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Feedforward Compensation Based on Process Inverse Model under FOUNDATION™ Fieldbus

Ramón Ferreiro García and Javier Pérez Castelo
Department of Industrial Engineering, University of A Coruña,
ETSNM, Paseo de Ronda 51, 15011, A Coruna, Spain

Abstract: This study deals with the problem of disturbance compensation by means of a novel feedforward control procedure. It is based in the association of a conventional feedback control action with the feedforward action consisting in 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 a neural network based inverse model which actuates as a control effort predictor. 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 back-propagation training algorithms.

Key words: Neural-network based models, backpropagation algorithms, conjugate gradient method, prediction methods, decoupling problems, disturbance rejection

INTRODUCTION

Most of the controller design methods are based on the plant models. Model based control systems are effective for making local process changes within a specific range of operation (Antsaklis and Passino, 1993). 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 (Ray, 1986). On the other hand, input-output data-based design methods have been proposed by many researchers (Bhat *et al*., 1990). These methods do not depend on the analytical plant model and utilise I/O data only. Therefore, they are inherently robust against plant model uncertainty and sometimes give us systematic approach to steady state prediction response. Additionally, the implementation of intelligent control technology based on soft computing methodologies such as Neural Networks (NN) and Genetic Algorithms (GA) (Hornik *et al*., 1989; Funahashi, 1989; Cybenko, 1989; Hornik *et al*., 1990; Narendra and Parthasarathy, 1990; Lewis *et al*., 1999) can remarkably enhance the regulatory and advanced control capabilities of many industrial processes such as oil refineries or chemical engineering processes (Bawazeer, 1996; Berkam *et al*., 1991).

This research deals with disturbance compensation using a feedforward strategy. Conventional feedforward compensation compensates disturbances mainly due to load variations (Goodwin *et al*., 2001; Luyben, 1989; Smith and Corripio, 1990; Shynsky, 1988). In the case of disturbances to manipulated variable, cascade compensation is currently being applied (Luyben, 1989; Smith and Corripio, 1990; Shynsky, 1988). During last two decades an alternative method known as model predictive control has successfully been applied to a wide range of industrial processes (Cutler and Ramaker, 1979; Ou and Rhinehart, 2003). Some of the most relevant characteristics are its ability to compensate disturbances to load and manipulated variables, large dead times and couplings.

The purpose of this research, is to describe the methodology used in a novel predictive feedforward control task destined to be applied on multivariable control loops affected by disturbances and internal couplings. The implementation of a neural network model using back propagation algorithm (Rosenblatt, 1961; Fausett, 1994; Demuth and Beale, 1998) based on collection of real-time data for a steady state operation condition is presented. The main relevant topic of the contribution in this research is the utilisation of Artificial Neural Networks (ANN) technology for the prediction of control effort in non-linear multivariable, disturbed and coupled processes, common in a wide scenario of industrial controlled plants (Weidong *et al*., 2004;

Corresponding Author: Ramón Ferreiro García, Department of Ingeniería Industrial, Universidade da Coruña, ETSNM, C/Paseo Ronda 51, 15011 A Coruña Spain

Pinsopon *et al*., 1999; Campos and Lewis, 1999). The proposed back-propagation neural networks architectures can accurately predict various properties associated with steady state plant 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.

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 disturbances 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 linearity 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 appreciated and proposed. Following sections will concern with neural network based predictor definitions, proposed control algorithm description, application examples, results and conclusions.

NEURAL NETWORK BASED PREDICTION

Causal processes can be modelled by means of universal functional approximation devices. A modelling property of causality is used in this research to predict steady state process input output relationships (Lippmann, 1987; Nekovie and Sun, 1995; Parlos *et al*., 1994).

Definition 1: A steady state predictor is defined as a causal dynamic process function, modelled from steady state data.

Proposition 1: A excited predictor defined under definition 1, responds in advance, a time equal to the prediction horizon.

Definition 2: The prediction horizon is a time equal to the transient response of the predicted variable.

Expanding the definition to transient states, direct dynamics determine the end-effector higher derivative (acceleration in mechanical systems), resulting from the given joint exciting inputs (torques in mechanical systems) and the possible end-effector forces outputs, while inverse dynamics determine the exciting inputs (joint torques) which are needed to generate the motion specified by the end-effector highest derivative (acceleration), once the possible end-effector forces (output and successive derivatives) are known.

In order to reaffirm the concept of Neural Network Based Modelling (NNBM) prediction, let us consider a causal process where V_1 is the output variable and V_2, V_3, …, V_N are input variables and P is a set of process parameters. Under such structure, the following steady state inputs/output relationship may be expressed:

$$V_1 = f(V_2, V_3, \cdots, V_N, P) \tag{1a}$$

Given a database containing steady state data supplied from the process defined by expression (1), following relationships can be stated as output predictions:

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

Where, $V_1 = f(V_2, V_3, \ldots, V_N, P)$ is a Direct Model Predictor (DMP), while $V_2 = f(V_1, V_3, \ldots, V_N, P)$, $V_3 = f(V_1, V_2, \ldots, V_n, P)$ and $V_N = f(V_1, V_2, \ldots, V_{N-1}, P)$ are Inverse Model Predictors (IMP).

Practical conditions for steady state inverse/direct models deals with steady state action/reaction balances such as mass flow rate balance, energy flow rate balance, force/torque/power balances and in general the mathematical balance of any steady state cause-effect equilibrium condition. Consequently, a steady state predictor may be defined as a universal functional approximation device according definition (1b), where, all variables can act as input or output variables depending on modelling requirements. This concept means that for instance, if a process is described by a function such as the one defined by expression (1a), an IMP not unique, could be defined as:

$$V_2 = f(V_1, V_3, \cdots, V_N, P) \tag{1c}$$

Where the process output is V_1 and the predictor output is V_2. Furthermore, in this case, V_1 is acting as an input variable to the predictor.

Feedforward control, which consists in the computation of the manipulated variable from the measurement of disturbances (most often corrected by a PID or a model predictive controller), is used in present work to predict the future control effort that will satisfy the steady state control demand, which means the control effort that will be demanded after transient state time response has expired.

The most obviously approach to implement the principle of additive feedforward is to use a dynamic feedforward. That is, an inverse model is trained. The feedforward component of the control input is then composed by substituting the system output for corresponding setpoint value (Madsen, 1995). If the inverse model is stable, the insertion of a feedforward controller will not change the stability properties of the closed loop system. However, it might be difficult to resolve whether or not the inverse model is in fact stable. Nevertheless, every steady state inverse model is stable.

The concept of feedforward control by means of an inverse model has more attractive features of practical relevance. Since it is assumed that a stabilizing controller is available in advance, the experiment conducted to collect a set of training data is easily performed. In applications where an inappropriate control input can cause damages, one can introduce the feedforward signal gradually or conveniently filtered (Norgaard *et al.*, 2003).

Neural networks will not be an accurate predictor (Bawazeer and Zilouchian, 1997, 2001; Borman, 1989) if operating input/output 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 (Fausett, 1994; Demuth and Beale, 1998; DeltaV™, 1994; DeltaV ™, 2001).

Variables dimensions for Database Size (DBS) are selected according required precision to the function implemented on the basis of a NNBM. Usually, database size could be defined as the product between the Number of Variables (NV) involved in a function and Number of Data Sets (NDS) involving all function variables. According this definition, follows that

$$\begin{aligned} NDS &= \prod_{i=1}^{NV} DP_i \\ DBS &= NV \cdot \prod_{i=1}^{NV} DP_i = NV \cdot NDS \end{aligned} \tag{2}$$

Where, DP_i is the number of datapoints for variable (i) and NV is the number of input and output variables including variable parameters involved in a function.

Data to be acquired must satisfy the steady state dynamic behaviour. In order to ensure such condition a signal conditioning task by proper filtering is to be carried out. Such signal conditioning task requires that a variable is enabled to enter the database when all inputs/output variables satisfy the condition of remaining at steady state.

Proposition 2: Data will be enable to enter the database if and only if all measured I/O variables remain at steady state

Such condition may be analytically expressed as:

$$\text{IF } \frac{dV_1}{dt} \text{ AND } \frac{dV_2}{dt} \text{ AND } \frac{dV_3}{dt} \text{ AND} \cdots \frac{dV_n}{dt} \cong 0 \\ \text{Then the data enable} \tag{3}$$

Once the 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 represents a predictor, which will be called a NNBM predictor. In order to define a steady state NNBM predictor, the output and inputs must be defined according the relationship (Draeger *et al.*, 1995; Miller *et al.*, 1990) required between variables with achieved data from the database.

To summarise the proposed method, the following task will be implemented, which consists in achieving a database containing the steady state process dynamics I/O data under the scheme shown in Fig. 1. The amount of achieved data must be representative of correct plant operation patterns. Process information entering database will flow according flag evaluation (enable or disable). When database is filled with updated data, old data in database is overwritten by new data. A large number of valid data sets provide much better accuracy in the training phase.

According the variable to be predicted, reorganisation of inputs-output sets of variables from

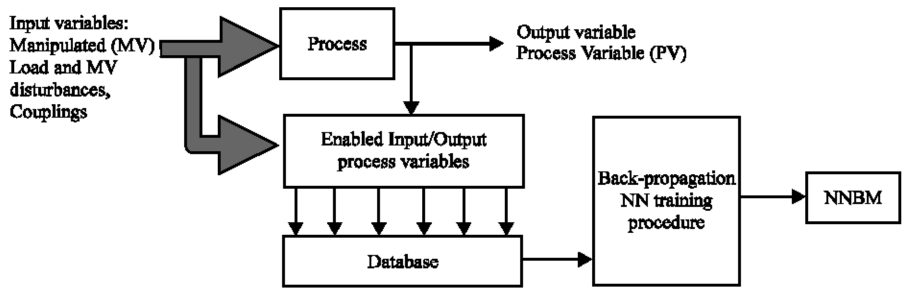

Fig. 1: Single process continuous data acquisition, data storing and NN training phase

data contained into database must be performed in order to initiate the training phase, where the NN output is the variable to be predicted and the rest of function variables are inputs.

PROPOSED FEEDFORWARD CONTROL STRATEGY

Proposed feedforward strategy computes the necessary steady state compensation action by means of an IMP, keeping IMP output within a predicted value as function of its inputs. Such algorithm compensates the effect caused by changes in disturbance variables (load changes, changes in characteristics of manipulated variable and interaction of coupling variables).

Definition 3: The IMP based compensation, is defined as the feedforward control action necessary to keep the loop controlled variable in equilibrium contition (steady state) under disturbances.

In order to satisfy definition 3, for an IMP to be is used as a general disturbance compensator, it must satisfy that its inputs are implemented by:

- The desired process future output for type zero systems.
- All measured and/or estimated disturbances including internal couplings.

Problem formulation: Practical conditions for steady state inverse/direct models deals with steady state action/reaction balances such as mass flow rate balance, energy flow rate balance, force/torque/power balances and in general the mathematical balance of any steady state cause-effect equilibrium condition. Consequently, the math-model of any type zero system excited by a manipilated variable MV subjected to addictive and multiplicative disturbances, such as load disturbances X_N, internal couplings X_C, disturbances to the manipulated variable X_{MV} and a set of measurable process parameters P_i, can be described by means of an action-reaction balance as:

$$MV = P_n \frac{d^n y}{dt^n} + P_{n-1} \frac{d^{n-1} y}{dt^{n-1}} + \cdots + P_1 \frac{dy}{dt} + P_0 y + X_N + X_C \quad (4a)$$

The manipulated variable is a function of the control variable U, a set of disturbances X_{MV} and a set of parameters. So that:

$$MV = f(U, X_{MV}, P_{MV}) \quad (4b)$$

Where P_{MV} are the measurable parameters involved in the final control element.

The steady state condition requires that:

$$f(U, X_{MV}, P_{MV}) = f(y, X_N, X_C, P_i) \quad (5a)$$

Consequently, a feedforward control action is then generated by using the IMP concept:

$$U = f(y, X_N, X_C, X_{MV}, P_i, P_{MV}) \quad (5b)$$

The equilibrium condition at nominal operating point generated by a feedforward action requires that the controlled variable be at setpoint values, yielding:

$$U_f = f(y_{SP}, X_N, X_C, X_{MV}, P_i, P_{MV}) \quad (6a)$$

Where U_f is the feedforward control signal and y_{SP} is the controlled variable setpoint.

If multiplicative disturbances are to be neglected:

$$U_f = f(y_{SP}, X_N, X_C, X_{MV}) \quad (6b)$$

according definition 3, the desired future output is the control loop setpoint. The sub-algorithm responsible for generating the compensation action U_f which satisfies the definition 3 and 4 is illustrated by means of Fig. 2.

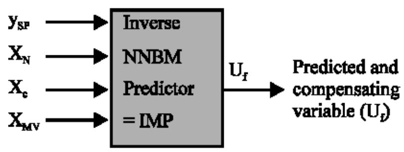

Fig. 2: Achieving the compensation action using an IMP

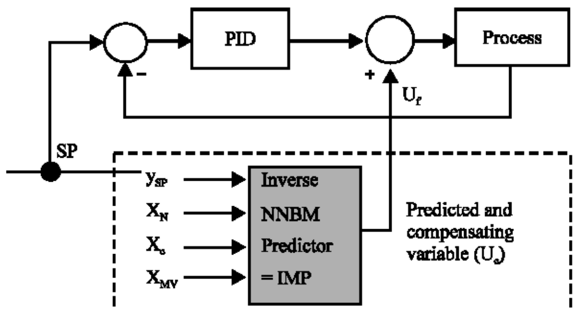

Fig. 3: The control algorithm: Feedback added to feedforward compensation implemented by an IMP

To complete the proposed control algorithm, achieved control action U_f generated by the IMP, is added to the output of a conventional feedback control algorithm as shown in Fig. 3, satisfying a feedforward strategy. The scheme depicted in Fig. 3 shows that the control effort is due to a feedforward action associated to a feedback control action responsible for responsible for correcting control error.

Compared with a conventional feedback-feedforward control philosophy, in this contribution the main control function is exerted in a feedforward mode by an IMP where the feedback controller is a control error corrector.

Applying such feedforward control action on the basis of NNBM predictor implemented as an IMP requires two conditions:

- The correct acquisition or estimate of real time data concerning all process inputs/output variables.
- The best possible approach to the process steady state model, which demands a training phase carried out with steady state correct data stored into a database.

APPLICATION PROCEDURE

Coupled level and temperature process control: Proposed application is based on a Foundation™ Fieldbus based control system installed on a multivariable pilot plant. At such pilot plant, exercises on individual level or temperature control and both coupled loops are possible.

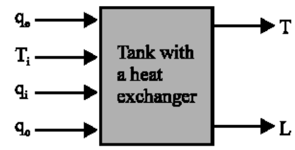

Fig. 4: Coupled process based on a heater inserted into a variable level CSTR

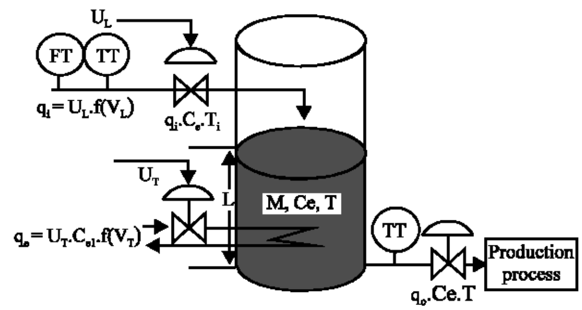

Fig. 5: Pilot plant configured for feeding a fluid line to a production process

The main objective of this application is to compare two control algorithms: conventional decoupling against neural network based compensation, which means to compare an adaptive scheme with a fixed feedforward decoupling network associated to PID feedback controllers.

Process description: The process consists in a heat exchanger inserted into a closed tank with variable level and temperature or a Continuous Stirred Tank Reactor (CSTR), where the output temperature T is a function of several input variables q_e, T_i, q_i as illustrated by expression (8) under the structure shown in Fig. 4 and 5.

$$\begin{aligned} T &= f(q_e, T_i, q_i) \\ L &= f(q_o, q_i) \end{aligned} \tag{8}$$

Where q_e is the supply energy flow rate or manipulated variable, q_i is the input fluid flow rate or process feed stream flow rate, T_i is the input fluid temperature, q_o is the output flow rate and T and L are the output temperature and tank level, respectively.

The pilot plant is configured to operate as a heat exchanger into a variable level tank process control. At same time, as consequence of actual tank level changes, mainly due to setpoint changes, pressure into the tank is also a variable. Pressure contributes to the process as a non-linear characteristic which exerts some influence on feed stream q_o. Let us consider an input fluid line to a production process. In order to keep some capacity

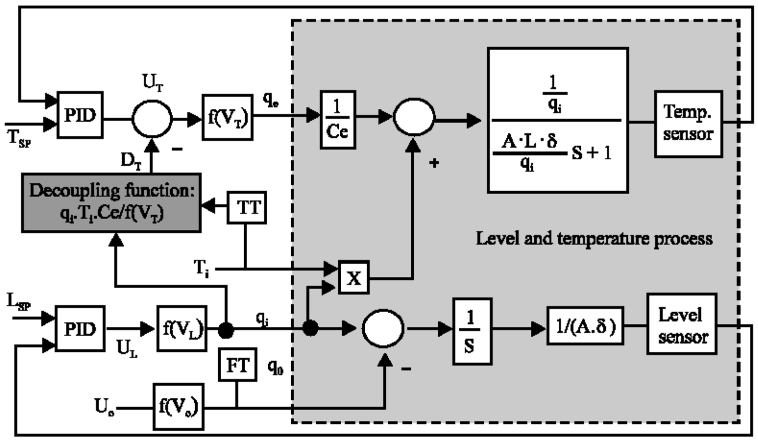

Fig. 6: Conventional PID level and temperature control associated to a decoupling network

demand from mentioned production process, a storing tank filed till certain setpoint level is being inserted in the feed fluid line. Furthermore, production process requires that feed fluid enter at a specified setpoint temperature T_{SP}.

According to Fig. 6, U_L and U_T are control variables to level and temperature process variables, $f(V_L)$, $f(V_T)$ and $f(V_0)$ are global valve characteristics for feed stream or input fluid to process line and heating system, respectively q_i is the fluid mass flow rate of the feed stream with temperature T_i and specific heat capacity Ce, M is the actual stored fluid into the tank and T is the output temperature, process or controlled variable.

The approximate analytic model of described process is approached as follows:

Mass balance

$$q_i - q_o = \frac{dM}{dt} = A \cdot \delta \cdot \frac{dL}{dT} \tag{9}$$

Steady state energy balance

$$\begin{aligned} & q_i - q_o = 0 \\ & q_{i(SS)} = U_L \cdot f(V_I)_{SS} \\ & q_{o(SS)} = U_O \cdot f(V_O)_{SS} \\ & U_L \cdot f(V_I)_{SS} = U_O \cdot f(V_O)_{SS} \end{aligned} \tag{10}$$

Energy balance

$$q_e + q_i \cdot Ce \cdot T_i = \frac{d}{dt}(Ce \cdot M \cdot T) + q_o \cdot Ce \cdot T \tag{11}$$

or

$$\begin{aligned} & q_e + q_i \cdot Ce \cdot T_i = Ce \cdot M \cdot \frac{dT}{dt} + Ce \cdot T \cdot \frac{dM}{dt} + q_o \cdot Ce \cdot T = \\ & = Ce \cdot M \cdot \frac{dT}{dt} + Ce \cdot T(q_i - q_o) + q_o \cdot Ce \cdot T = \\ & = Ce \cdot M \cdot \frac{dT}{dt} + q_i \cdot Ce \cdot T \end{aligned}$$

which means that

$$\begin{aligned} & U_T \cdot f(V_T) \cdot + U_L \cdot f(V_L) \cdot Ce \cdot \\ & T_i = Ce \cdot M \cdot \frac{dT}{dt} + U_L \cdot f(V_L) \cdot Ce \cdot T \end{aligned} \tag{12}$$

Where

$$q_i = U_L \cdot f(V_L) \tag{13}$$

and

$$f(V_L) = f_1(L) \tag{14}$$

with

$$f(L(t)) = \frac{1}{T_{VI}S + 1} \delta \cdot C_{VI} \cdot \sqrt{\frac{2(P_i - P)}{\delta}} \tag{15}$$

Where T_{VI} is the valve time constant, C_{VI} is the valve flow coefficient, P_i is the pressure before the feed valve, P is the actual approximated pressure into the tank, L_T is the total height of the tank and δ is the feed stream fluid density. Approaching the value of P requires the consideration of its dependence from variable T. Nevertheless, considering that T varies slowly and that deviation of its nominal point will rarely occur, then could be assumed as:

$$P \approx \frac{P_i L_T}{L_T - L} \tag{16}$$

Such assumption which contributes with some modelling error don't affect the control problem because such math models will not be applied. Instead, the proposed NNBM predictors are to be used.

Furthermore, the output valve model is such that

$$q_o = U_o \cdot f(V_o) \tag{17}$$

Where

$$f(V_o) = f_2(L) \tag{18}$$

with

$$f_2(L(t)) = \frac{1}{T_{Vo}S+1}\delta \cdot C_{VO}\sqrt{\frac{2(P-P_o)}{\delta} + 2gL} \tag{19}$$

so that

$$q_o = U_o \frac{1}{T_{Vo}S+1}\delta \cdot C_{VO}\sqrt{\frac{2(P-P_o)}{\delta} + 2gL} \tag{20}$$

which means that any command value of signal U_o on the output valve as result of a change in fluid demand, is a non-linear disturbance to the level control loop and consequently, to the temperature loop due to coupling effect of level loop on temperature loop. Consequently the system is highly non-linear. In the above expressions T_{Vo} is the output valve time constant, C_{VO} is the valve flow coefficient and P_o is the downstream pressure after the output valve.

The dynamics of the manipulated variable to temperature control loop is affected by the control valve dynamics as

$$q_e = U_T \cdot C_{el} \cdot \Delta T \cdot f(V_T) \tag{21}$$

Where the mass flow rate is approached as

$$f(V_T) = \frac{1}{T_{VT}S+1} C_{VT}\sqrt{\frac{2\Delta P}{\delta}}$$

Where C_{el} is the specific heat of a heating fluid (water), T_{VT} is the valve time constant, C_{VT} is the valve flow coefficient, ΔP is the pressure gradient of the heating valve, ΔT is the temperature gradient of the heater tube bundle.

Steady state energy balance

$$U_T \cdot f(V_T)_{SS} + U_L \cdot f(V_L)_{SS} \cdot Ce \cdot T_i - q_o \cdot Ce \cdot T = 0 \tag{22}$$

$$U_T = (q_o \cdot Ce \cdot T - U_L \cdot f(V_l)_{SS} \cdot Ce \cdot T_i) / f(V_T)_{SS} \tag{23}$$

or

$$q_e + q_o \cdot Ce \cdot (T_i - T) = q_e + q_i \cdot Ce \cdot (T_i - T) = 0 \tag{24}$$

and consequently,

$$U_T = q_i \cdot Ce \cdot (T - T_i) / f(V_T)_{SS} \tag{25}$$

Conventional decoupling control: In this research, it will be compared a conventional control scheme with proposed control strategy, via an application. According described model, conventional control scheme is shown in Fig. 6 where a decoupling network is being implemented to cancel the effects of interactions between level control loop with temperature control loop. Under such scheme, if fluid flow rate q_i or its temperature T_i changes, it does not affect the temperature control loop due to the compensation action of a model based decoupling function. So that, PID control actions will reacts only against changes in temperature setpoint or changes in output temperature. If non-linearity or modelling error of coupled process is negligible, then, compensation by means of a decoupling network is expected to be effective and perhaps the best method due to its simplicity. This case is a god paradigm if process variables remain at its nominal operating points.

In order to show how the proposed adaptive scheme improves against a fixed feedforward decoupling, a comparative analysis on the controlled pilot plant is to be carried out. Thus, for decoupling purposes, the conventional scheme is achieved from (12) by assuming a model with $M = A \cdot L \cdot \delta$ where A is the constant cross-sectional area of the tank, L is the actual level and δ is the fluid density.

Level loop is inherently decoupled from temperature loop as shown in Fig. 6 because temperature does not influence the level control loop. So that, decoupling level control loop from temperature loop has no sense. Decoupling function D_T on temperature loop is applied under the scheme according to the balance

$$D_T \cdot f(V_T) + Ce \cdot q_i \cdot T_i = 0 \tag{26}$$

which yields

$$D_T = -\frac{Ce \cdot q_i \cdot T_i}{f(V_T)} \tag{27}$$

Decoupling by means of function (26) is effective for temperature variations T_i but is not for fluid flow rate variation q_i because variations of q_i are influencing the temperature loop gain by $1/(q_i.Ce)$ and the pole place in the rate M/q_i This means that disturbances to input stream fluid q_i can not be physically decoupled.

It must be taken into account that complete dynamic decoupling is not possible due to the properties of causality and physical realisability on servo-valves and sensors. In other words, q_i and T_i must be measured and updated every sample cycle. Such measuring task is filtered by the inherent time constant of sensors which contributes to the dynamics with some delay. Furthermore, the actuator servo-valve operates with certain inherent delay. Both delays due to sensors and actuator are responsible for a total delay on the decoupling variable. Consequently, dynamic decoupling is sometimes efficient and static decoupling is only efficient at steady state. Figure 7 shows the response under disturbances compensated by means of conventional methods.

For experimentation purposes, process is started under the scheme depicted in Fig. 6 where level setpoint is fixed at 0.5 m and temperature. setpoint is fixed at 42°C, with water as feed stream and a constant flow rate demand of 0.4 kg s^{-1}. After 600 sec, flow rate demand is increased till 1 kg s^{-1}. After 1000 sec a step input to the level setpoint is applied and its response recorded. Under visual inspection, such disturbances (flow rate demand and level setpoint) affect scarcely to the loop temperature. By running the conventional control scheme under a fixed feedforward decoupling network, the results shown in this study.

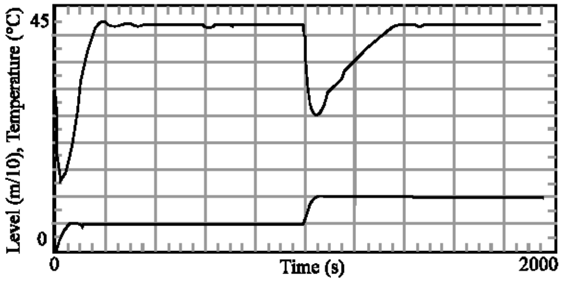

Fig. 7: The temperature and level output responses under disturbances in level control loop

Proposed adaptive algorithm: In order to implement proposed control strategy, steady state data has been stored into a database under some nominal operating conditions, which was used in training the compensator (IMP) and the process model (NNBM). Selected inputs to database are those inputs identified as potentially influencing the process dynamics. Training algorithm (DeltaV) identify the inputs that are influencing the process dynamics and consequently are most significant to be used in training the neural networks.

If disturbances to manipulated variable q_e exists, or are to be taken into account, then, the corresponding NNBM predictor has the structure shown in Fig.8a and b. On the other hand, if no disturbances assists, or are not considered then the NNBM predictor results very much simple as shown in Fig. 8c and d. The structure adopted in Fig. 8c and d is implemented as the feedforward controller applied for experimentation purposes in this research.

Data into database must contain the possible range of variation for T, Ti, q_i and q_e. Furthermore, acquiring proper data requires going outside from the current operating points. According mentioned constraints, pilot plant data acquisition limits are shown in Table 1. Such limits are the maximum and minimum values between them, variables must be changed to create a consistent data set into the database.

Figure 9 shows the proposed alternative scheme to be compared against a fixed feedforward decoupling shown in Fig. 6. Coupling variables q_i and external disturbances T_i are included into IMP feedforward compensator. At IMP feedforward compensation for level control loop level setpoint is not a relevant input. So that, such IMP uses only the flow sensor as operating input. Decoupling action is inherent to IMP compensation.

For experimental purposes, the pilot plant is started by running the proposed control scheme depicted with Fig. 9 with water as process feed stream. After 800 sec (steady state) demanded flow rate is changed from 0.4-1.0 kg s^{-1}. As in the case of fixed decoupling example, such disturbance affects scarcely to the controlled variable (temperature). After 1000 sec level setpoint is changed from 0.5-1 m. Results are shown in Fig. 10. Reaction of this strategy to a change in flow demand at

Table 1: Pilot plant operating data limits

Variables	Limits	Units
T	20-150	C
Ti	20-40	C
q_i	0.25-1.0	kg s^{-1}
q_o	0.25-1.0	kg s^{-1}
Uc	0-100	%

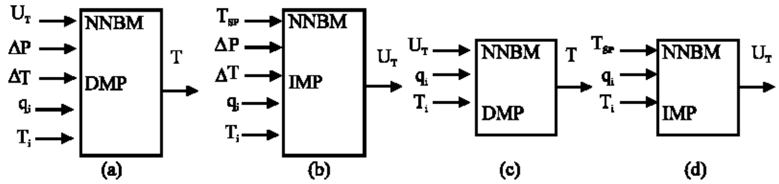

Fig. 8: The structure of plant model and compensator model

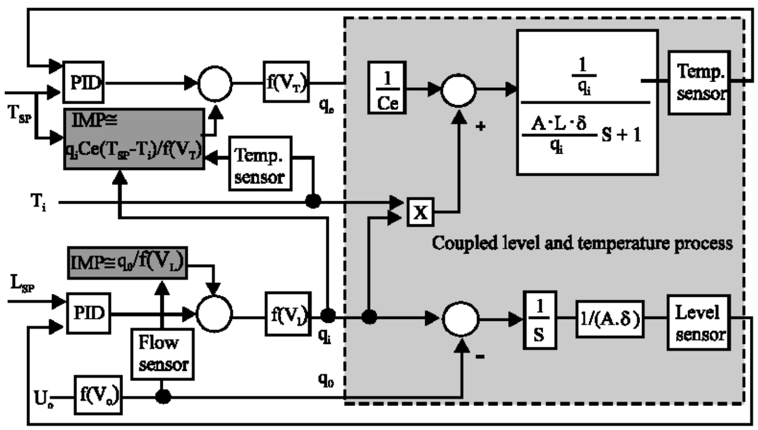

Fig. 9: Adaptive level and temperature control using IMP compensation and model error detection with NNBM

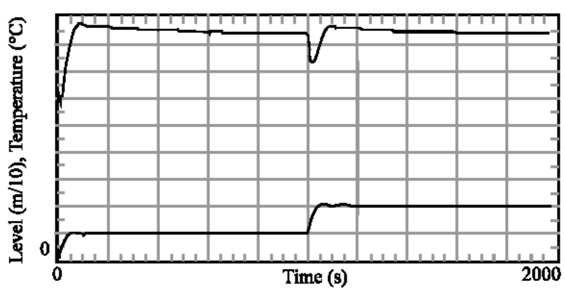

Fig. 10: The time response of temperature and level control loops under disturbances in level control for the proposed adaptive feedforward control scheme

time equal to 800 sec is correct and the response to setpoint changes is better than the conventional case.

Characteristics of database: Table 2 shows the database structure where data has been stored from plant operating conditions. The database must contain all data related to the steady state input output variables, which are loop represented in Table 2. Database data represents the function T = f(qi, Ti, qe).

Because backpropagation based neural networks are good interpolators, database for NNBM2 is structured such that for every I/O variable only four representative datapoints (every 33.3% of variable range) are acquired.

Table 2: Database for heat exchanger steady state dynamics

Ti qe	20	30	40	50
qi = 0.25 kg s^{-1}				
10	29.60	39.60	49.60	59.60
20	39.00	49.00	59.00	69.00
30	48.70	58.70	68.70	88.70
40	58.30	68.30	78.30	88.30
qi = 0.50 kg s^{-1}				
10	24.80	34.80	44.80	54.80
20	29.60	39.60	49.60	59.60
30	34.35	44.35	54.35	64.35
40	39.00	49.00	59.00	69.00
qi = 0.75 kg s^{-1}				
10	23.20	33.20	43.20	53.20
20	26.40	36.40	46.40	56.40
30	29.60	39.60	49.50	59.60
40	32.80	42.80	52.80	62.80
qi = 1 kg s^{-1}				
10	23.40	33.40	43.40	53.40
20	24.80	34.80	44.80	54.80
30	27.20	37.20	47.20	57.20
40	29.60	39.60	49.60	59.60

Discussion of results: In order to show the influence of coupling based disturbances on temperature control, changes in process feed stream flow demand were applied. As a logic consequence of those changes, input fluid q_i will change commanded by level controller. Such manipulated variable q_i is coupled to the temperature control loop by means of the input fluid temperature Ti and it will be expected to cause disturbances to the temperature loop and the consequent deviation of temperature from operating setpoint.

Typically the reaction of a conventional PID controller to any kind of disturbance, by itself is not able to compensate such effects in a satisfactory way. Results shown in Fig. 7 and 9 indicates that in both control algorithms (fixed feedforward decoupling against IMP compensation) are tolerable but not so efficient as IMP compensator. In practice it can not be assumed that adaptive IMP compensation is better than fixed feedforward for the case studded except when handling load disturbances and level setpoint changes. Nevertheless, fixed feedforward control showed lower control effort against disturbances but this topic is prejudicial to compensate abrupt load disturbances or setpoint changes. The most important drawback of the adaptive IMP is the impossibility to update a database after modelling errors were detected without going outside from nominal plant operation points unless a priori knowledge regarding plant model exists.

On the other hand, proposed control algorithm reacts against such disturbances successfully. The compensating variables added to the outputs of feedback control algorithms (in this case are PID's but not necessarily must be PID's) are shown in Fig. 9, where after a disturbance applied by modifying the feed stream flow rate substantially, no abnormal response is noted in any of the control loops. Furthermore, no limit cycles appear which means a robust response.implemented by means of a CALC1 function block. For the alternative case of IMP feedforward compensation the control sub-module is depicted by Fig. 12.

Implementation features: Implementation of proposed methodology has been carried out with the facilities provided by a FOUNDATION™ Fieldbus compliant tool DeltaV™ (2001). For the case of fixed feedforward decoupling the control sub-module is depicted by Fig. 11. Four external analog inputs are needed. Decoupling network is

Proposed control algorithm (IMP compensator plus NNBM supervisor) is implemented as an alternative to

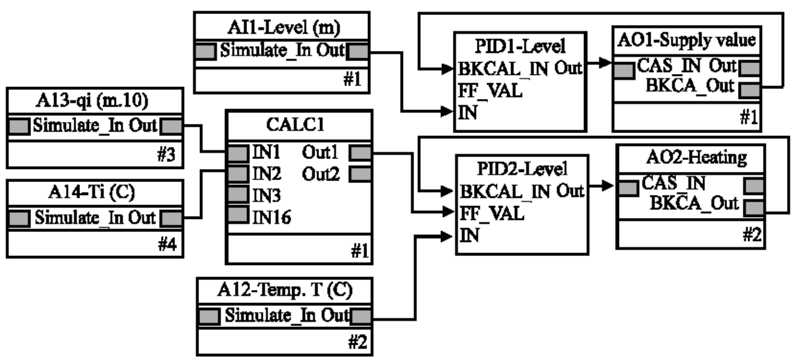

Fig. 11: Layout of the sub-module of control strategy for fixed decoupling algorithm implemented with DeltaV facilities

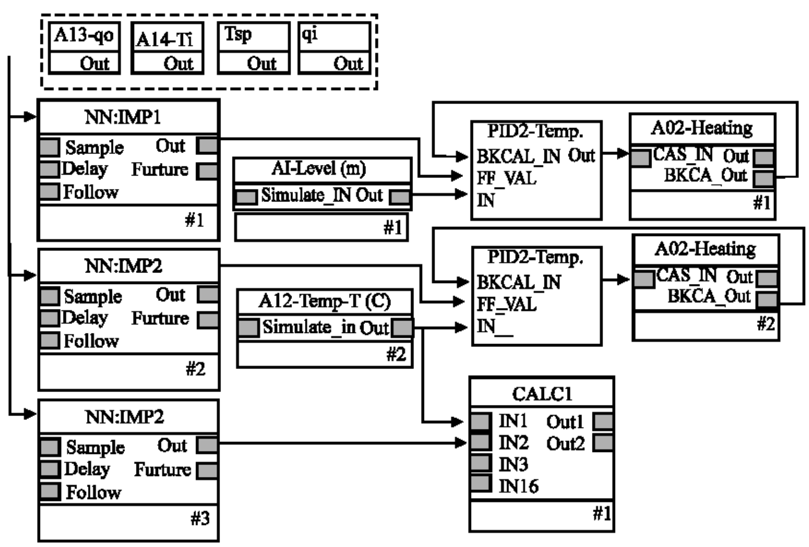

Fig. 12: Layout of the sub-module of proposed control strategy implemented with DeltaV facilities

conventional control, being shown in Fig. 12. Only 4 external analog inputs are necessary to operate with this control algorithm. Setpoint T_{SP} and input flow rate q_i are estimated from internal control module values. IMP compensators implemented by means of neural network function blocks for both control loops are connected to the feedforward pins of every PID function block.

To implement neural networks architectures including training phases, an object oriented tool is used: DeltaV Neural. The DeltaV Neural application is part of DeltaV and has its roots in multi-layered feed forward neural network algorithm which is trained using backward propagation using an conjugate gradient algorithm. Such training algorithm is integrated into the DeltaV Neural tool and determines automatically the number of epochs as well as the number of hidden neurons, which means a complete autonomous training phase ones specified the required precision of the NNBM. Compared to traditional neural network products, such tool permits advanced features, such as automatic network update based onanalyser 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.

CONCLUSION

Previously to described application on the pilot plant, a variety of examples based on type zero systems had been successful carried out by simulation, which demonstrates that if measurable parameters were included in the NNBM, multiplicative disturbances could also be compensated. Furthermore, accessible or measurable couplings, load disturbances and disturbances to the manipulated variable, were compensated, including parameter variations.

With the experimental results o a pilot plant described in this research, a coherent methodology to implement a feedforward control strategy on the basis of a NNBM prediction is presented. The ability of this algorithm to handle and compensate disturbances to process including measurable couplings between loops and load disturbances is a relevant characteristic. Such characteristics makes this strategy an alternative to conventional control based in a combination of feedback, feedforward, cascade and decoupling control algorithms and consequently to model predictive control.

The same and uniform principle and methodology is useful to compensate all types of accessible disturbances, which include multiplicative and additive, (changes in parameters, manipulated variable, load changes, couplings).

The fact by which no parameter tunings (except PID) are necessary, suppose also an important advantage, if it is compared with conventional feedforward or model predictive control. For that reason, proposed compensation strategy supposes a serious alternative. The unique drawback of the method is the impossibility to handle transportation lags on the manipulated variable.

Due to the use of Foundation™ Fieldbus based tools, understanding the details of the neural network algorithm is not necessary to successfully use the DeltaV Neural product. The availability of advanced Foundation™ Fieldbus based tools brings an appropriate gap between the proposed control algorithm and its implementation requirements.

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