METHOD FOR ALARM PREDICTION

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Abstract: The goal of this paper is to show a predictive supervisory method for the trending of variables of technological processes and devices. The data obtained in real time for each variable are used to estimate the parameters of a mathematical model. This model is continuous and of first-order or second-order (critically damped, overdamped or underdamped), all of which show time delay. An optimization algorithm is used for estimating the parameters. Before performing the estimation, the most appropriate model is determined by means of a backpropagation neural network (NN) previously trained. Virtual Instrumentation was used for the method programming.

1 INTRODUCTION

The antecedents are methods for supervising technological processes (Juricek, Seborg and Larimore, 1998) and more specifically, the algorithms that devices use to detect special or abnormal conditions. These conditions will be determined by the values taken up by their variables in the chosen algorithm. Alarm algorithms by limits and hysteresis may be used, but they are limited to diagnose conditions that exist already or that are likely to occur in a short period of time. This paper aims at developing more detailed algorithms using mathematical models representing the dynamics of the processes that will be supervised. The presented method makes it possible to predict, in short time, possible abnormal conditions. This will give rise to one of two possibilities. The first is a series of preventative actions to prevent the system from operating in such a way. The second is a series of actions for the successful operation of the process upon reaching the critical state that may or may not be abnormal (as it happens with hydraulic canals whose dynamics are complex).

The backpropagation network (NN) was chosen due to it's ability to successfully recognize diverse patterns. In our case, it is used to recognize signal patterns of first and second order dynamic systems (Ogata, 2001) in which the dynamics of a considerable amount of technological processes can be represented. The methodology used consists of estimating the parameters of the models through an optimization algorithm (Edgar and Himmelblau, 1988). Before such parameters are estimated, the most appropriate model is determined by means of a NN, thus reducing the total processing time.

A broad range of mathematical techniques, ranging from statistics to fuzzy logic, have been used to great advantage in intelligent data analysis (Robins, 2003).

The following transfer functions are used:
First order model:

$$Gm(s) = \frac{K e^{-\theta s}}{T_1 s + 1} \quad (1)$$

Second order model:

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$$Gm(s) = \frac{Ke^{-\theta s}}{s^2/\omega n^2 + 2\xi s/\omega n + 1} \quad (2)$$

where the parameters to be estimated are:
T_1 : time constant; K : gain; w_n : natural oscillation frequency; θ : time delay.
ζ: coefficient of damping. $\zeta<1$ (underdamped). $\zeta=1$ (critically damped). $\zeta>1$ (overdamped).

2 BLOCK CHART OF THE METHOD

Figure 1 displays the simplified flow chart of a cycle of the predictive alarm algorithm. A circular buffer of changeable dimensions is used. This cycle begins with the permanent storing of N last data of the variable of the technological process or device under supervision.

As shown in Figure 2, the ***instant for recognizing and estimating the parameters*** of the model representing by the points stored in the circular buffer is determined by an algorithm of lineal trend prediction. On predicting by lineal trend, the behavior of the variable is considered to be that of a straight line from the current sampling instant.- Figure 2 shows an example of a variable versus time plot V(t) with the following parameters:
HAL: high alarm limit; v(k): current value; v(k-1): previous value; T: sampling period. The current sampling instant in this example is 2T.

Regarding Figure 2, it can be stated that:

$$\frac{V(k)-V(k-1)}{2T-T} = \frac{LSA-V(k)}{tp} \quad (3)$$

Obtaining tp as:

$$tp = \left(\frac{T}{V(k)-V(k-1)}\right)[LSA-V(k)] \quad (4)$$

The minimum prediction time T_{mp} must be set, such that if tp < $T_{mp,}$ then the recognition process of the signal pattern represented by the samples stored in the circular buffer begins.

Afterwards, ***digital filtering*** by the moving average filter (Oppenheim, Schafer and Buck, 1999) is performed according to the following expression:

$$Y(k) = \frac{1}{2M+1}\sum_{i=-M}^{+M} X(k-i) \quad (5)$$

where M = 2 was used.

The latest data are selected if it is ***the time for recognizing and estimating the parameters*** of the model.

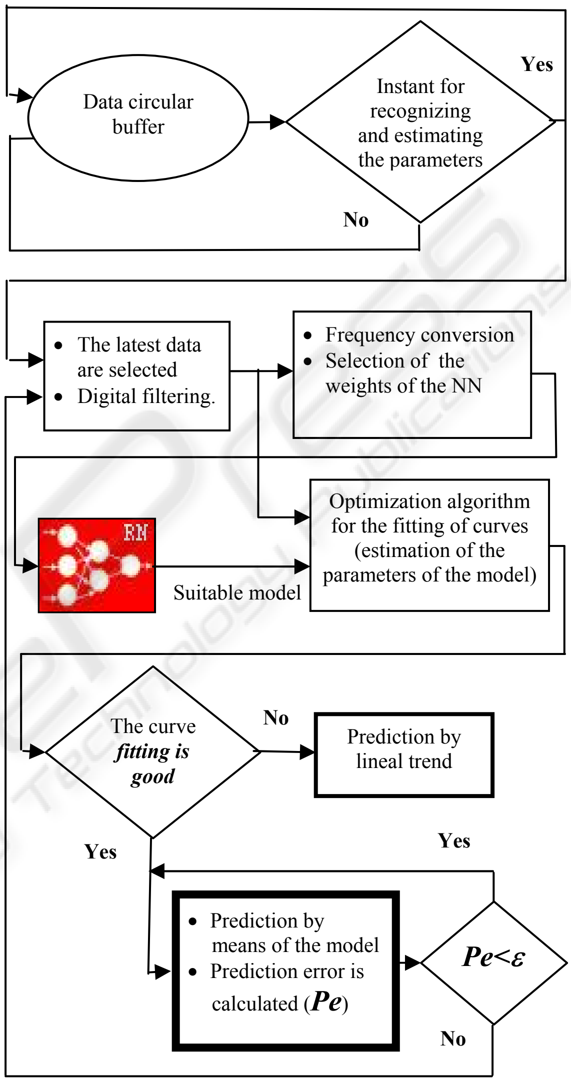

Figure 1: Flow diagram of the predictive alarm algorithm cycle

Then, a sampling ***frequency conversion*** with a non-integer factor combining interpolation and decimation is performed (Oppenheim, Schafer and Buck, 1999) which makes it possible to obtain 30 points. This is the number of input neurons of the NN. Later, the ***selection of the weights of the NN*** is accomplished in accordance with the sign of the 30-point-curve slope, since it was trained for the patterns with a positive and negative slope. As an output, the NN will produce the most suitable model with its parameters estimated through an

optimization algorithm ***for the fitting of curves*** using all the selected points. Hooke and Jeeves´s (Hooke and Jeeves, 1961) optimization method of direct search is used. This method returns the minimized index. If the returned index is smaller than a value that has been pre-established as fair, then it is considered that the curve ***fitting is good*** (estimation of the parameters of the model), and the ***prediction by means of the model*** will be made in order to predict the time when the variable will reach its limit value. The algorithm establishes the value considered as fair for the optimization index by default. The user can increase or reduce this value considered as fair if he wants the model to have more or less accuracy. The ***prediction error*** is ***calculated*** periodically. If the ***fitting*** of the model ***is not good***, the ***prediction by lineal trend*** is made.

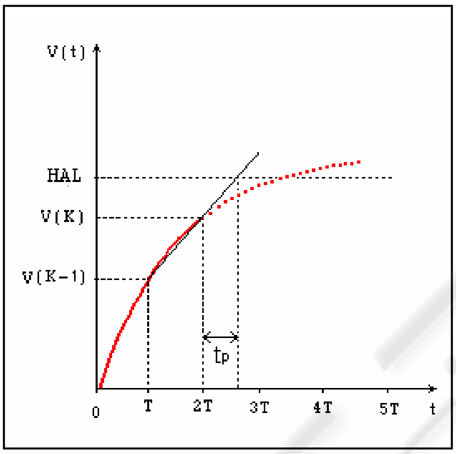

Figure 2: Prediction based on the linear-trend of the variable

2.1 Prediction error

Whenever the prediction is made, an approximate prediction error (***Pe***) is calculated. If this error is smaller than a pre-established value ε (***Pe<ε***), the prediction is continued according to the model; otherwise, as points keep on being stored in the circular buffer, another process for estimating parameters is performed. \

3 NEURAL NETWORK TRAINING PATTERNS

The selection of the NN training patterns was based on the behavior of the dynamic responses of first- and second-order systems to step input function, because this is the most frequent type of disturbance. In other cases, even though it might not strictly be an ideal step, it can be considered as such, provided that for instance, the time constants of the process are relatively larger than the time constants of an exponential signal. Figure 3 displays the responses of critically damped second order systems, with natural oscillation frequencies w_n equal to 1, 0.5 and 0.25 respectively. 30 points are shown for every curve. They have been taken up from sampling frequencies of 4, 2 and 1 samples per second, respectively. That is why every time interval in axis X will be the sampling period of each curve. If the points of the three curves were graphically represented using the same time interval for axis X, they would be superimposed, as shown in Figure 4.

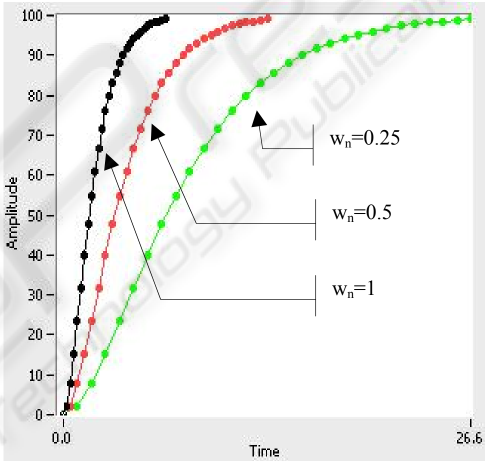

Figure 3: Responses of critically damped systems

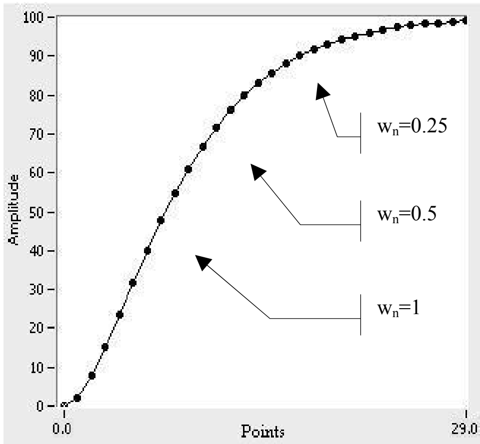

Figure 4: The three curves of Figure 3, superimposed

A similar behavior will occur in first order systems with respect to the time constant, as well as in overdamped and underdamped second order systems, in which only its coefficient of damping will show any difference.

For NN training patterns, the variations in signal amplitude are taken up in %, standardized, from 40% to 90%.

After numerous tests, training was carried out with 858 input patterns, distributed in the following way:

- For overdamped second order systems (OSO):

  For every ζ value, 11 patterns are obtained corresponding to the variations of the amplitude from 40 to 90, with an increase of 5 (40, 45, 50, 55, 60, 65, 70, 75, 80, 85, 90).

  The ζ varies from 1.2 to 3, with an increase of 0.09, thus obtaining a total of **220 patterns.**

  For ζ greater than 3, the behavior of the system is similar to a first order system.

- For underdamped second-order systems (USO):

  As for every ζ value, 11 patterns corresponding to amplitude variations are obtained.

  The ζ varies from 0.1 to 0.7, with an increase of 0.0667, thus obtaining a total of **99 patterns**.

- For first- (F) and critically damped second-order (CSO) systems, **11 patterns** are created, respectively, corresponding to amplitude variations from 40 to 90.

In order to have a similar number of patterns for each model and achieve a better training of the NN, the F and CSO patterns are repeated 20 times, respectively, for a total of 440 patterns. For the USO pattern they are repeated twice for 198 patterns. 858 PATTERNS IN ALL.

Once the patterns were chosen, varied topologies were used until the simplest with the most suitable response was obtained. Eventually, a 30-input neural network was used, 11 neurons in the hidden layer and four-output neurons. Very good results were obtained in the training and generalization of the NN. The training error was 0.15%. Over 1000 test patterns were used, obtaining a correct response, with an error of 0.9% of failures.

4 CONCLUSIONS AND FUTURE WORK

Satisfactory results were obtained on training the neural network, having a high level of generalization. During the operation, the neural network recognized the signals used, even those affected by noise.

The research and the technological advances presented are a satisfactory step forward in facilitating the use of advanced and efficient algorithms of predictive alarm by trend, with minimum processing time. The presented algorithm guarantees that the prediction will be corrected in each period of analysis of the alarm condition states. This method of predictive alarm has been applied with good results on several occasions, in managing hydraulic canals for irrigation and research purposes, and in controlling sequential processes. For example, a more efficient operation of a set of tanks was developed by predicting the time in which a tank level will reach a limit value.

Moreover, work has began to enhance the neural network to not only select the most appropriate model, but also make a pre-estimation of such a model. This optimization algorithm would be extremely efficient as its initial operation conditions would be the values pre-estimated by the neural network.

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