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The Use of ANFIS and ANN Models for Failure Time Series Forecasting in Industrial Systems

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Abstract— The objective of this paper is to test the accurace of Neural and Neural Fuzzy Networks to forecast failures in industrial equipment. An effective operation of industrial systems is vital. The necessity to get to know and control any possible failure that might compromise the production mission is a must. The target becomes the extension of the system activity at full load and in a continuous manner, at the required timing, without it being affected by defects of its integral parts.

Index Terms— Failure Forecast, Industrial Systems, ANFIS, ANN Models, Fuzzy Logic; Neural Fuzzy Networks, ANOVA.

1 Introduction

Predictive maintenance has the advantage of predicting the status of components by informing when they will have a defect within a good certainty margin. For this, it is necessary to carry out what is called “diagnosis”. This will evince the status of given components, when they will have a flaw and how to schedule their replacement before the occurrence of a critical situation leading to breakage and subsequent equipment stoppage [1].

In this paper, a time series is formed on the basis of a five-year survey on maintenance stoppage interventions to an industrial production system at the finishing plant of Petroflex Ind. e Com. S/A, the largest synthetic rubber producer in Latin America and one of the largest in the world. In this way, the objective is to introduce ANN- and ANFIS-based models with an aim to verify their system stoppage prediction capability so that in the future it could be possible to intervene in an optimum time before the systems fail, so that operation time is extended and, consequently, their availability is improved.

Neural network-based models have been successfully used for forecast time series in which there is a strong non-linearity component. This fact can be explained by the capability of a neural network to act as a “universal approximator” of continuous functions [2]. This approach has been frequently used in financial time series [3], [4], [5] and [6], as well as in the forecast of electric load consumption [7] and [8], in which other statistical techniques have showed less effective.

In the past few years, hybrid neuro-fuzzy systems have developed greatly, since they can combine the advantages of the fuzzy logic and those of the artificial neural networks, being able to incorporate in a single system the explicit knowledge of experts and the implicit knowledge inherent to a set of data. A significant number of references on these systems can be found in [9] and [10].

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2 Artificial Neural Networks (ANN)

The Artificial Neural Networks (ANN) are technological information processes inspired in studies of the brain and the nervous system [11]. Haykin [12] defines the ANN as follows:

“The ANNs are processors, massively parallel and distributed, which are naturally prone to store the knowledge from experience and make it useful. Thus, resembling the human brain in two aspects:
1- Knowledge is acquired by the network through a learning process, and
2- The intensities of the connections among neurons, known as synaptic weights, are used to store knowledge”.

Driven by the wish to understand and simulate how the brain works, the neural network models have been developing throughout the years by means of generalizations of mathematical models. Due to their capability to learn from examples and to generalize the information learned, the ANNs have proposed interesting solutions in several fields such as business administration, economics, medicine, agronomy, engineering etc.

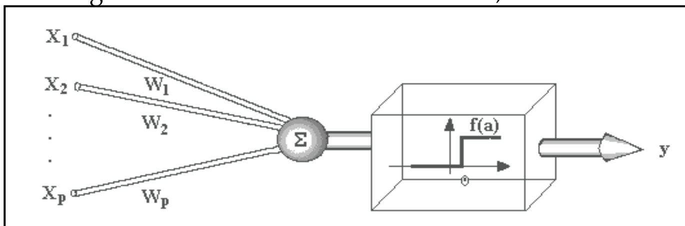

Fig. 1. McCulloch’s neurons model.

The artificial neuron’s mathematical model was initially idealized by the researchers W. S. McCulloch and W. H. Pitts in 1943 [13]. McCulloch and Pitts’s neurons main limitations were rigid weights, non-adjustability, only capable of implementing separate linear functions.

In figure 1 the input signals are expressed by Xp and should arrive at the neuron at the same time in order to be processed and sent to the output. The weights expressed by

Wp are attributes of great relevance in the artificial neuron, for it represents a degree of importance (intensity) that a specific input possess in regards to the neuron in question. The weight's role is to multiply the Xp signal in the synaptic input connected to the neuron.

Mathematically the weights are seen as value vectors [W1, W2,...,Wp] for a neuron or a weight matrix, vectors collection for a group of neurons.

The sum function adds the pondered inputs by the respective weight. A neuron's excitement signal is the sum result of the product of input signals expressed by the [X1, X2, ...,Xp] vector.

Subsequently, the process encounters the activation function f(a) together with the Φ threshold. If the product result of the sum of the input signal by the respective weights reaches the boundary it will be repassed, on the contrary, the signal won't be transferred. The activation function works as a neuron output amplitude limit, in other words, the input is normalized within a closed interval. Finally, y is the neuron's output.

Learning is the process through which the parameters of a neural network have adapted by means of a continuous stimulus from the environment where the network is operating, being the specific type of learning carried out defined by the particular way of how the adjustments performed in the parameters occur [12].

The learning process usually begins by random weights. The difference between the actual output (Y or Yt) and the desired output (Z) is called Δ. The objective is to minimize Δ (or at least reduce it to zero). The Δ reduction occurs through the weight's incremental change".

Undoubtedly, the greatest appeal of neural networks lies in the learning capability, by which the network extracts relevant information on the patterns presented and generates its own representation of the problem.

Supervised networks have been successfully used to solve several problems involving high degrees of non-linearity. Its training is of the supervised type and it uses a very popular algorithm called error backpropagation. This algorithm is based upon a learning rule that "corrects" the error during the training [12].

The "backpropagation" algorithm was created by Rumelhard, Hinton and Williams in 1986 [13], [12] stemming from the generalization of "Widrow-Hoff's" learning rule, which had been introduced in 1960-1962 for "feedforward perceptron"-type networks. The "Widrow-Hoff's" learning rule, also known as "Delta Rule" – LMS (minimization of the mean square error) – which adjusts the weights by the connections of the neurons in the network according to the error, that is, this rule aims at finding a set of weights and polarizations that minimize the error function.

The "Widrow-Hoff" learning rule is also known as the "Delta Rule" – LMS (Least Mean Squared Error) – that adjusts the connection weights among the net's neurons according to the error, in other words, this rule's objective is to find a group of weights and polarizations that minimize the failure function.

$$E = ½ \sum_{p=1}^{R} \sum_{p=1}^{S} (Y p, i - Y' p, i)^2 \quad (1)$$

where,
R = quantity of patterns or input vectors;
S = quantity of output neurons – output vector dimension;
yp,i = desired output in the nth neuron, when the eth pattern is presented;
y'p,i = obtained output by the net in the nth neuron, when the eth pattern is presented.
The change in the weight of Wi,j in the "Widrow-Hoff" rule is calculated by:

$$\Delta W_{i,j} = -\eta \,\partial E / \partial W_{i,j} \quad (2)$$

where η = learning rate and ∂ E / ∂ Wi,j is the partial derivation of the failure in relation to the respective connection's weight – gradient.

The main restriction in the minimization of the error towards the decreasing gradient is that the neuron transfer function has to be monotonic and distinguishable at any point.

The topology of the network architecture that uses this learning rule is generally made up of one or more hidden layers (intermediate) of non-linear neurons (with a sigmoidal propagation function) and a linear neuron output layer. Due to the great diffusion of the network architecture this learning rule is applied to, it is common to refer to it as the learning rule's own name, namely, BP network. BP networks having polarizations of, at least, one intermediate layer are theoretically capable of promoting the approximation of any mathematical function, still being widely used in the association and classification of standards.

3 ADAPTATIVE NEURO-FUZZY INFERENCE SYSTEMS (ANFIS)

The Adaptive Neuro-Fuzzy Inference System (ANFIS) is a neural network proposed by Jang [9]. Given an input-output set, the ANFIS builds up an equivalent neuro-fuzzy inference system. The parameters associated to the membership functions are adjusted by a learning algorithm. Adjustment for such parameters is carried out by using the backpropagation algorithm or a combination of it with a minimum square-type algorithm.

The fuzzy logic is based upon the theory of fuzzy sets and fuzzy rules (IF-THEN type), proposed by Zadeh and Mamdani, and is closely related to linguistic and the cognition science. Fuzzy is suitable for creating models from an explicit knowledge (rational and linguistically treatable), originating in human experts, whilst the artificial neural networks are appropriate for creating models from implicit knowledge (and not obvious) embedded in a set of data. As a consequence, many researchers have attempted to integrate these two modeling techniques in order to generate a hybrid model that can associate the advantages of each approach and minimize their deficiencies. From this, the hybrid neurofuzzy systems, or simply neurofuzzy systems (SNF), were born.

Jang [9] proposed a type of fuzzy modeling that utilizes an adaptive neural network structure jointly with estimates of minimum squares for the implementation of fuzzy systems. The utilization of this structure with such an objective is due to the inexistence of standardized methods to transform human knowledge into a base of rules to a fuzzy inference system, and to the need of efficient methods to adjust the membership functions and consequent minimization of the output error. In this way, the Adaptive Neuro-Fuzzy Inference System (ANFIS) can be a powerful tool for building up a set of IF-THEN fuzzy rules with membership functions suitable for being applied in the case study under focus.

4 Case Study

The study was conducted with a chemical industry company, that core business is the development, manufacturing and marketing of chemical intermediates, additives, specialty chemicals and plastics.

At present, twenty-three reasons for stopping industrial plants were knowed, in other words, equipment or systems that, in case of failure, stop the production system. Was selected one type of stop of the twenty-three to be study in this work.

The data used are related with the days on which stoppages (failure) occurred and with the amount of stopped hours in a system of industrial equipment accountable for the addition of sulfur acid using an H chemical pump, that is a single suction cantilever type centrifugal pump. It is a vital production system in the studied industrial plant.

The sample data were organized by the daily sum throughout 5 (five) years, that is, a series of 1,826 days in a row with their respective stopped hours.

4.1 Building the Networks

With an aim at accelerating the training phase, the data were normalized (Haykin, 2001), also providing input data between 0 and 1.

The data were divided in three different groups each with 1,826 data to train, validate and test.

The test data were the same for the two networks to be compared.

It was used the MSE (mean squared error) as a measure error that was computed using the real values of the time series and the output of the networks. It was used ANOVA statistical tests to determine the differences between errors.

The best neural network was that with lowest MSE.

It was used six architectures, containing 02, 03, 04, 05, 10 and 20 neurons in the hidden layer with sigmoid transfer functions, and one linear neuron in output layer. For each arquitecture it was used different number of interactions and MSE to stop training. The best neural network was that with ten neurons in the hidden layer.

In this paper it was used the ANFIS model to test if a fuzzy neural network could be used. This network has a fuzzyfication layer as input, a fuzzy inference system as a hidden layer and a real number as output.

The same data was used for training and testing. The input layer were the real data and some of networks were with Gaussian membership functions and others with sigmoid membership functions, with the same arquitecture and a Sugeno neuron in output neuron.

It was used the MSE as a measure error that was computed using the real values of the time series and the output of the fuzzy networks. It was used ANOVA statistical tests to determine the differences between errors.

The best neural fuzzy network was that with lowest MSE and that with Gaussian membership functions in the hidden layer.

The simutations done with these neural and neural fuzzy networks had good results with a low MSE for both.

In figure 2 it is presented as an example, a neural network configuration. In figure 3 it is presented as an example, a fuzzy neural network configuration.

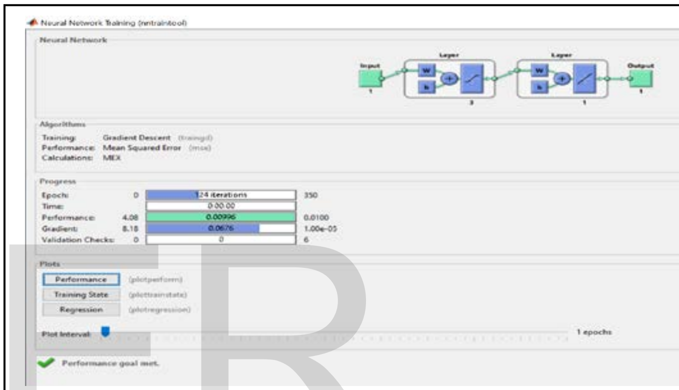

Fig. 2. Example of a neural network.

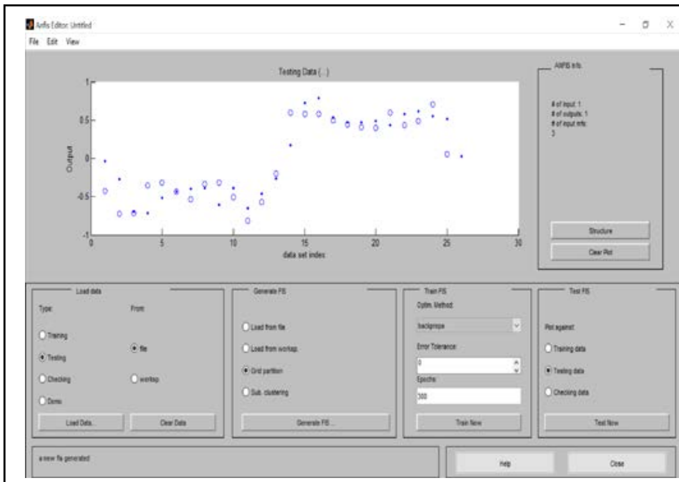

Fig. 3. Example of a fuzzy neural network.

5 Conclusions

The results achieved in this paper demonstrate, initially, the applicability of the Artificial Neural networks (ANN) and the

Adaptive Neuro-Fuzzy Inference System (ANFIS) for forecast maintenance stoppages, evincing the best ANN performance when compared with statistical methods.

From the analysis of the association of the MAD errors, it was verified that on the days when the stoppages were extended (outliers), the biggest errors occurred; however, both models had forecasted system stoppages, thus allowing for a programming interventions on a date close to that and with a higher hit margin.

It can be said that Artificial Intelligence using ANN or ANFIS models forecast time failure series for systems are very usefull, especially due to market demand and undoubtedly this is a technique that still evolve greatly in the field of industrial maintenance, aiming at subsidizing relevant management decision-making. It still relies on the possibility to be inserted in the computing systems that currently provide baseline information collected in its everyday operations, as is the case of this paper. Also, it has a substantially lower cost in relation with other predictive maintenance techniques.

Forecasting techniques, such as the ones presented hereby, acting jointly with the maintenance planning, can provide in the medium term, as long as they are carefully implemented and followed up, a substantial increase in the amount of available operating hours.

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