Unsupervised Neural Network for Forecasting Alarms in Hydroelectric Power Plant[‡]

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Abstract - Power plant management relies on monitoring many signals that represent the technical parameters of the real plant. The use of neural networks (NN) is a novel approach that can help to produce decisions when integrated in a more general system. In this paper we introduce a NN module using an ART-MAP to discriminate different situations from the plant in order to prevent future malfunctions. A special process to generate of a complete training set has been designed. This process is developed in order to deal with the absence of data in abnormal plant situations. This module belongs to a more general system for predictive maintenance that has been implemented and incorporated in an hydroelectric plant.

1. Introduction

Monitoring systems, in general, are able to analyze the input values and make decisions, and consequently generate alarms when the numerical value of the variables is out the range fixed by human experts. The main advantages to be gained with predictive modules are productivity optimization, operation safety, and protecting equipment against damage caused by malfunctioning. The results could also be adapted to any system dependent on distributed control centers, since the general philosophy is to model the plant and predict future situations instead of merely taking precautionary measures [1].

Some Artificial Intelligence (AI) techniques have been suggested in the literature to develop automatic surveillance systems for power plants [2] [3]. The analysis of data coming from vital components of a power plant gives additional information for the identification of potential future failures and their causes, making it possible to perform effective preventive maintenance. Using the expert knowledge of plant operators [4], it is possible not only to provide valid ranges for variables but to predict future abnormal situations that could be avoided. Some machine learning techniques [5] have also been applied for this problem. Particularly, neural networks are good approaches for control predictive system because of highly non linear relationships between data and abnormal situation [6] [7] [8].

The use of NN when dealing with real situations (not simulations) adds an important problem. The acquisition of a complete set of data corresponding to

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abnormal situations is not possible due to security and productivity restrictions in the plant. In this work a special procedure of generating complete training sets (under those restrictions) is developed.

The generating training set has been used to train an unsupervised NN. This NN has been designed to forecast alarms in a hydroelectric power plant and it is included in a hybrid predictive system named MAPAIS (Spanish abbreviation of advanced system for predictive maintenance incorporating audio and video).

This system relies on advanced artificial intelligence techniques, audio and video signal processing, expert knowledge systems and neural networks modeling. Within the predictive modules of the system, the main goal of the neural network maintenance module is to take advantage of the data recorded at every point of the hydroelectric plant, acting as a future-incident-predictor in the sense that it learns to detect potentially conflictive situations.

The system has been installed and it is working in a hydroelectric plant named Villalcampo I (IBERDROLA), which is located in the Zamora province of Northwest Spain. This plant has also been used for implementing and further testing the MAPAIS project.

The organization of the rest of the paper is as follows: the second section presents an overview of the general system. The third section describes the variables acquired used as input of the predictive NN. The fourth section is a detailed description of the selected neural net and the special training process. The real system performance at the Villalcampo plant is given in the fifth section and some conclusions are presented.

2. System Architecture

The system could be decomposed in three levels: acquisition, this level records values of the input variables (digital/analog values); prediction, the main part of the work composed by several modules; and presentation, using graphical interfaces, alarms are displayed and the plant staff is alerted.

In order to acquire the data necessary to predict future situations, three different acquisition systems have been installed: SCADA, this system allows the acquisition of the plant internal data as pressure, temperature, levels, etc.; COMPASS, this system records the audio signal in the generating group; and TV cameras that scan the electric switches that translate the energy out the plant.

In figure 1 a general view of the graphical supervisory system is presented, consisting in a schematic image of the electricity generating machine group constituted by three independent generators named Group #1, Group #2 and Group

#3 respectively. The plant operator is able to obtain information about any system parameter by descending a hierarchical hyperlink structure.

Fig. 1: Monitoring System Interface.

The predictive maintenance system can be decomposed in several modules, each one is independent and predicts individually. All of the modules are integrated in a distributed architecture. A briefly description of the modules is as follows:

- The neural network predictive maintenance module produces predictions about future malfunctioning using a model of the plant. It relies on a neural network model generated from past data and present events. The main drawback to this approach is that abnormal incidents seldom occur, and it is therefore difficult to isolate the main variables involved in every process.
- The image processing module was designed to reinforce measurements from several electrical transceptrors. Thus, image processing is included to assess the functioning of the power switching systems.
- The rule-based diagnosis module will collect all the information available from expert human controllers in order to predict problems.

- The neural network acoustic prediction module takes advantage of audio data recorded in different points of every energy group to generate a warning signal of future abnormal situations.
- Finally, the data fusion and decision module collects all the available data to integrate the information by means of Dempster-Shafer theory.

A general data flow scheme of the system is shown in figure 2.

Fig.2: Data flow diagram between modules.

The predictive modules have been included in a subtree of the monitoring system. When a module generates an alarm activates the interface panel shown in figure 3.

3. Data Acquisition

As mentioned above, an electricity-generating machine group, constituted by three independent generators named Group #1, Group #2 and Group #3 respectively, are monitored constantly. Every one of the groups can be sketched as in figure 4, where part “A” represents the alternating current generator and “B” represents the hydraulic turbine (obviously, this part is underwater). Many sensors located at different points in the machinery serve to monitor the group.

A generating group is decomposed in functional units. Each unit is divided in different elements. The data acquisition equipment, which was already working in the plant is a SCADA system, is able to register the values of a set of variables in an element. The decomposition of each generating group is shown in Table 1.

Functional Unit	Element	Example of Variable
Water Intake	Intake gate	<i>Gate_Intake_Gate</i>
	Chain Drive	<i>Motor_Pressure</i>
Turbine	Pressure Equipment	<i>Level</i>
	Velocity Regulator	<i>Deposit_Level</i>
	Pressure Boiler	<i>Level</i>
	Power Distributing	<i>Position</i>
	Stamping Junction	<i>Temperature</i>
	Pillow Lock	<i>Oil_Temperature</i>
	Belt Wheel	<i>Temperature</i>
	Bailing Bomb	<i>On</i>
Alternating Current Generator	Rotor	<i>Velocity</i>
	Stator	<i>Intensity_Generator</i>
	Stimulation Equipment	<i>Regulator_Position</i>
	Push Pillow Lock	<i>Metal_Temperature</i>
	Low Pillow Lock	<i>Low_Metal_Temperature</i>
	High Pillow Lock	<i>High_Metal_Temperature</i>
	Brakes	<i>Normal_Pressure</i>
	Cooling System	<i>Air_Temperature</i>
Current Transformer		<i>Differential_Protection</i>
Dammed Up Waters		<i>Closed</i>
Exhaustion System		<i>Fired</i>

Table 1: Decomposition of a generating group

The number of variables, for a generating group, is 106 and they are stored to obtain serial data that represent the normal power plant functioning over several years.

The variable values are inputs of the Predictive Neural Network. The output is an alarm, that represents a future abnormal situation of the power plant. An alarm predicts a future abnormal functioning of one of the elements.

4. Predictive Neural Network

The ultimate goal of the system is to carry out a predictive maintenance. This task could be reduced to a classification task by introducing each different set of input signals in a different category. Each class can be related with a different prediction

for the power plant behavior. The acquisition system is able to record 106 variables, v_i , and the classified vector is composed by a value of each variable, $(v_1, v_2, v_3, \dots, v_{106})$.

When dealing with NN, a complete set of vectors is needed for the training phase. The set must include vectors representing normal situations and vectors for each possible alarm. Considering an alarm as an output signal that predicts a specific future abnormal situation, from a power plant state. Relations between power plant states and alarms are highly dynamic and non linear. Thus, a good method for approximate those relations are NN.

It is interesting to outline some specific features of these kind of systems. Firstly, it is not possible to know previously how many classes will be needed. In second place, the dynamical nature of input data makes necessary the "on line" creation of new classes if none of existing ones is correct. And finally, the training set is reduced to the stored data from real situations. This stored data correspond with situations in which normal working has been produced or if it corresponds to an alarm situation, the specific alarm is unknown or even there is no knowledge about whether or not it is an alarm.

Due to first and second characteristics, ART-NN models [9] are the best candidates. They are unsupervised, have continuously learning and thus can produce new categories as the system is working (classifying).

In order the NN (ART) to produce a generalized behavior, a complete training set is needed. The generation of the mentioned training set with real data from the power plant is not possible, so it is necessary to generate an artificial training set. The special generation process is based on an expert system and a set of neural networks, NN_i , one for each variable, v_i considered by the expert system.

The expert system generates alarms based on human experts knowledge. This system is composed by a small number of rules (two or three) for each possible alarm. The expert system do not relate more than four variables in each rule and globally only consider 15 variables. The expert system produces the alarm category and the responsible variables of that alarm. As the expert system only knows the relations among 15 variables from the 106 system variables, it is impossible to generate a complete vector defined by all the variables values representing this alarm.

The generation of the values of the remaining variables in abnormal situations are based on the relations of these variables with the variable that produces the alarm. This relation is only known in normal situations and it is non-linear so a NN is proposed to obtain the complete vector, $(v_1, v_2, v_3, \dots, v_{106})$, from the variable value. The NN_i ($i=1$ to 15) is trained with a backpropagation algorithm using normal working data stored.

The training set generation for the ART model is as follows:

1. The expert system generates an alarm, A_k , and the variable that produces it, v_i .
2. The variable, v_i , with its value is introduced in its corresponding neural network, NN_i , (previously trained for that variable).
3. The output of NN_i is a complete vector, $(v_1, v_2, v_3, \dots, v_{106})$, that represents all the variables values for that alarm, A_k .
4. This vector is introduced in the training set labeled with the name of the alarm, A_k .
5. The previous four steps are repeated until the training set is complete.
6. The real stored data (normal situations) are added to the training set with the label “no-alarm”.

A scheme of the process is shown in figure 5. The training set built in this way has been used to train an ART-Map NN.

Figure 5. Special training process.

5. System Performance on Hydroelectric Plant: Final Conclusions

During a period of a week tests were carried out on the maintenance system under strict supervision from technical staff of the plant. During the test period final tuning of the system was needed due to special weather conditions under which the system was tested (heavy rainfall that overloaded the dam capacity and flood-gates had to be opened to allow run-off of the excess water). This unusual situation allowed us to evaluate generalization capacity of the system because the network had to deal with unusual data.

After that, the system was considered to have reached an ideal working behavior, this way, it was definitely included in the monitoring system on January 1996 and it is nowadays being used as a decision-making aid.

The good performance of the ART model developed for forecasting proves the ability of the generating training set procedure to estimate variable values related with future abnormal situations.

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