NEURO FUZZY SYSTEM
FOR INDUSTRIAL PROCESSES FAULT DIAGNOSIS

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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 .Recently, the research has focused on non-linear systems FDI. Traditionally, the FD problem for non-linear dynamic systems has been approached in two steps. Firstly, the models linearized at an operating point, and then robust techniques are applied to generate residuals. This method only works well when the linearization does not cause a large mismatch between linear and non-linear models and the system operates close to the operating point specified. To deal with systems with high non-linearity and wide operation range, the FD problem has to be tackled directly using non-linear techniques. In the last decade considerable research efforts have been spent to seek for systematic approaches to Fault Diagnosis in dynamical systems..

I. 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. As for the case of nonlinear dynamical systems the fault detection methods can be roughly regrouped in three main classes: observer-based approaches, parameter estimation techniques and algorithms based on learning methodologies Recently, soft computing methods, integrating quantitative and qualitative modelling information, have been developed to improve FD reasoning capabilities. In order to develop better - fast, accurate and robust - process control, model-based modern control methods and efficient adaptive and learning techniques are required. . 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. In process engineering, even a small improvement in the operation of the process can have great economic and environmental influences. Control problems in the industry are dominated by nonlinear and time-varying behaviour, many sensors that measure all kinds of variables, many loops and interaction among the control loops. The extraction of (fuzzy) information out of raw data is very important and contains saving potential for industrial applications and time. Fuzzy control can be based on human experience and can mimic actions of human operators.

During recent years, the developments in these fields have introduced new tools for use in control engineering: neuro-fuzzy systems, guided random search techniques, predictive control, model reference control, etc. In process engineering, these new tools have found applications in non-linear process modelling and control, plant optimisation, monitoring, scheduling, etc. The application area of control engineering methods can be extended also to systems beyond the realm of traditional process engineering. Modern techniques for control system design, including robust design for stochastic and

nonlinear systems as well as intelligent control, are expected to lead to an increase in quality and productivity of manufacturing processes. The manufacturing and industrial sectors of economy are increasingly called to produce at higher throughput and better quality while operating their processes at maximum yield. As manufacturing facilities become more complex and highly sophisticated, the quality of the production phase has become more crucial. The manufacture of such typical products as textiles and fibres, aircraft, automobiles, appliances, etc, involves a large number of complex processes most of which are characterized by highly nonlinear dynamics coupling a variety of physical phenomena in the temporal and spatial domains. It is not surprising, therefore, that these processes are not well understood and their operation is “tuned” by experience rather than through the application of scientific principles. Machine breakdowns are common limiting uptime in critical situations. Failure conditions are difficult and, in certain cases, almost impossible to identify and localize in a timely manner. Scheduled maintenance practices tend to reduce machine lifetime and increase downtime, resulting in loss of productivity. Recent advances in instrumentation, telecommunications and computing are making available to manufacturing company’s new sensors and sensing strategies, plant-wide networking and information technologies that are assisting to improve substantially the production cycle.
In many practical situations, uncertainty in the process can affect the performance of the system significantly no matter how the uncertainty is described (vagueness or ambiguity). This realization provides the motivation for a possible fuzzy logic approach to FDI. This has the ability to directly describe the potential failure modes in the parameters while handling a class of nonlinear systems.

II. The Diagnostic 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: failures (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. 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.

The diagnostic module

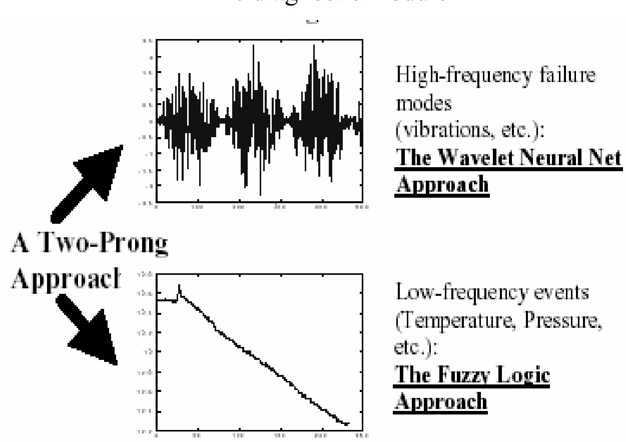


Figure 1 The two-prong approach of the diagnostic module

The preprocessing 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.)

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.

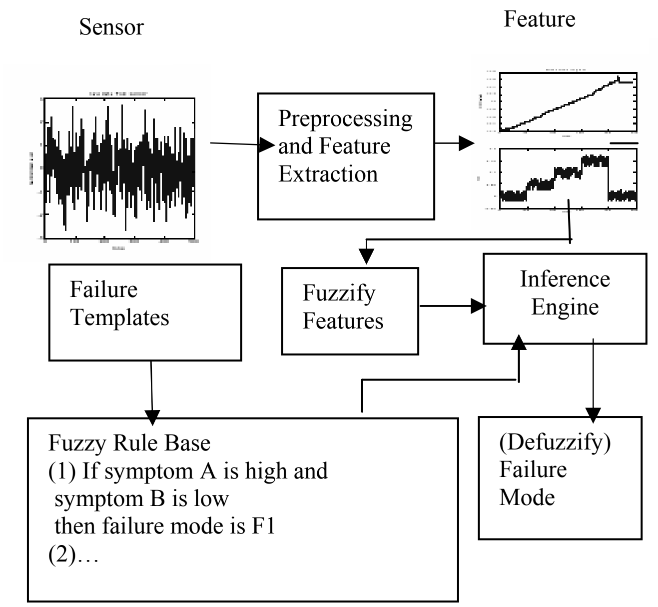


Figure 2. Fuzzy diagnostic system layout with feature extraction

Figure 3 depicts the essential elements of the diagnostic process. 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.

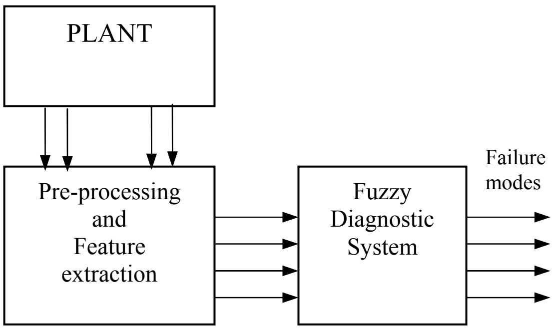


Figure 3 The fuzzy logic and evidence theory approach

III.Fuzzy Diagnostic System

The fuzzy diagnostic system takes features as inputs and then outputs any indications that a failure mode may have occurred in the plant. The fuzzy logic system structure is composed of four blocks: fuzzification, the fuzzy inference engine, the fuzzy rule base, and defuzzification, as shown in Figure 4:

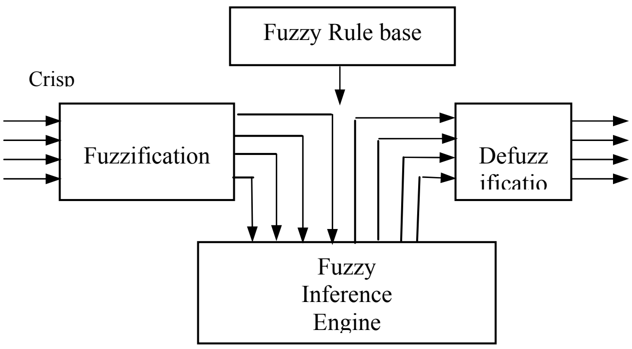


Figure 4. The fuzzy logic diagnostic system

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.

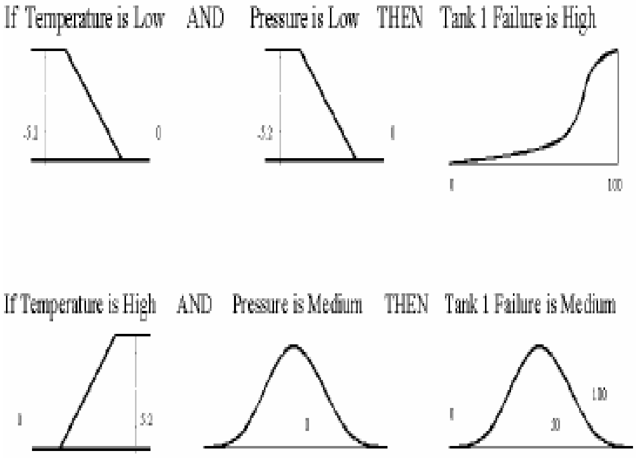


Figure 5. A graphical representation of a fuzzy rulebase

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 fulfilment 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).

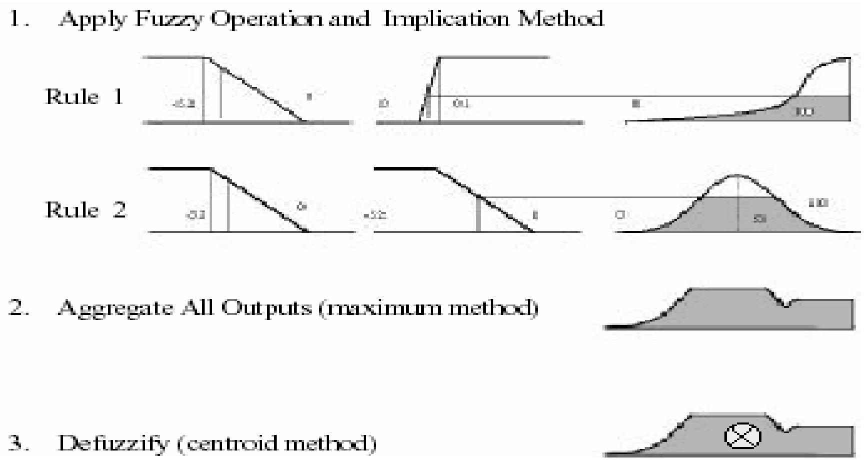


Figure 6 Graphical Inference and Defuzzification

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

IV.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).

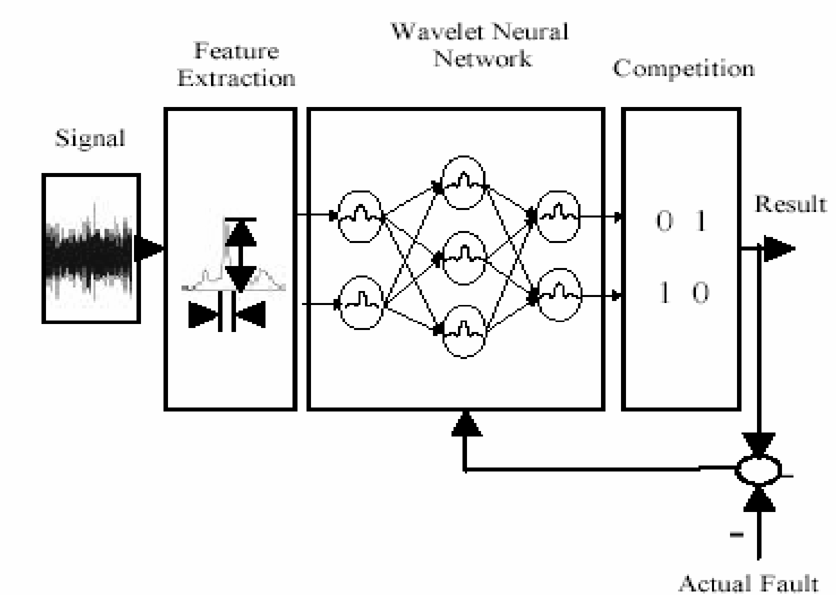
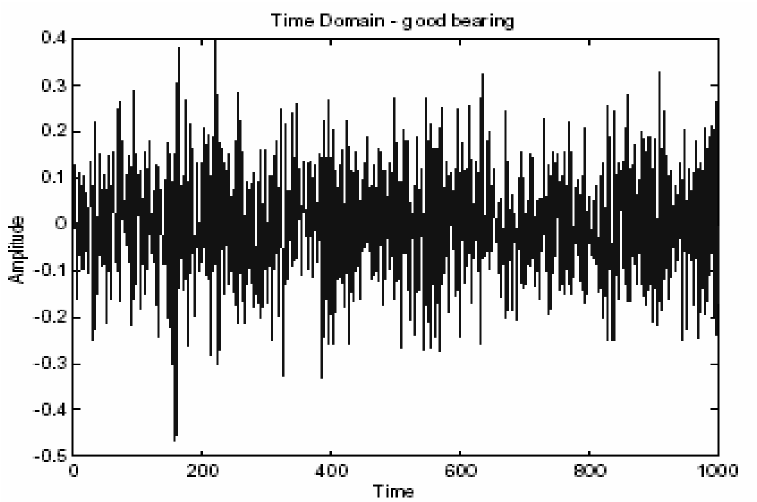


Figure 7 Classification using the wavelet neural network

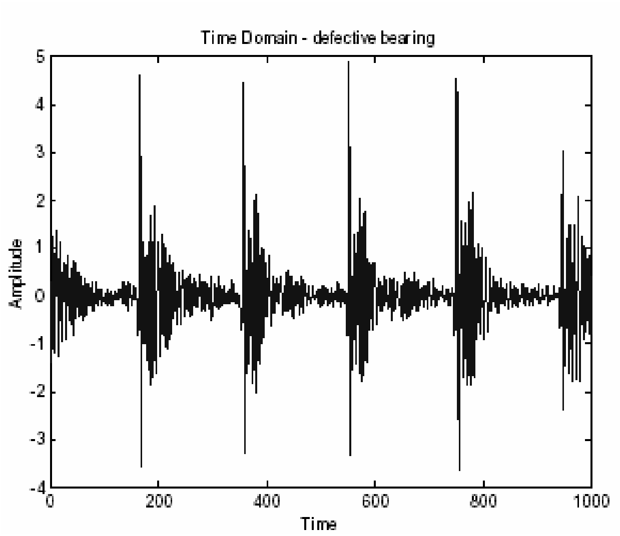
Critical process variables are monitored via appropriate sensors. The data obtained from the measurements are processed and features are extracted. The latter are organized into a feature vector, which is fed into the WNN. Then, the WNN carries out the fault diagnosis task. In most cases, the direct 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.

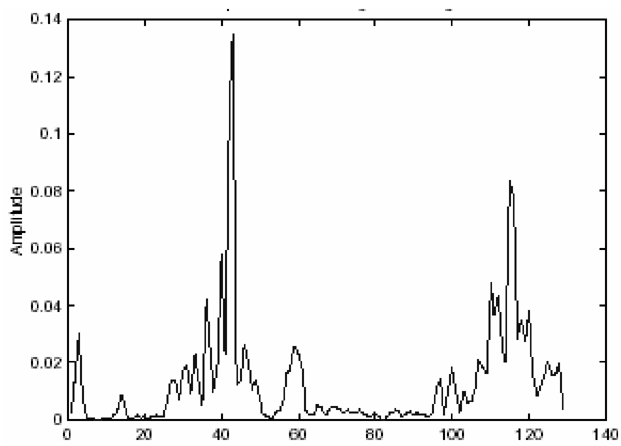
Once trained, the WNN can be employed to perform the fault diagnosis. Signals a from a normal bearing and a defective one and their spectrum domain are shown in Figure 8.



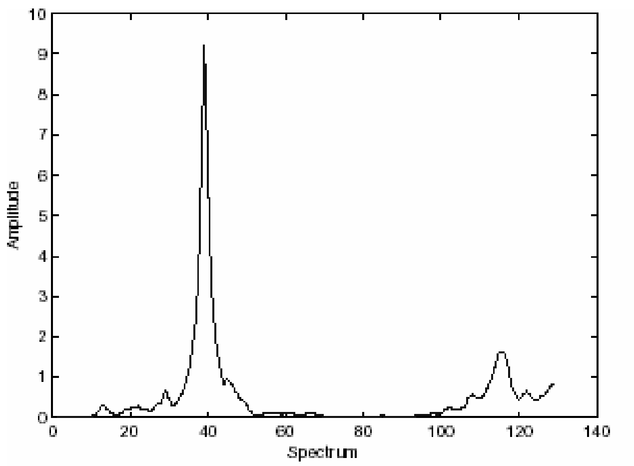
Signal from a good bearing



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

V. 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.

A dual approach is pursued: High-bandwidth fault symptomatic evidence, such as vibrations, current spikes, etc., are treated via a feature extractor/neural network classifier construct while low-bandwidth phenomena, such as temperature, pressure, corrosion, leaks, etc., are better diagnosed with a fuzzy rule base set as an expert system.

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. The main motivation for applying a neuro-fuzzy computing approach is that it combines the computational merits of neural networks with the representational power and transparency of fuzzy inference systems.

Acknowledgements

This paper was developed within the generous framework offered by type TD project " Neuro-fuzzy systems for quality assurance systems" financed by CNCSIS - Romania.

References

[1] Konrad, H. and Isermann, R., „Diagnosis of different faults in milling using drive signals and process models", *Proceedings of the 13th World Congress, International Federation of Automatic Control*, Vol.B., Manufacturing, p.91-6, 30 June-5 July 1996.

[2] Chow, E. Y., and Willsky, A. S., „Analytical Redundancy and the Design of Robust Failure Detection Systems*", IEEE Transactions on Automatic Control*, Vol.AC-29, No. 7, July 1984, pp. 689-691.

[3] Isermann, R., 2On fuzzy logic applications for automatic control, supervision and fault diagnosis", *Third European Congress on Intelligent Technologies*, EUFIT`95, Aachen, Germany

[4] . Ayoubi, M., „Neuro-fuzzy Structure for Rule Generation and Application in the Fault Diagnosis of Technical Processes", *American Control Conference* ACC`95, Seattle, USA

[5] Sajidman, M., Kuntze, H.-B., Jacubasch, A., „A Fuzzy-Logic Concept for Highly Fast and Accurate Position Control of Industrial Robots", *IEEE International Conference on Robotics and Automation ICRA`95*, Nagoya (Japan), 21-27 Mai 1995

[6] M. Pîslaru, G. Condurache, A. Trandabăț „Expert neuro-fuzzy system for production process surveilance" The International *Conference on Integrated Engineering* C2I 2005 16-18 October Timişoara, pp. 153-154, ISBN 973-625-259-0

[7] M. Pîslaru, A. Trandabăț, C. Schreiner "Automatic techniques for industrial process surveillance" 4th International *Conference on Electrical and Power Engineering*-EPE 2006 October 12-14; 2006, Iasi, Romania , Romania.Buletinul Insitutului Politehnic Iasi, Tomul LII (LVI), Fascicol 5B, ISSN 1223-8139, pag 864-869