STATIC COMPENSATION ON THE BASIS OF NNBM PREDICTOR UNDER FOUNDATION™ FIELDBUS

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ABASTRACT

This paper deals with the problem of disturbance compensation by means of a novel feedforward control procedure. It consists in the additive association of a conventional feedback control action with the prediction of the steady state control effort necessary to keep the controlled plant under setpoint requirements. Such steady state control effort is achieved by means of inverse neural network based modelling prediction. Predictors are based in an inverse neural network steady state plant model. Implementation procedure is carried out with the facilities supplied by a FOUNDATION™ Fieldbus compliant tool which manage databases, neural network structures and training algorithms.

KEYWORDS: Neural networks, Back propagation, Neural predictor, Decoupling, Disturbance rejection.

1. INTRODUCTION

Model based control systems are effective for making local process changes within a specific range of operations [1]. However, the existence of highly non-linear relationships between process input/output variables have bogged down all efforts to come up with reliable mathematical models mainly for large scale plants. In addition, the old inferred property predictors are neither sufficiently accurate nor reliable for utilisation of advanced control applications [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 such as oil refineries or chemical engineering processes [3, 8, 11].

The implementation of a neural network 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 prediction of control effort in a non-linear multivariable, disturbed and coupled processes common in a wide scenario of industrial controlled plants.

The proposed neural networks architectures can accurately predict various properties associated with plant performance behaviour, mainly steady state behaviour. The back-propagation network is the most popular feedforward predictive network deployed in process industries. The back-propagation network assumes that all processing elements and connections are somewhat responsible for the difference of expected output and the actual output. The training algorithm is an iterative gradient descent algorithm designed to minimise the mean square error (RMS) between the actual output and the desired output. It requires a continuous differentiable non-linear search space, which will be achieved by storing proper steady state input/output plant data into a database .

2. NEURAL NETWORK BASED PREDICTOR

Given a plant where V_1 is the output variable and V_2, V_3, …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 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 is used in present work to predict the future control effort, that means the control effort that will be demanded after transient state time response has expired.

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

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

Once database is filled with enabled data, a predictor based NN can be achieved by training the back propagation NN. Prediction time horizon is limited by the transient state response time.

The admitted data set into the database may be used to obtain a steady state model (system balance) but also to train the NN based predictor. Each trained NN represent a predictor, which will be called a neural network based model (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.

To summarise the proposed method, the following task will be implemented: To achieve a database containing the steady state process dynamics with the plant input/output variables under the scheme shown at figure 1. According to the variable being predicted, reorganisation of input output sets of variables from data contained into database must be performed in order to initiate the training phase, where the variable to be predicted is the NN output and the rest are inputs.

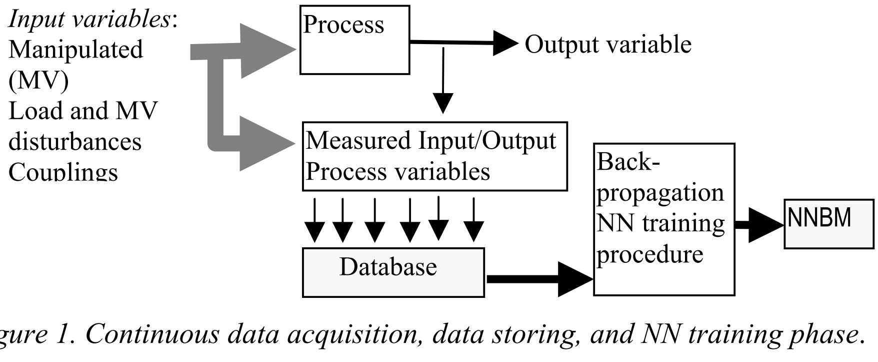

Figure 1. Continuous data acquisition, data storing, and NN training phase.

2.1. Proposed Predictive control Strategy

Disturbances to process control enter mainly by the manipulated variable due to some changes in its characteristics, by the process variable through load changes and by coupled internal variables in a multivariable process control. Disturbances rejection is an objective of all process control algorithms. To eliminate the effect of disturbance on manipulated variable, cascade control strategy is being conventionally applied. To eliminate the effects of disturbances due to load changes, feedforward compensation strategies are conventionally applied. To remove the interaction between loops or in order to compensate the effect of coupling variables, decoupling networks are typically applied. Actually, a well known alternative to mentioned strategies is the model predictive control (MPC) algorithm in any of its multiple versions. In cases where non linearities associated to parameter variations, couplings and all types of disturbances are relevant, no general control algorithm could perform satisfactory and due to such reason further research looking for new contributions is proposed.

Proposed algorithm computes the necessary steady state control action to keep the functional approximator output constant within a desired value. Such algorithm compensates the effect caused by changes in disturbance variables (load changes, changes in characteristics of manipulated variable and interaction of coupling variables). The algorithm that best satisfy the requirement of adjusting the control action to keep the NN output in a desired value is the pure integral action of the pseudo-error signal between desired value and predictor actual steady state output value. The sub-algorithm responsible for generation the compensation variable is illustrated with figure 2

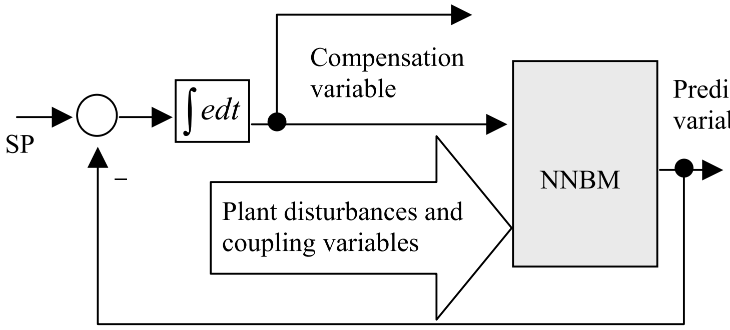

Figure. 2. Achieving the compensating variable by pure integral action on the error signal

3. APPLICATION PROCEDURE

Let us consider a process where its output Y is a function of several input variables U, X_N,..., X_C. as illustrated by expression (6) under the structure shown at figure 5.

$$Y = f(U, X_N, X_C) \qquad (7)$$

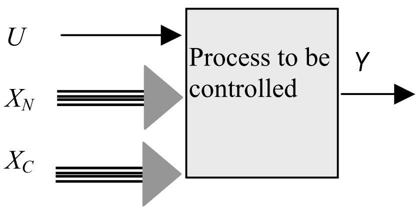

Figure. 4. Structure of a multivariable process

where U is the manipulated variable, X_N is a set of disturbance variables and X_C is a set of coupling variables. In order to implement the proposed control algorithm, following tasks must be performed:
A database containing data reporting normal openloop plant operation of the whole operating range must be achieved. Data into database must contain the whole range of U, X_N, X_C, Y.
Achieve a dynamic model by training a back propagation NNBM predictor
Arrange the structure shown at figure 3 to get the control algorithm shown at figure 5.

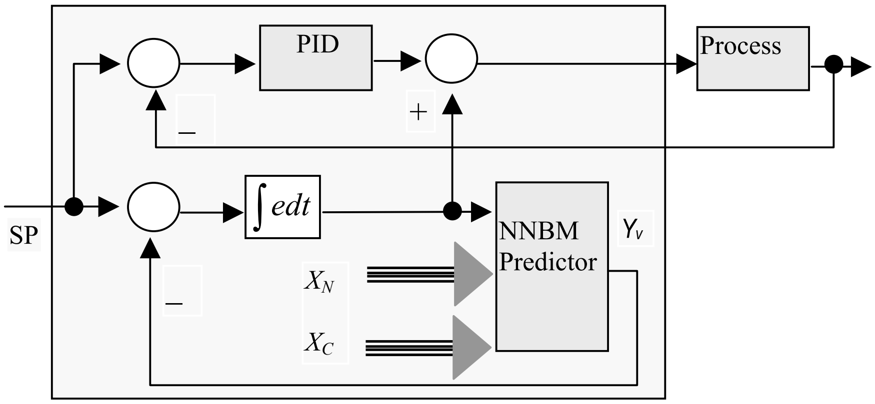

Figure 5. The control algorithm

3.1. Application 1: 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 (12) under the structure shown at figure 7

$$T = f(q_e, T_e, q_f) \qquad (12)$$

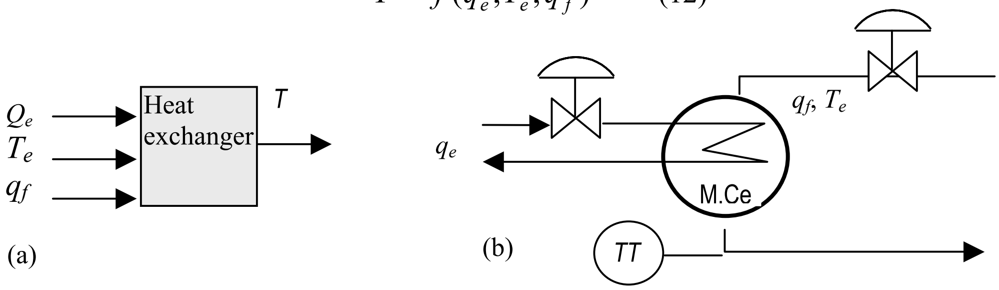

Figure. 7. Heat exchanger: (a) block diagram. (b) physical layout

The database must contain all data regarding to process input output variables. Predictor based on NNBM is achieved from heating system database by a back propagation training phase.
Heater system response is shown in figure 8. Load disturbances are shown in figure 9. Two responses are shown: the system controlled by a conventional feedback PID controller and the heating system controlled with the association of conventional PID plus proposed NNBM predictor. Both responses are quite different.
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.

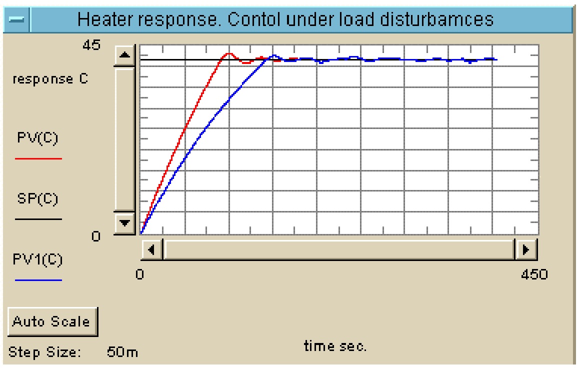

Figure. 8. Comparison of heater responses to a setpoint change and load disturbances

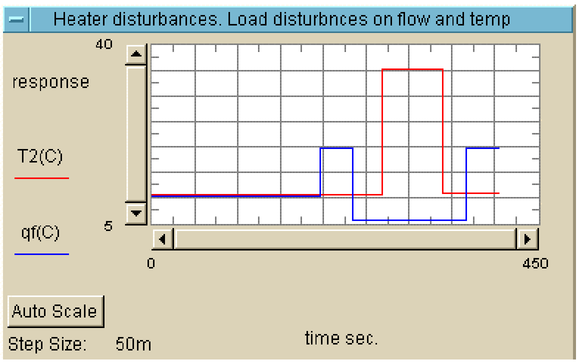

Figure. 9. Load distrubances on fluid temperature and fluid flow

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.

4. CONCLUSIONS

A simple and coherent methodology to implement a Predictive Control Algorithm on the basis of a NNBM predictor is presented. The ability of this algorithm to compensate disturbances to manipulated variables, disturbances to process load and disturbances due to couplings between loops is a guarantee of the quality of this algorithm. The fact of a lack for parameter tunings suppose also an advantage. Compared with conventional model predictive control supposes an serious alternative.

The availability of advanced FOUNDATION™ Fieldbus based tools bring the gap between the proposed control algorithm and its implementation.

5. ACKNOWLEDGEMENT

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