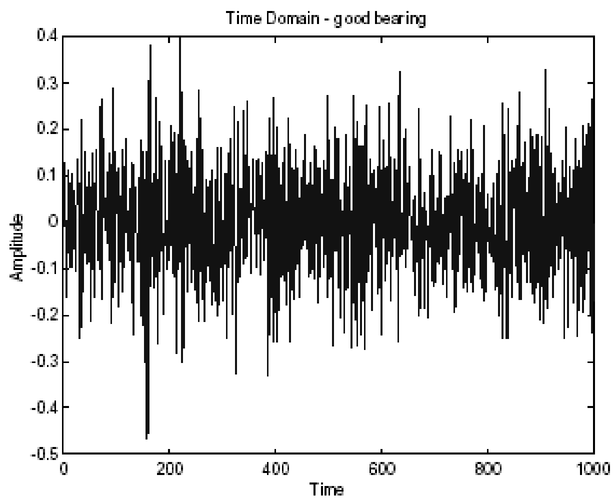
Figure 7. Classification using the wavelet neural network.

Critical process variables are monitored via appropriate sensors. The data obtained from the measurements are processed and features are extracted. The latter are organized into a feature vector, which is fed into the WNN. Then, the WNN carries out the fault diagnosis task. In most cases, the direct output of the WNN must be decoded in order to produce a feasible format for display or action.

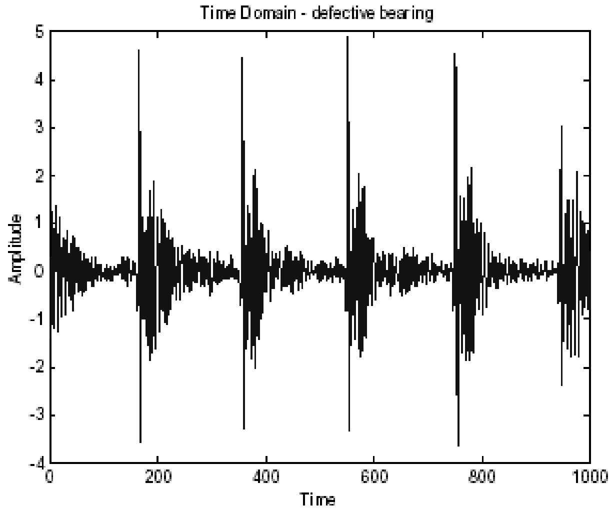
For example, the WNN can be used to perform the diagnosis of a bearing failure typically found on races, rolling balls and lubrication materials

Here, for simplicity, the focus is placed on the diagnosis of whether the bearing is normal or defective. Through vibration measurements, a number of vibration signals for a bearing are collected and the peaks of the signal amplitude chosen as the features. Such other quantities as the standard deviation, wavelet, maps, temperature, humidity, speed, mass, etc. can be selected as candidate features. From the vibration signals, a training data set is obtained, which is then used to train the WNN.

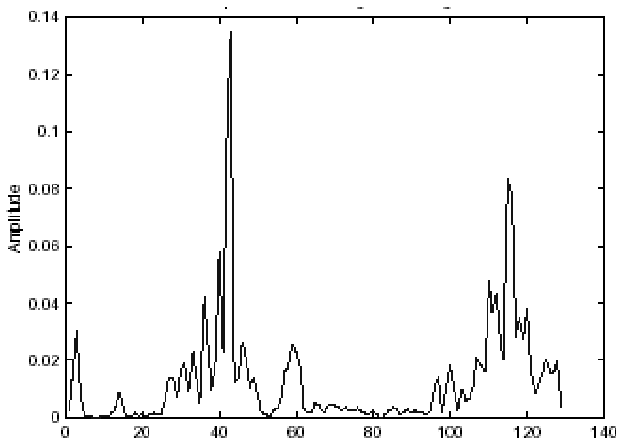
Once trained, the WNN can be employed to perform the fault diagnosis. Signals from a normal bearing and a defective one and their spectrum domain are shown in Figure 8 [4].



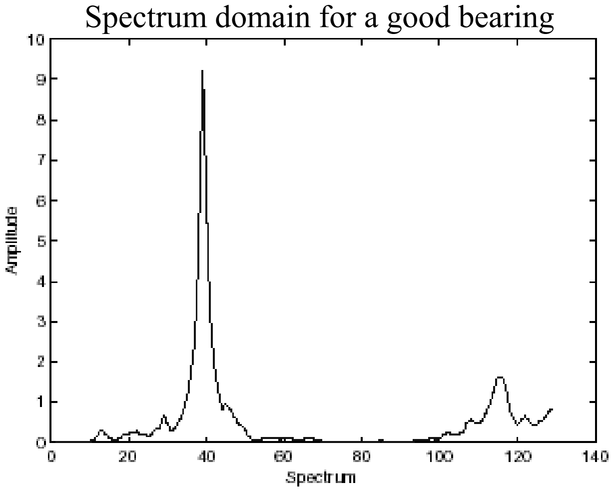
Signal from a good bearing



Signal from a defective bearing



Spectrum domain for a good bearing



Spectrum domain for a defective bearing

Figure 8. Signals and spectrum domain from a normal and a defective bearing.

Conclusions

This paper proposes a methodology to monitor and diagnose machine faults in complex industrial processes. This kind of analyze could be applied to diverse industrial plants which can operate critical processes and may require continuous monitoring and maintenance procedures. We provide a brief discussion about fault detection system for industrial processes and we think that neuro-fuzzy system can be another efficient mathematical tool to deal with the study of failure occurrence risk. For the sake of reducing this risk, such an accidents-modelling can help in singling out the corrective actions.

Neuro-fuzzy techniques are shown to be applicable to the industrial process fault diagnosis problem. The diagnostic models developed are capable of providing diagnosis of single or multiple faults based on noisy data.

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