PROCESS SUPERVISION USING HYBRID MODELLING UNDER FOUNDATION™ FIELDBUS

FERREIRO GARCÍA R, UNIVERSITY OF A CORUÑA, SPAIN,ferreiro@udc.es
MEIZOSO M. C., UNIVERSITY OF A CORUÑA, SPAIN, mmeizoso@cdf.udc.es
PEREZ CASTELO F.J., UNIVERSITY OF A CORUÑA, SPAIN, javierpc@udc.es
PIÑÓN PAZOS A. UNIVERSITY OF A CORUÑA, SPAIN, andrespp@cdf.udc.es

ABSTRTACT

The objective of this work is to describe a coherent methodology for detect deviations between plant and model responses assuming multivariable and non linear processes. It is proposed to supervise a process modelled by applying Hybrid Modelling (HM). Here hybrid modelling is understood as the process model achieved experimentally on the basis of backpropagation NN associated to first order plus delay models.

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) 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 regarding NN architectures related to a particular process. Such technique will be 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. 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.

2. NEURAL NETWORK BASED PREDICTION

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

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

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

Input transient responses are defined as

$$Y_{TRi}(s) = V_i(s) \cdot \frac{e^{-D_i s}}{T_i s + 1} \qquad (2)$$

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 all process inputs, where the set of input values to the NNBM is given as

$$\begin{aligned}
V_{TR1}(t) &= V_1(t) \cdot \frac{e^{-Ds}}{T_1 s + 1} = V_1(t) \cdot TR_1 \\
V_{TR2}(t) &= V_2(t) \cdot \frac{e^{-Ds}}{T_2 s + 1} = V_2(t) \cdot TR_2 \qquad (3) \\
&\vdots \\
V_{TRN}(t) &= V_N(t) \cdot \frac{e^{-Ds}}{T_N s + 1} = V_N(t) \cdot TR_N
\end{aligned}$$

and the vector of partial transient inputs is given by

$$\begin{vmatrix} V_{TR1} \\ V_{TR2} \\ \vdots \\ V_{TRN} \end{vmatrix} = \begin{bmatrix} TR_1 \\ TR_2 \\ \vdots \\ TR_N \end{bmatrix} \begin{vmatrix} V_1 & V_2 \cdots V_N \end{vmatrix} \qquad (4)$$

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

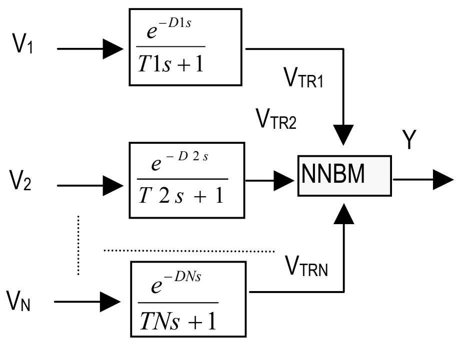

Figure 1. Neural Network based predictor using a dynamic modelling approach.

3. PROPOSED FAILURE ANALYSIS STRATEGY

Fault detection into the time horizon of transient responses is possible by applying parity equation procedures. Applying parity equations requires two conditions:

- the best possible approach to the process dynamic model
- the correct real time measuring variables concerning all process inputs/output variables.

The detection logic applying the procedure of parity equations is shown at figure 2, where a rule based logic is added to implement decision making strategies.

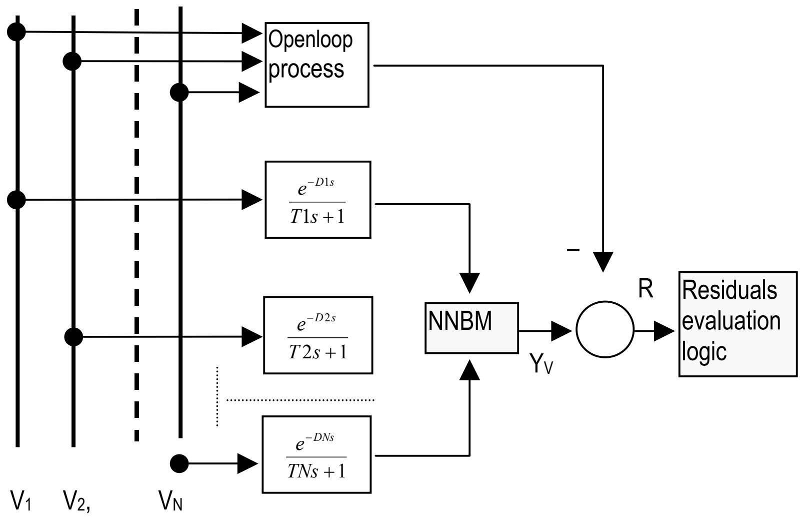

Figure 2. Fault detection by parity equations based on neural network predictor.

4. APPLICATION: FAILURE ANALYSIS OF A HEAT EXCHANGER

Let us consider a heat exchanger where its output *T* is a function of several input variables *qe*, *Te*, *qf* as illustrated by expression (5) under the structure shown in figure 3.

$$T = f(q_e, T_e, q_f) \qquad (5)$$

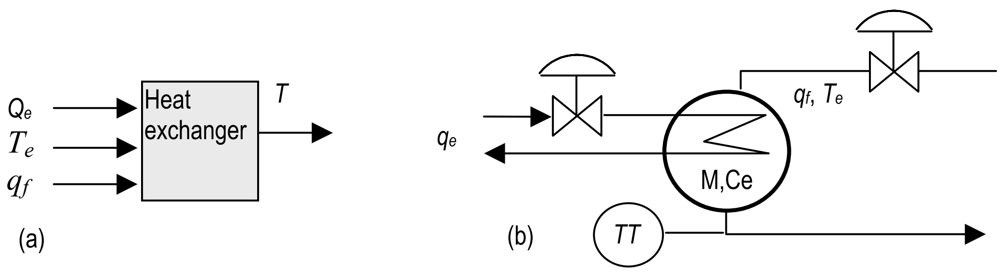

Figure. 3. Heat exchanger: (a) block diagram. (b) physical layout

Predictor based on NNBM is achieved from steady state exchanger system database using a back propagation training phase. Alternativelly, exchanger system steady state parameters can be obtained from table 1 by applying its math-model as:

Steady state conditions at two different times

$$T_{t1} = \frac{q_{e1}}{q_{f1}} C_1 + T_{e1} C_2$$
$$T_{t2} = \frac{q_{e2}}{q_{f2}} C_1 + T_{e2} C_2 \qquad (6)$$

In matrix form it yields

$$\begin{vmatrix} T & t_1 \\ T & t_2 \end{vmatrix} = \begin{bmatrix} \dfrac{q_{e1}}{q_{f1}} & T_{e1} \\ \dfrac{q_{e2}}{q_{f2}} & T_{e2} \end{bmatrix} \begin{vmatrix} C_1 \\ C_2 \end{vmatrix} \qquad (7)$$

$$\begin{vmatrix} C_1 \\ C_2 \end{vmatrix} = \begin{bmatrix} \dfrac{q_{e1}}{q_{f1}} & T_{e2} \\ \dfrac{q_{e2}}{q_{f2}} & T_{e2} \end{bmatrix}^{-1} \begin{vmatrix} T_{t1} \\ T_{t2} \end{vmatrix} = \begin{vmatrix} 1/4180 \\ 1 \end{vmatrix} \qquad (8)$$

resulting that coefficient C_1 is 1/4180, and C_2 is 1.
From the analysis of transient response , D1=0, D2=0, D3=0, $T_{(i)}=f(q_f)$ that means T1=T2=T3 $=5/q_f$. With such parameters predictor is configured with the structure shown in figure 4

Consequently, dynamic response is identified on line with the predictor shown at figure 8

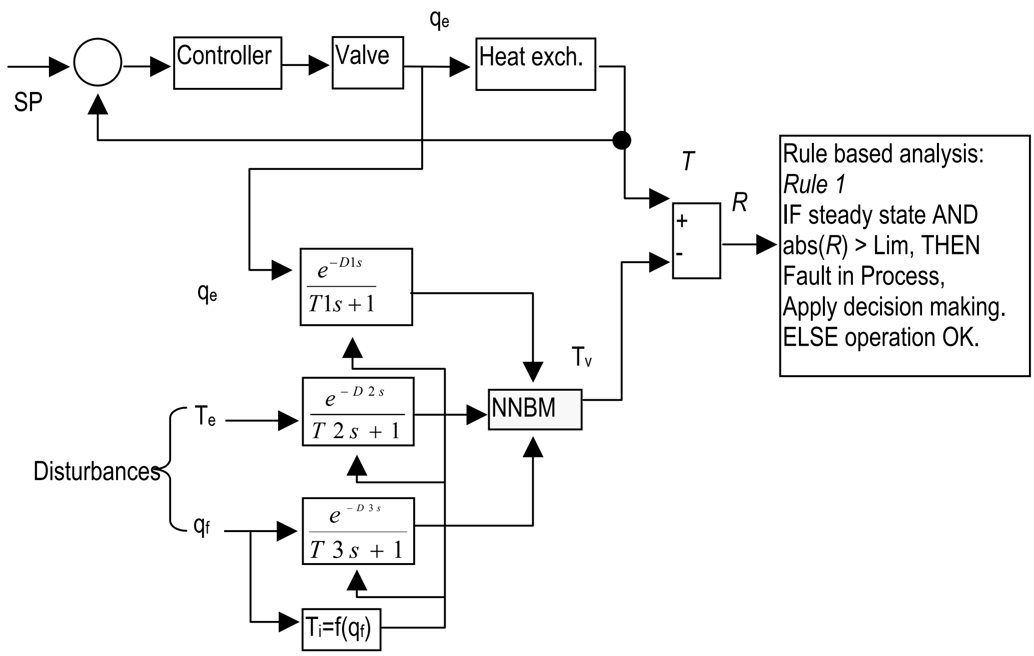

Figure 4. Fault detection scheme based on dynamic NNBM.

When a light change in the specific heat capacity of fluid (from 4180 to 4000), has occurred, some difference between steady state responses of the process and model appeared, which has been reported by the rule based system by the proper alert. Figure 6 shows the responses of both process and mode*l*, modelled according the procedure shown in f1gure 1 and 2.
Implementation of proposed methodology is carried out with the facilities provided by a FOUNDATION™ Fieldbus compliant tool [17]. Selected FOUNDATION™ Fieldbus compliant tool belongs to Emerson Process Management: DeltaV. The DeltaV Neural application has its roots in multi-layered feed forward neural network algorithm which is trained using backward

propagation. Compared to traditional neural network products, such tool permits advanced features, such as automatic network update based on analyser or lab entry of new sample values and estimation of future value of the measurement based on current upstream conditions.
The accuracy of the measurement estimate is substantially improved as a result of these enhancements. Understanding the details of the neural network algorithm is not necessary to successfully use the DeltaV Neural product.
The rule-based procedure is carried out by means of a CALC1 function block, which permits the edition and execution of a rule base in which decision-making task is included. With such procedure, prevention of failures is successfully carried out mainly by means of faults isolation and possible reconfiguration technique at affective cost.

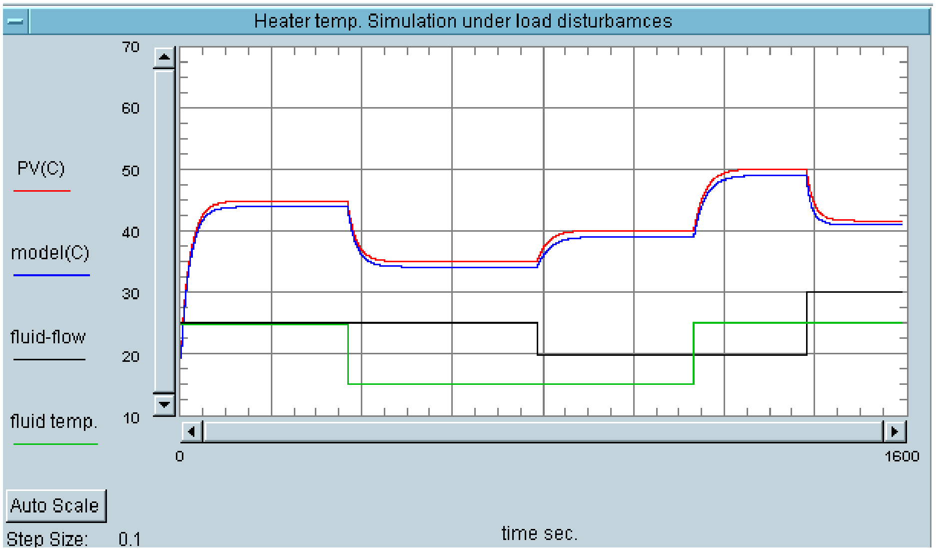

Figure 5. Supervision task by analysing the responses of both, process and model to detect steady state changes.

5. CONCLUSIONS

A systematic and coherent methodology to implement the supervision task of industrial processes is presented. Failure analysis is carried out 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 brings the opportunity to develop and implement supervision systems using proposed methodology with a minimum effort.

6. ACKNOWLEDGEMENT

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