NEURAL NETWORK CONTROL OF A HEAT EXCHANGER PILOT PLANT

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Abstract- In this paper, a neural network based predictive controller is designed to govern the dynamics of a heat exchanger pilot plant. Heat exchanger is a highly nonlinear process; therefore, a nonlinear prediction method can be a better match in a predictive control strategy. Advantages of neural networks for the process modeling are studied and a neural network based predictor is designed, trained and tested as a part of the predictive controller. The dynamics of the plant is identified using a Multi Layer Perceptron (MLP) neural network. Then, the predictive control strategy based on the neural network model of the plant is applied to provide set point tracking of the output of the palnt. Also, The performance of the proposed controller is compared with that of Generalized Predictive Control (GPC) through simulation studies. Obtained results demonstrate the effectiveness and superiority of the proposed approach.

Keywords- Predictive control, neural networks, heat exchanger pilot plant.

I. INTRODUCTION

Predictive control is now widely used in industry and a large number of implementation algorithms. Most of the control algorithms use an explicit process model to predict the future behavior of a plant and because of this, the term model predictive control (MPC) is often utilized [1,2]. The most important advantage of the MPC technology comes from the process model itself, which allows the controller to deal with an exact replica of the real process dynamics, implying a much better control quality. The inclusion of the constraints is the feature that most clearly distinguishes MPC from other process control techniques, leading to a tighter control and a more reliable controller. Another important characteristic, which contributes to the success of the MPC technology, is that the MPC algorithms consider plant behavior over a future horizon in time. Thus, the effects of both feedforward and feedback disturbances can be anticipated and eliminated, fact, which permits the controller to drive the process output more closely to the reference trajectory.

Although industrial processes usually contain complex nonlinearities, most of the MPC algorithms are based on a linear model of the process. Linear models such as step response and impulse response models derived from the convolution integral are preferred, because they can be identified in a straightforward manner from process test data. In addition, the goal for most of the applications is to maintain the system at a desired steady state, rather than moving rapidly between different operating points, so a precisely identified linear model is sufficiently accurate in the neighborhood of a single operating point. As linear models are reliable from this point of view, they will provide most of the benefits with MPC technology. Even so, if the process is highly nonlinear and subject to large frequent disturbances, a nonlinear model will be necessary to describe the behavior of the process. Also, in servo control problems where the operating point is frequently changing, a nonlinear model of the plant is indispensable [3-5].

In situations like the ones mentioned above, the task of obtaining a high-fidelity model is more difficult to build for nonlinear processes. Recently, neural networks have become an attractive tool in the construction of models for complex nonlinear systems [6,7]. A large number of control and identifications structures based on neural networks have been proposed [8-15]. Most of the nonlinear predictive control algorithms imply the minimization of a cost function, by using computational methods for obtaining the optimal command to be applied to the process. The implementation of the nonlinear predictive control algorithms becomes very difficult for real-time control because the minimization algorithm must converge at least to a sub-optimal solution and the operations involved must be completed in a very short time (corresponding to the sampling period). This paper analyzes an artificial neural network based nonlinear predictive controller for a heat exchanger, which is a highly nonlinear process. The procedure is based on construction of a neural network model for the process and the proper use of that in the optimization process. The method eliminates the most significant obstacles for nonlinear MPC implementation by developing a nonlinear model, designing a neural predictor and providing a rapid, reliable solution for the control algorithm. Using the proposed controller, the output temperature tracking behavior of the plant is studied. Also, the performance of the proposed neural network based predictive controller is compared with that of GPC one, which the former leads to better performance.

II. HEAT EXCHANGER PILOT PLANT

The problem of heat-exchanger control with sensors and actuators limitation represents a serious problem from the point of optimal energy consumption [16-18]. The problem lies in the nonlinearity of the system behavior [19-22]. There are a large number of phenomena associated with flow and heat transfer that are perhaps simple to solve singly, but when combined result in a system that is impossible to compute. Some of these are: complicated heat and fluid flow geometries, turbulence in the flow, existence of hydrodynamic and thermal entrance regions, non-uniform local heat transfer rates and fluid temperatures, secondary flows in the tube bends, vortices in the neighborhood of the tube-fin junctions, air-side flow development in fin passages, heat conduction along tube walls, natural convection within the tubes and between fins, and temperature dependence of fluid properties.

The objective of our investigation, a real temperature plant, consists of a plate heat-exchanger, a reservoir with heated water, two thermocouples, and a motor driven valve. The plate heat exchanger, through which hot water from an electrically heated reservoir is continuously circulated in the counter-current flow to cold process fluid (cold water). The thermocouples are located in the inlet and outlet flows of the exchanger; both flow rates can be visually monitored. Power to the heater may be controlled by time proportioning control using the external control loop. The flow of the heating fluid can be controlled by the proportional motor driven valve. A schematic diagram of the plant is shown in Figure 1.

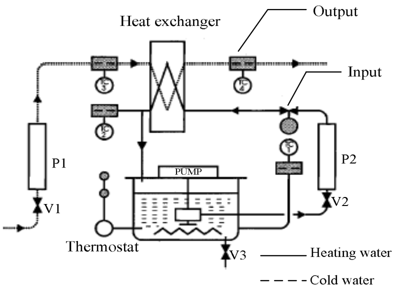

Figure 1 The heat-exchanger pilot plant.

III. NEURAL NETWORK BASED PREDICTION

This section presents the role and architecture of the neural predictors resulting from the following nonlinear modeling techniques based on neural network principles.

a) Modeling of nonlinear systems using neural networks

The use of neural networks for nonlinear process modeling and identification is justified by their capacity to approximate the dynamics of nonlinear systems including those with high nonlinearities or dead time [23-25]. In order to estimate the nonlinear process, the neural network must be trained until the optimal values of the weight vectors (i.e. weights and biases in a vector form organization) are found. In most applications, feedforward neural networks are used, because the training algorithms are less complicated. When it comes to non-linear models, the most general one, which includes the largest class of non-linear processes, is doubtless the NARMAX model [6] given by

$$y(k)=F[u(k-d-1),...u(k-d-m),y(k-1),...y(k-n)] \qquad (1)$$

where *F(·)* is a nonlinear function, *d* is the dead time, *n* and *m* are the orders of the nonlinear system model. A neural network-based model corresponding to the NARMAX model may be obtained by adjusting the weights of multi-layer perceptron architecture with adequately delayed inputs. In this case, the neural network output will be given by

$$y(k) = F^N[U(k-d-1), Y(k-1)] \qquad (2)$$

where F^N denotes the input–output transfer function of the neural network which replaces the nonlinear function *F* in (1), and $U(k-d-1)$, $Y(K-1)$ are vectors which contain *m*, respectively, *n* delayed elements of *u* and *y* starting from the time instant *k-1*, i.e.

$$U(k-d-1) = [u(k-d-1),...,u(k-d-m)]^T \qquad (3)$$

$$Y(k-1) = [y(k-1),..., y(k-n)]^T \qquad (4)$$

The neural NARMAX corresponds to a recurrent neural network, because some of the network inputs are past values of the network output.

b) Neural network based predictors

The predictors are necessary for the prediction of future values of the plant output that are considered in the predictive control strategy. The implementation approach of this paper uses neural predictors obtained by appropriately shifting the inputs of the neural based model. The predictive control algorithm utilizes them in order to calculate the future control signal. Neural predictors rely on the neural-based model of the process. In order to obtain the model of the nonlinear system, a neural network with a hidden layer is considered. A sequential algorithm based on the knowledge of current values of *u* and *y* together with the neural network system model gives the *i*-step ahead neural predictor. In this case one can properly derive the network output at the *k+1* time instant:

$$y(k+1)=\sum_{j=1}^{n} w_j \sigma_j \left(w_j^u U(k-d)+w_j^y Y(k)+b_j\right)+b \qquad (5)$$

where *N* is the number of neurons in the hidden layer, σ_j is the activation function for the j^{th} neuron from the hidden layer, w_j^u is the weight vector (row vector) for the j^{th} neuron with respect to the inputs stored in $U(k-d-1)$, w_j^y *is* the weight vector (row vector) for the j^{th} neuron with respect to the inputs stored in $Y(k-1)$, b_j is the bias for the j^{th} neuron from the hidden layer, and w_j is the weight for the output layer corresponding to the *j*th neuron from the hidden layer, and *b* the bias for the output layer.

Extending (5) one step further ahead, *y(k+2)* can be obtained and generally, the *i*-step ahead predictor can be derived:

$$y(k+i)=\sum_{j=1}^{n} w_j \sigma_j \left(w_j^u U(k-d+i-1)+w_j^y Y(k+i-1)+b_j\right)+b \qquad (6)$$

where

$$U(k-d+i-1)=[u(k-d+i-1),...,u(k-d+i-m)]^T \qquad (7)$$

$$Y(k+i-1) = [y(k+i-1),..., y(k+i-n)]^T \qquad (8)$$

The neural predictors will be used by the predictive control algorithm for calculating the *future control signal* to be applied to the non-linear system.

c) Neural network model of a heat exchanger

In order to construct a neural network model for the heat exchanger, the input-output data of the plant is considered [19], where the output variable is the outlet liquid temperature and the input variables is the liquid flow rate. In this experiment the steam temperature and the inlet liquid temperature are kept constant to their nominal values. A multilayer perceptron neural network with *10* neurons in the hidden layer and $d=0; m=3, n=2$ is used0. The output of the model for the test data is compared with the actual output in Fig. 2. As it is seen, the error is acceptable, so the model can be used for the objective of predictive control.

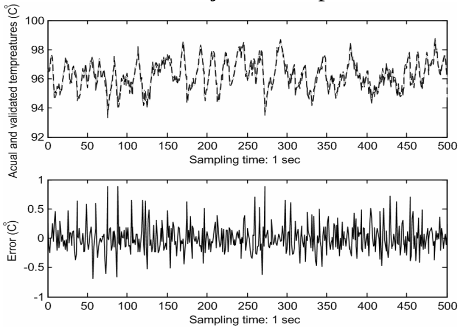

Figure 2 Model validation: actual output and the output of the neural network model for test data.

IV. PREDICTIVE CONTROL OF A HEAT EXCHANGER BASED ON NN

The objective of the predictive control strategy using neural predictors is twofold: *(i)* to estimate the *future output* of the plant and *(ii)* to minimize a *cost function* based on the error between the predicted output of the processes and the reference trajectory. The cost function, which may be different from case to case, is minimized in order to obtain the optimum control input that is applied to the nonlinear plant. In most of the predictive control algorithms a quadratic form is utilized for the cost function:

$$J = \sum_{i=N_1}^{N_2} \left[y(k+i) - r(k+i)\right]^2 + \lambda \sum_{i=1}^{N_u} \Delta u^2 (k+i-1) \qquad (9)$$

with the following requirements

$$\Delta u(k+i-1) = 0 \qquad 1 \le N_u < i \le N_2 \qquad (10)$$

where N_u is the control horizon, N_1 and N_2 are the minimum and maximum prediction horizons respectively, i is the order of the predictor, r is the reference trajectory, λ*is* the weight factor, and Δ is the differentiation operator.

The command u may be subject to amplitude constraints:

$$u_{\min} \le u(k+i) \le u_{\max} \qquad i = 1,2,..., N_u \qquad (11)$$

The cost function is often used with the weight factor λ=0. A very important parameter in the predictive control strategy is the control horizon N_u, which specifies the instant time, since when the output of the controller should be kept at a constant value.

The output sequence of the optimal controller is obtained over the prediction horizon by minimizing the cost function J with respect to the vector U. This can be achieved by setting

$$\frac{\partial J}{\partial U} = 0 \qquad U = \left[u(k-d),...,u(k-d+N_u-1)\right]^T \qquad (12)$$

However, when proceeding further with the calculation of $\partial J/\partial U$, a major inconvenience occurs. The *analytical approach* to the optimization problem needs for the differentiation of the cost function and, finally, leads to a nonlinear algebraic equation; unfortunately this equation cannot be solved by any analytic procedure. This is why a *computational method* is preferred for the minimization of the cost function, also complying with the typical requirements of the real-time implementations (guaranteed convergence, at least to a sub-optimal solution, within a given time interval).

For the minimization of the cost function, the Matlab's Optimal Toolbox functions *fminunc* and *fmincon* were used, which allow dealing with either unconstrained or constrained optimization problems. Unlike the *fminunc* function, *fmincon* allows imposing constraints with respect to the value of the control input such as upper or lower bounds, which are often required in practice. The cost function J is given as an input parameter for the functions mentioned above together with the initial values for the control input vector and some options regarding the minimization method (the maximum number of iterations, the minimum error value, the use of analytical gradients, etc.). In the case of *fmincon* the constraints must also be specified as input parameters in a matrix form.

The advantage of this nonlinear neural predictive controller consists in the implementation method that solves the key problems of the nonlinear MPC. The implementation is robust, easy to use and fulfills the requirements imposed for the minimization algorithm. Changes in the parameters of the neural predictive controller (such as the prediction horizons, the control horizon, as well as the necessary constraints) are straightforward operations. A simple block diagram of predictive control strategy is depicted in Fig. 3.

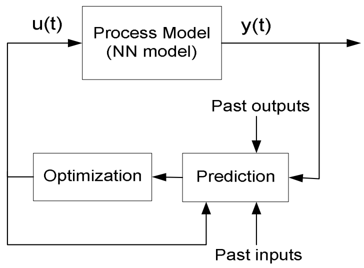

Figure 3 The scheme of neural network based predictive control.

The *optimization problem* was addressed in accordance with the computational scenario built in the above. With respect to the notations introduced in the above, the following concrete values were chosen for the tuning parameters of the predictive control algorithm: $N_1 = 1, N_2 = 10, N_u = 5$. Next, the cost function J is constructed:

$$J = \sum_{i=1}^{10} \left[y(k+i) - r(k+i)\right]^2 \qquad (13)$$

the minimization algorithm gives the control input vector $U=[u(k),u(k+1),u(k+2),u(k+3),u(k+4)]^T$ to be applied to the plant described by (3). The set point tracking results of the simulation on the plant and the corresponding input signal are depicted in Fig. 4. Clearly the system could track the set points with satisfactory settling time.

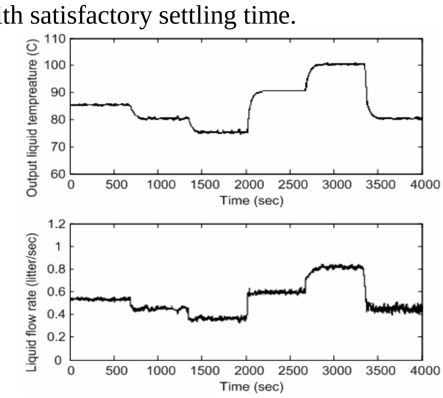

Figure 4 Response of the plant with proper control signal for tracking the desired set points.

In order to investigate the effectiveness of the neural network based predictive controller, we will compare the performance of that with that of GPC controller. It is remarkable that the controllers are applied to a process which is modeled by neural network. The comparison is depicted in Figure 5. As it can be seen, the closed loop system with neural network based control action performs much better than the other one and the output temperature can track the set point values better.

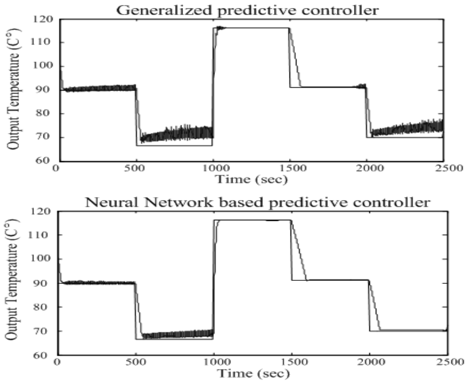

Figure 5 Response of the plant for tracking the desired set points using neural network based controller and GPC.

V. CONCLUSIONS

In this apper, a neural network based predictive control strategy was applied to a heat exchanger pilot plant. Heat exchanger is a highly nonlinear process; therefore, a nonlinear prediction method, e.g. neural network based one, can be a better match in a predictive control strategy. Using the neuro predictive controller, the outlet liquid temperature of the plant tracked the desired set points by applying the liquid flow rate as a control signal. A neural network model for the plant was constructed. Once having such a model, *i*-step ahead predictors were obtained and a quadratic form cost function was utilized to compute the prediction error and to derive the optimal predictive control strategy. The performance of the proposed control strategy was compared with that of Generalized Predictive Control strategy, which uses a linear model for prediction. Simulation results showed that the former strategy performs much better than the latter one, when dealing with the tracking problem of output temperature.

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