HYBRID MODELLING USING NEURAL NETWORK BASED PREDICTION UNDER FOUNDATION™ FIELDBUS

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ABSTRACT

The objective of this work is to describe a novel methodology for modelling MV and NL processes, useful among other applications, in fault detection tasks, possibly to be applied on plant supervision, including transient state fault detection and decision making according the well known method based on parity equations and rule based residuals evaluation.

KEYWORDS: Neural networks, Residual generation, Fault detection, Neural predictor

1. INTRODUCTION

Model based control systems are effective for making local process changes within a specific range of operation [1]. However, the existence of highly non-linear (NL) relationships between process input/output variables represents a serious difficulty to achieve reliable mathematical models [2, 10]. On the other hand, the implementation of intelligent control technology based on soft computing methodologies such as neural networks (NN) and genetic algorithms (GA) can remarkably enhance the regulatory and advanced control capabilities of many industrial processes [3, 8, 11]. Nevertheless, modelling the dynamic response of a multivariable (MV) and NL process by means of NN based back propagation methodologies requires a priori deep knowledge with regard to NN architectures related to a particular process. The demand of such knowledge may be avoided by applying Hybrid Modelling (HM). The implementation of a NN model using back propagation algorithm [12, 13, 14] based on collection of real-time data for a steady state operation condition is presented. The main relevant topic of the contribution in this work is the utilisation of artificial neural networks (ANN) technology for the inferential analysis of performance in a wide range of industrial controlled plants. The proposed NN's architectures can accurately predict various properties associated with plant performance behaviour. The back-propagation network is the most popular feedforward predictive network deployed in process industries.

2. NEURAL NETWORK BASED PREDICTION

Given a plant where V_1 is the output variable and V_2, V_3, $\ldots V_N$ are input variables, the following relation may be defined for the steady state:

$$V_1 = f(V_2, V_3, \cdots V_N) \qquad (1)$$

Given a steady state database achieved by processing expression (1), following output steady state predictions can be obtained:

$$\begin{aligned} V_1 &= f(V_2, V_3, \cdots V_N), \\ V_2 &= f(V_1, V_3, \cdots V_N), \\ V_3 &= f(V_1, V_2, \cdots V_N), \\ V_N &= f(V_1, V_2, \cdots V_{N-1}) \end{aligned} \qquad (2)$$

Consequently, a steady state predictor may be defined as a universal functional approximation device according the definition (2), where for convenience all variables can operate as input or output variables. This concept means that if a process is described by the function described by expression (1), a predictor can be defined as

$$V_2 = f(V_1, V_3, \cdots V_N) \qquad (3)$$

where the process output is V_1 and the predictor output is V_2. Furthermore, V_1 is acting as an input variable to the predictor. This concept may be implemented by a proper back propagation NN technique to achieve a neural network based model (NNBM). Neural networks will not be an accurate predictor [4, 5], if operating inputs/outputs data are outside their training data range. Therefore, the training data set should possess sufficient operational range including the maximum and minimum values for both inputs/output variables [13, 14, 17]. Data to be acquired must satisfy the steady state dynamic behaviour [9]. In order to ensure such condition a pre-filtering stage is to be carried out. This means that a variable is enabled to enter the database if and only if all inputs/output variables are in steady state. Such condition may be expressed as

$$IF \ \frac{dV_1}{dt} \ AND \ \frac{dV_2}{dt} \ AND \ \frac{dV_3}{dt} \ AND \cdots \ \frac{dV_n}{dt} \cong 0 \ THEN \ ENABLE \qquad (4)$$

Once database is filled with enabled data, a predictor based NN can be achieved. Prediction time horizon is limited by the transient state response time. The admitted data set into the database may be used to train the NN based predictor . Each trained NN represent a predictor which consists in a neural NNBM. In order to define a steady state NN based predictor, the output and inputs must be defined according the relationship [9,11] required between variables with achieved data from the database. A transient state model can be obtained by means of the association of a transfer function in series with the proposed steady state process model represented by NNBM. The most direct way of obtaining an empirical linear dynamic model of a process is to find the parameters (deadtime, time constant, and damping coefficient) that fit the experimentally obtained response data. The process being identified by analysis of the time response is openloop. It can be modelled by a gain, a deadtime and one lag. In the SISO case, the output/input ratio or transfer function can be expressed as

$$\frac{output}{input} = G(s) = K \frac{e^{-Ds}}{Ts+1} \qquad (5)$$

The steady state non-linear gain K is obtained by the NNBM for SISO case. The deadtime D can be easily read from the time response curve analysis. The time constant, under the assumption of a first order lag, can be estimated from the time it takes the output to reach 62.3 percent of the final steady state change.

An approach to the transient response model for a non-linear multi-input single output process, can be formulated from expression (5), by considering that

- steady state response is given bay the NNBM predictor output (Y_{SS}) and
- transient response is defined as the association of inputs transient responses (Y_{TR}) with NNBM predictor

Consequently input transient responses are defined as

$$Y_{TRi}(s) = V_i(s) \cdot \frac{e^{-D_i s}}{T_i s + 1} \qquad (6)$$

where $Y_{TR}(t)$ is the time response or virtual output due to the input $V_i(t)$.

In the general case there are several input variables and consequently, the response is due to the contribution of all process inputs. Superposition principle can not be applied due to non linear characteristics. Then, the set of input values to the NNBM is given as:

$$V_{TR1}(t) = V_1(t)\cdot\frac{e^{-Ds}}{T_1 s+1} = V_1(t)\cdot TR_1$$
$$V_{TR2}(t) = V_2(t)\cdot\frac{e^{-Ds}}{T_2 s+1} = V_2(t)\cdot TR_2 \qquad (7)$$
$$\vdots$$
$$V_{TRN}(t) = V_N(t)\cdot\frac{e^{-Ds}}{T_N s+1} = V_N(t)\cdot TR_N$$

and the vector of partial transient inputs is given by

$$\begin{vmatrix} V_{TR1} \\ V_{TR2} \\ \vdots \\ V_{TRN} \end{vmatrix} = \begin{bmatrix} TR_1 \\ TR_2 \\ \vdots \\ TR_N \end{bmatrix} \begin{vmatrix} V_1 & V_2 \cdots V_N \end{vmatrix} \qquad (8)$$

Dynamic modelling approach from definitions of expressions (2-3), can be summarised with the scheme shown in figure 1.

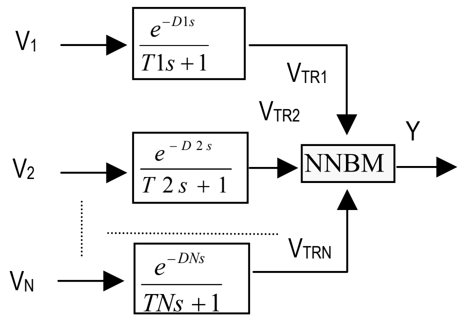

Figure 1. Neural Network based predictor using a dynamic modelling approach.

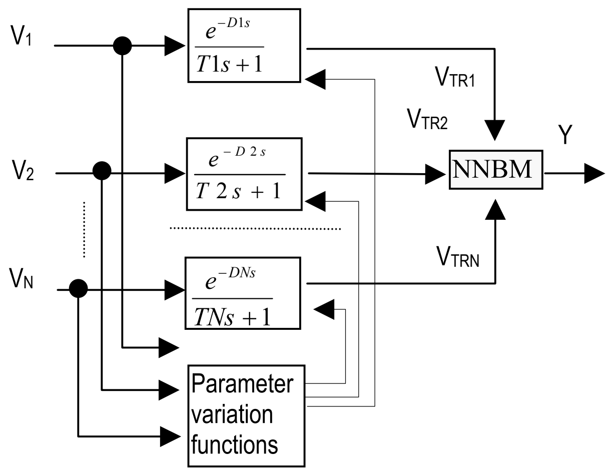

Figure 2. Parameter updating technique for the case of parameters variation

In many cases process parameters are time variant. Under such circumstance an adaptive procedure is to be carried out according to a conventional technique shown at figure 2, known as gain scheduling. Time constants of transfer functions responsible for modelling partial transient responses are updated by a gain scheduling strategy.

3. HM VALIDATION

Detection of some deviation between process response and hybrid model response into the time horizon of transient responses is possible by applying parity equation procedures. This is due to some modelling errors. Detection logic by applying the technique of parity equations is shown at figure 3, where a rule based logic procedure is added to implement some decision making strategy. Then, proposed method on failure analysis for error detection in transient and steady states is carried out by applying the following steps:

Step 1: At the first stage of supervision task, correct operation pattern must be transferred to the ANNs by means of a training phase with representative data contained into the database. If the transient and steady state operation pattern change, updating the ANNs as well as transient state models is strongly recommended as priority action, beginning by training and identification phases [6, 7, 17]. After training phase, new NN based model is applied.

Step 2: Deviation detection.- This step is cyclically realised during each sample time period in order to carry out an error model detection task: Consists in evaluate residuals (*Ri*) achieved by comparing the actual value of a variable *(Y)* with the output of proposed HM predictor (*Yv*) which consists of a back propagation trained neural network associated to dynamic models as shown in figure 4.

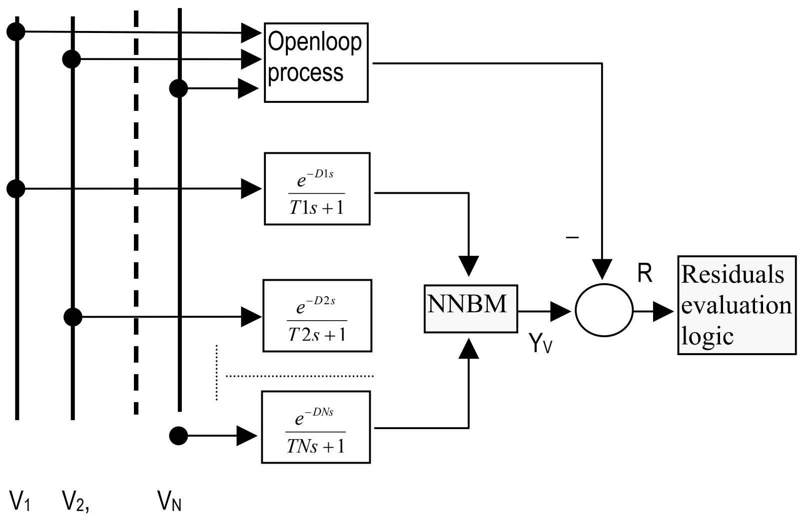

Figure 3. Modelling error detection by parity equations based on neural network prediction.

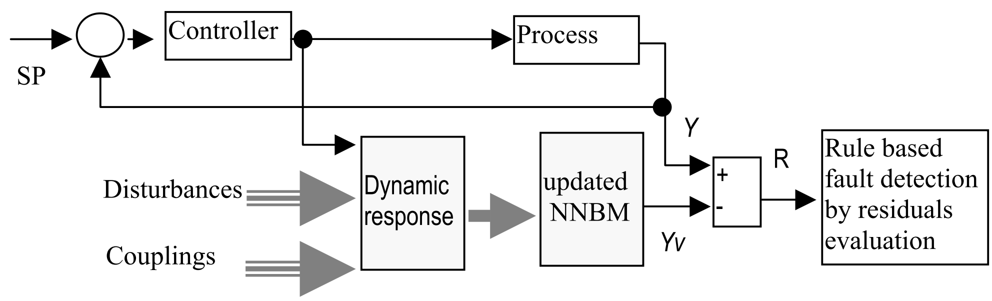

Figure 4. Fault detection scheme based on dynamic NNBM.

4. APPLICATION PROCEDURE

Let us consider a heat exchanger where its output T is a function of several input variables qe, Te, qf as illustrated by expression (10) under the structure shown at figure 5

$$T = f(q_e, T_e, q_f) \qquad (10)$$

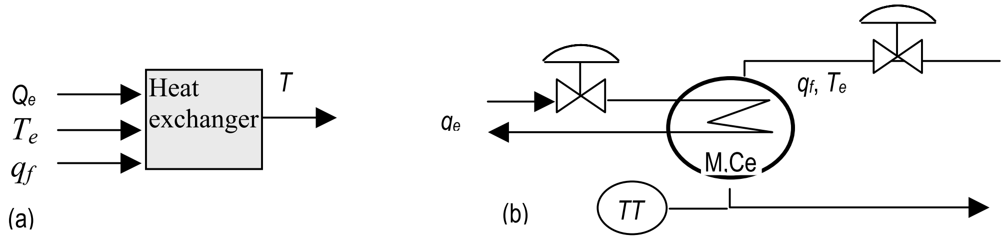

Figure 5. Heat exchanger: (a) block diagram. (b) physical layout

Predictor based on NNBM is achieved from tank system database by a back propagation training phase. From the analysis of transient response , D1=0, D2=0, D3=0, T1=T2=T3 =5/qf. With such parameters predictor is configured with the structure shown in figure 3. Consequetly, dynamic response is identified on line with the scheme of figure 6 using a predictor shown in same figure.

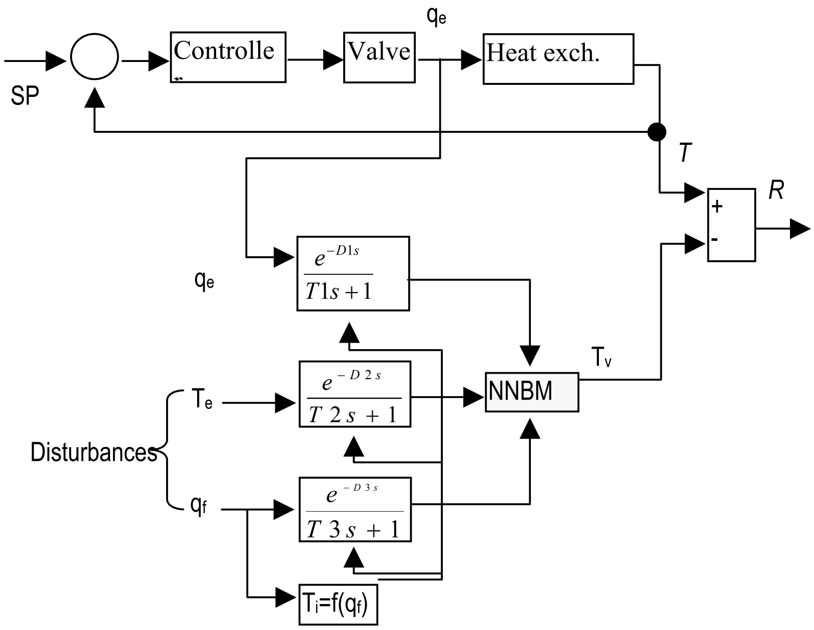

Figure 6. Fault detection scheme based on dynamic NNBM.

Achieved HM performance is validated by simulation whose results are shown at figure 7.

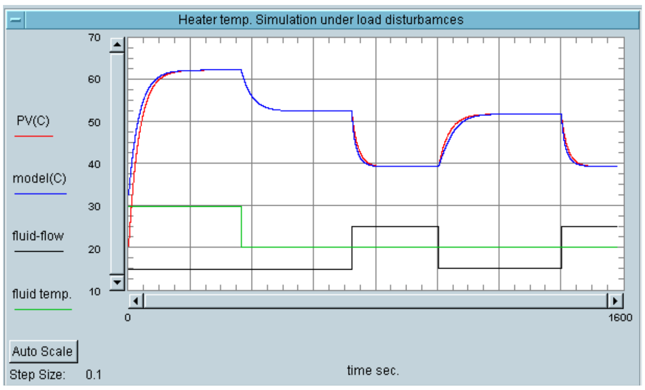

Figure 7. Heater exchanger HM performance

The model and the process are excited simultaneosly with supply energy. At same time both processess are disturbed with input fluid temperatute and input fluid flow.Predictor behaviour is satisfactory under mentioined disturbances such as input fluid temperature, input flow rate and manipulated variable. This means that processess for which a math-model is difficult to achieve, it may be modelised by proposed method in order to be supervised for failures or parameters variatuions. Implementation of proposed methodology is carried out with the facilities provided by a FOUNDATION™ Fieldbus compliant tool [17]. The DeltaV Neural application, a toolbox of DeltaV[17], has been selected for this purpose

5. CONCLUSIONS

A simple and coherent methodology to implement a transient response predictor is presented. Such predictor could be applied on all cases where a model is to be applied, such as failure analysis to detect plant potential faults due to measuring instrumentation failures and/or changes in process dynamic conditions. The availability of advanced FOUNDATION™ Fieldbus based tools bridge the gap between the proposed methodology and its implementation.

6. ACKNOWLEDGEMENT

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7. REFERENCES

[1] Antsaklis, P. J. and Passino, K. M. (eds), *An Introduction to Intelligent and Autonomous Contro*l, Kluwer Acadmic Publishers, Norwell, MA, 1993

[2] *Ras Tanura refinary Facilities Manual*, Ras Tanura Refinery: Refining Division, Sec 3,, 1995.

[3] Bawazeer, K. H., Prediction of Crude Oil Product Quality Parameters Using Neural Networks, MS Thesis, Florida Atlantic University, Boca Raton, FL, August, 1996

[4] Bawazeer, K. H. and Zilouchian, A., Prediction of Crude Oil Production Quality Parameters Using Neural Networks, *Proc. Of IEEE int Conf. On Neural Networks*., New Orleans, 1997

[5] Borman, S., Neural Network Applications in Chemistry Begin to Appear, *Chemical Eng. News*, Vol. 67, No. 17, 24-29, 1989.

[6] Parlos, A. G., Chong, K. T., and Atiya, A. F., Application of recurrent Neural Multilayer Perceptron in Modeling Complex Dynamic, *IEEE Trand. On Neural Networks*, Vol. 5, No 2, March 1994

[7] Nekovie, R., and Sun, Y., Back propagation Network and its Configuration for Blood Vessel Detection in Angiograms, IEEE Trans. On Neural Networks, Vol 6, No 1, 1995

[8] Berkam, R. C., Upadhyaya, B., Tsoukalas, L., Kisner, R., Bywater, R. Advanced Automation Concepts for Large-Scale Systems, *IEEE Control Syst. Mag*., Vol 11, No 6, 4-13, Oct., 1991.

[9] Draeger, A., Engell, S., and Ranke, H., Model Predictive Control Using Neural Networks, *IEEE Control Mag*., Vol 15, No. 5, 61-67, 1995

[10] Ray, W., Polymerization Reactor Control, *IEEE Control Syst. Mag*., Vol 6, No 4, 3-9, August, 1986

[11] Bhat, N., Minderman, P., McAvoy, T., and Wang, N., Modeling Chemical Process Systems via neural Networks Computation, *IEEE Control Syst. Mag*., Vol 10, No. 3, 24-31,April, 1990.

[12] Rosenblatt, A., *Principles of Neurodynaimcs*, Spartan Press, Washinton, DC, 1961.

[13] Fausett, L., *Fundamentals of Neural Networks*, Prentice-Hall, Englewood Cliffs, NJ, 1994

[14] Demuth, H. And Beale, M., *Neural Network Toolbox for Use with MATLAB*, the Math Works Inc., Natick, MA, 1998

[15] Miller, W. T.,Sutton, R.,and Werbos, P.,*Neural Networks for Control*, MIT Press, MA, 1990.

[16].-Lippmann, R. P., An Introduction to Computing with Neural Networks; *IEEE Acoustic, Speech, and Signal Proc*. Mag. 4-22, April, 1987.

[17].- DeltaV ™. Books on line. Copyright © 1994-2001, Fisher-Rosemount Systems, Inc. USA