A neural networks approach of process fault diagnosis using time series collected data through oil condition monitoring

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Abstract. In this paper was used the data set collected in a research project between private companies from Romania and Italy, for the development of a basic approach of artificial neural network techniques, as an application in Matlab, aiming to detect the degree of degradation of oil, an automated installation, measuring online the physicochemical properties of the oil. Physical-chemical parameters measured lead to the creation of generous time series, but accessible by numerical and statistical calculation, for the application of artificial intelligence techniques. Applying neural network techniques to parameters that measure oil degradation, oxidation and humidity have generated the results of this work. The main function of monitoring the state of operation of a mechanical system, machine, or plant is to provide the almost correct diagnosis of the machine's state and rate of change so that preventive measures can be taken at a given time .

1. Introduction

Condition monitoring and machine status classification are actions of great practical importance in the manufacturing industry as it provides online up-to-date state-of-the-art information, thus avoiding losses in production processes and minimizing chances of catastrophic machine failure [1].

Monitoring status, followed by the status classification, is an essential step in detecting failures in supervised machines, which is a model recognition problem as an approach. Currently, there are many techniques in this field, and the purpose of this paper is to investigate the various commonly used recognition techniques and to evaluate the results in correlation with the technical solutions given by the dynamic models and the transfer functions, respectively.

As has been mentioned here, [2] the literature abounds in surveys in which a wide variety of different neural network architectures [3] for the detection and diagnosis of malfunctions have been studied and experimented, [4], [5], [6]. The techniques for detecting and diagnosing malfunctions are typically divided into two categories: estimation methods and pattern recognition methods, respectively. Estimation methods are generally dependent on mathematical models, which must be as realistic as possible and not too complicated, with the cost of computing being excessive for complicated systems.

2. Some notions about simple Neural Network architectures

Error diagnosis literature, in the automation industry modern practice, focuses on linear or accurate methodologies, or with a high precision approximation rate. It is known that industrial processes are often difficult to model. These are complex and not always known precisely: induced noise and measurement uncertainty or manufacturing, error-prone sensors, corrupted measurements, vibrations, damage to the state of lubricating oils, etc. Therefore, some researchers have perceived artificial neural networks as an alternative to representing knowledge about dysfunctions but also to find ways to solve technical problems with infinitesimal errors that are sometimes also influenced by an incorrect or overly relaxed approach, design errors or exploitation errors.

Neural networks can filter noise and disturbance; they can provide a stable diagnosis, failures without standard types of models, extremely sensitive, and economic efficiency due to insignificant computing and design efforts. Another feature accepted as defining neural networks is that exact patterns are not always needed to reach the decision stage.

Using a neural network with appropriate parameters and a logical structure and weights, any non-linear continuous relationship can be approximated with arbitrary accuracy, a significant feature that a relatively complicated but controllable algorithm as a mathematical process can be parametrically defined by MATLAB specific functions or applications, or dedicated software. Neural networks are composed of simple elements that work in parallel. Biological nerve systems inspire these elements. As in nature, the efficiency of a neural network is primarily determined by the connections between the elements. We can train a neural network to perform a specific function by weighing the weights.

Typically, conventional neural networks are adjusted or trained so that a special entry leads to specific target output. Such a situation is presented in Figure 1, [4]:

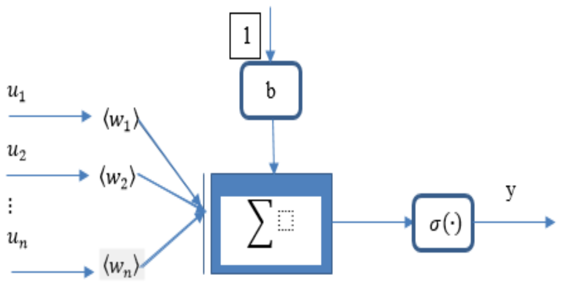

Figure 1. A simple Neuron scheme, with n inputs(u_i), w_i −weights, bias(b), $\sigma(\cdot)$ is the non-linear activation function and the only one output (y)

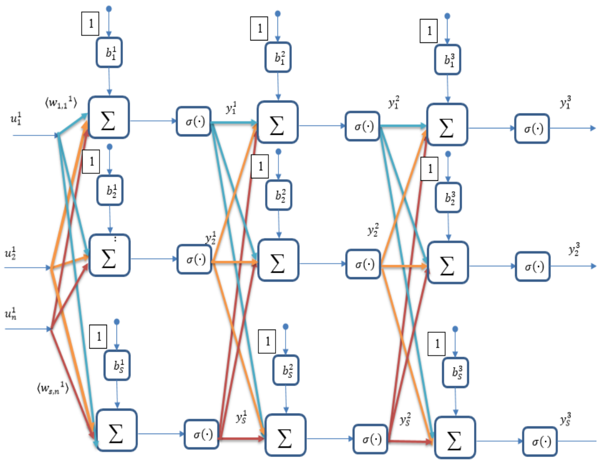

Figure 2. The 3-layer neural network, with n inputs and S neurons, [7]

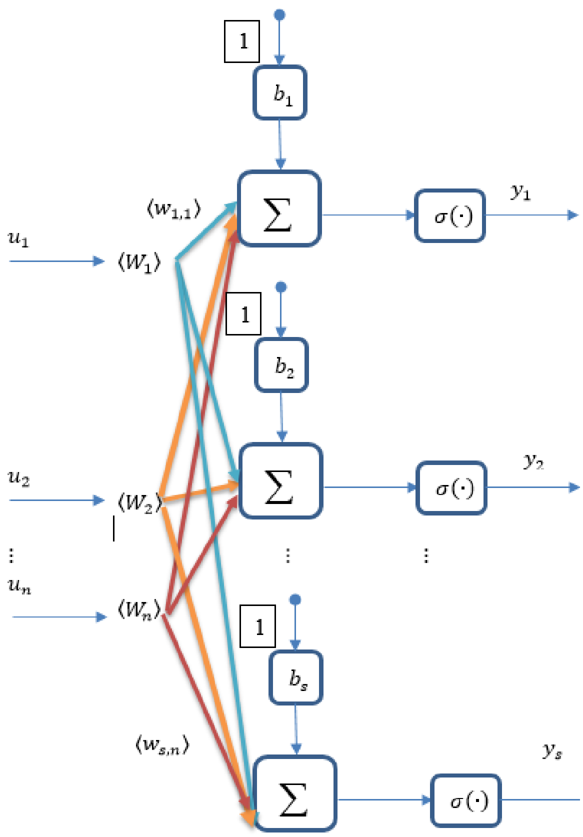

Figure 3. A single layer network, with n inputs and S neurons

Figure 2 shows a single-layer neural network with S neurons. Note that each of the network inputs is connected to each of the network neurons, for this reason the input matrix matrix now has S rows. Figure 3 presents a multilayer neural network (3 layers, here, for comprehensibility). This neural network, has an architecture defined as follow: each layer is characterized by its own weighting matrix, its own vector also biases the n inputs and an output vector, y.

3. Estimation methods [1]

3.1Fault Detection Based on State Variable Estimation,
The state variables are rarely all measurable, so unmetric variables have to be estimated (in this case, the dynamic model of the process linearises around the operating point). Estimation can be done using different methods, whether statistical or not, depends on how stochastic the system is. After estimation, an immediate assessment of the residuals is made as a difference between the estimated and actual measured values that were generated by the system, then the malfunction is detected, using statistical test and validation methods as well.

3.2 Fault Detection Based on Parameter Estimation
It is known that in many cases the process / system model parameters are in a complicated relationship with the physical coefficients of the process / system. Poor system operation generates effects that affect physical coefficients, the result of these influences being observable in process parameters. Since not all physical process parameters can be measured directly, the changes produced in the structure of some of the unmeasurable parameters must be calculated by the estimated values of process model parameters. Obviously, in this case, relationships between model parameters and physical coefficients must be known exactly.

3. Pattern recognition methods,
Used to detect and diagnose malfunctions, these methods do not strictly require mathematical process models. For these methods, the idea is that the operation of a process / system is ranked in full accord with the measured data. Formally this procedure is actually a mapping of the measurement space over the decision space. Generally, pattern recognition and classification methods can be structured into three stages of evolution: collecting measured data; feature extraction; and classification.

The mathematical model, quite comprehensive, of a process can be characterized by a equation, [1]:

$$\boldsymbol{Y} = \boldsymbol{f}\left\{\boldsymbol{U}, \boldsymbol{N}, \theta, \boldsymbol{X}\right\} \quad (1)$$

in which Y represents outputs, measurable quantities; U represents the measurable input signals; N represents the non-measurable disruptive signals of the process, the measurement and control equipment; θ represent the immeasurable process parameters; X represents the state variables, partially measurable or partially nonmeasurable.

Depending on the category of processed signals, there are, therefore, four classes of fault detection methods:

(1) - measurable inputs U and Y outputs respectively - the input and output signals can be easily monitored to observe the accidental changes in the process based on the lower or upper limits of the output signal;

(2) -nonmeasurable state variables, X - this case requires the existence of a model to be defined on the basis of the measurable state variables, and on these grounds to estimate the values of the non-measurable variables, respectively the reconstruction of the data set characterizing this kind of variables. Defining models are defined by system types:

(2.a)- The static systems (the state variable, estimated, is $\hat{\boldsymbol{X}} = \boldsymbol{f}\left\{\bar{\boldsymbol{U}}, \bar{\boldsymbol{Y}}\right\}$);

(2.b)-Dynamic systems the state variable, estimated to be given by the state equation $\boldsymbol{X}(\boldsymbol{t}) = \boldsymbol{f}\left\{\boldsymbol{U}, \boldsymbol{Y}, \boldsymbol{t}\right\}$. By linearization we obtain:

$$\dot{\boldsymbol{x}}(\boldsymbol{t}) = \boldsymbol{A}\boldsymbol{x}(\boldsymbol{t}) + \boldsymbol{B}\boldsymbol{u}(\boldsymbol{t}) \quad (2)$$

$$\boldsymbol{y}(\boldsymbol{t}) = \boldsymbol{C}\boldsymbol{x}(\boldsymbol{t}) \quad (3)$$

where $y = \Delta Y, u = \Delta U$ *şi* $x = \Delta X$ are the deviations of **Y**, **U** and **X.**

(3)-nonmeasurable process parameters- the simple polynomial mathematical model is, in fact, a relation between the input parameters and the output parameters of the system, in which there are weighting coefficients of the various parameters or coefficients:

$$\boldsymbol{Y}\left(\boldsymbol{U}\right)=\beta_0+\beta_1\boldsymbol{U}+\beta_2\boldsymbol{U}^2+\ldots \tag{4}$$

In literature, [1] there are different procedures for addressing this class of study and analysis in the following stages:

I-establishing the mathematical model describing the dependence between measurable inputs and outputs:

$$\boldsymbol{Y}(\boldsymbol{t})=\boldsymbol{f}\left\{\boldsymbol{U}(\boldsymbol{t}),\theta\right\} \tag{5}$$

II-determination of the relation between the parameters of the model θ_i and the coefficients of the physical process p_j: $\theta = f(p)$;

III-estimation of the parameters of the model θ_i as a result of the dependence of the inputs and outputs: U (t), Y (t);

IV-calculating process coefficients: $p = f^{-1}(\theta)$, and determining their deviation Δp_j;

(4) - non-measurable characteristics - these characteristics can be determined using the measurable state variables: $\eta = g\{U, Y\}$. Examples of unmeasurable quantities could be: process yield; fuel consumption; consumption of lubricating oil; wear of tools per unit of production, or per unit of time; wear residues deposited in oil tanks.

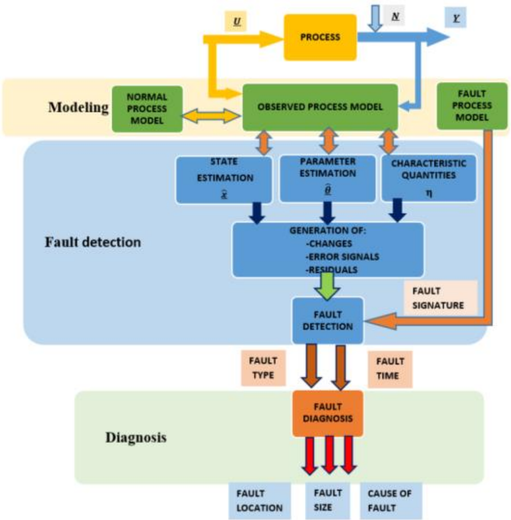

Figure 4- A general structure of process fault detection methods [1]

In figure 4 a structured general diagram is presented, [1], for the process fault detection and diagnosis of a process, based on the model for normal operation (which is supposed to be known), the fault model (which must contain, by means of definition, effects of faults on the analyzed quantities, effects concentrated in the fault signature), respectively the model for the observed process.

4. Conclusion and Results

The experiment was carried out in several stages, being part of a research program, supported by private companies in Romania and Italy, which proposed the creation of a data set allowing the development of a scientific opinion regarding the automatic monitoring system operation status, fault detection by determining the state of the lubricating oil [5], [8], [9], [10]. A first step in testing, an experimental physical model that took place at Mecoil (Italy) in the company's lab on a demo system was to test the operating parameters of the stand designed to simulate the operation of an automated mechanical system, but also to determine by direct measurement and detection by specialized sensors the state of oil degradation in various positions: cooling with coolant, impregnation with debris or accidental increase in oil temperature, thus measuring its oxidation degree . The elements that were tested (physicochemical parameters) were evaluated in the first stage, on a single level. Data processing and computing have generated positive results in obtaining the necessary data points to advance in the actual monitoring of a physical system, [11], [12], [13], [14]. The overcoming of this early phase allowed the installation of a hydraulic system containing sensor sets and transducers designed and physically installed in industrial installations (pilot systems) at EMSIL Techtrans SA Oradea-Romania, as well as in four other locations in Italy, to Mecoil partners.

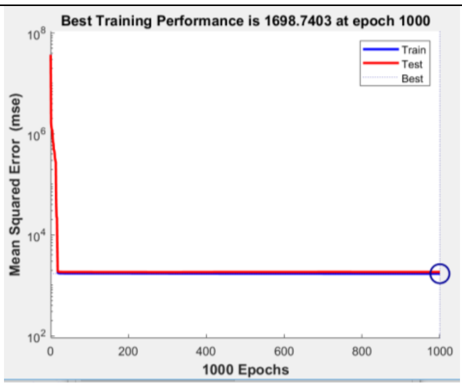

Figure 5. Performance

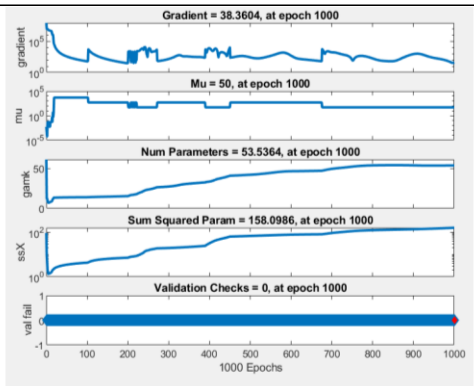

Figure 6. Training State

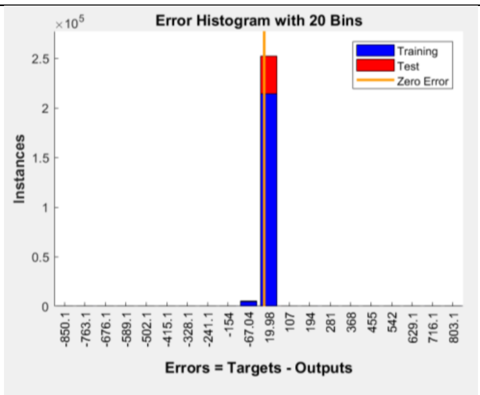

Figure 7. Error Histogram

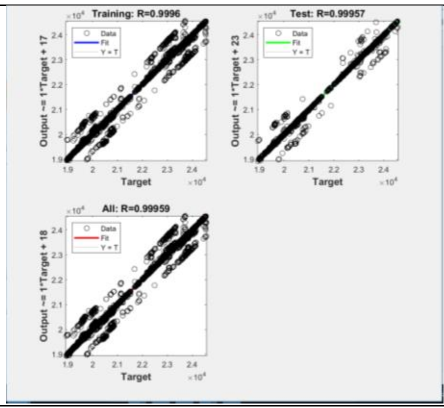

Figure 8. Plot regresion

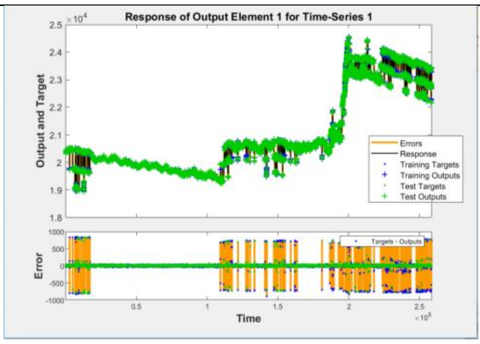

Figure 9. Time Series Response-Plotresponse

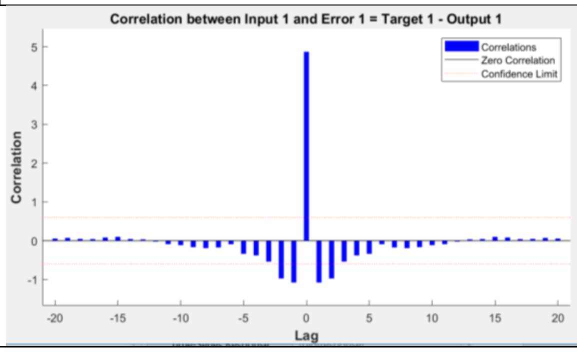

Figure 10. Input Error Cross Correlation

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