



## Neural network based model predictive control for a steel pickling process

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### ABSTRACT

A multi-layer feedforward neural network based predictive control scheme is developed for a multivariable nonlinear steel pickling process in this paper. In the acid baths three variables under controlled are the hydrochloric acid concentrations. The baths exhibit the normal features of an industrial system such as nonlinear dynamics and multi-effects among variables. In the modeling, multiple input, single-output recurrent neural network subsystem models are developed using input–output data sets obtaining from mathematical model simulation. The Levenberg–Marquardt algorithm is used to train the process models. In the control (MPC) algorithm, the feedforward neural network models are used to predict the state variables over a prediction horizon within the model predictive control algorithm for searching the optimal control actions via sequential quadratic programming. The proposed algorithm is tested for control of a steel pickling process in several cases in simulation such as for set point tracking, disturbance, model mismatch and presence of noise. The results for the neural network model predictive control (NNMPC) overall show better performance in the control of the system over the conventional PI controller in all cases.

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### 1. Introduction

It has been known that many chemical industrial plants cause environmental problems due to the usage of chemicals in their production lines. One such industry is the steel pickling plant which is a fundamental industry in Thailand and has long existed and served the country's steel demand. The steel pickling process utilizes concentrated chemicals in the production lines and the wastewater released from the process contains hazardous materials and usually causes major environmental problems. Therefore, production scheduling and control of this pickling process are inevitably needed to minimize the amount of hazardous material contained in the released wastewater and also to maintain the concentration of acid solution in the tanks in order to obtain the maximum reaction rate at the same time.

The steel pickling process presents many challenging control problems, including: nonlinear dynamic behavior; multivariable interactions between manipulated and controlled variables and constraints on manipulated and state variables. A number of control approaches and algorithms that are able to handle some of the above process characteristics have been presented in the academic literature in recent years. Bequette [1] gives a review of these various approaches such as the internal model approaches,

differential geometric approaches, reference system synthesis techniques, including internal decoupling and generic model control (GMC), model predictive control (MPC) and also various special and ad hoc approaches. Many of these approaches are not able to handle the various process characteristics and requirements met in industrial applications and some of the approaches can only be applied for special classes of models.

MPC appears to be one of the general approaches which can handle most of the common process characteristics and industrial requirements in a satisfactory way. It also seems to be the approach which is most suitable for the development of a general and application independent software, which is essential for the development of cost-effective applications. However, the key in the successful use of MPC in solving these process problems is the existence of an accurate model. Chemical processes such as this steel pickling process have been traditionally controlled using linear system analysis even though they are inherent nonlinear process. However to obtain accurate model for the steel pickling process and predicting its interacting and nonlinear behavior is actually highly difficult.

Recently, neural networks have been successfully applied in the identification and control of nonlinear processes. Neural networks offer alternative nonlinear models for implementing MPC in industrial systems [2–5]. Different ways of neural models being embedded in MPC systems were reviewed by two recent surveys [6,7]. It is noted that while neural network modeling and control

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### Nomenclature

$A$	area of operating tank	$V$	volume of operating tank ( $\text{m}^3$ )
$C$	concentration of HCl (mol/l)		
$C_{20}$	20% by weight concentration of HCl	<i>Subscripts</i>	
$F$	volumetric rate (l/min)	w	water
$h$	height of operating tank (m)	sp	setpoint
$k$	reaction rate constant		
$q$	amount of acid solution that stuck with samples		
$t$	time (min)		

techniques are investigated for nonlinear systems, the current methods proposed and tested by simulations and some implementations to laboratory rigs are mainly for single-input single-output (SISO) systems [8,9]. Others applications of neural networks for chemical process modeling and MPC have also been investigated for SISO systems [10–13] but very few investigations into iterative multistep neural network predictions in MPC based control for MIMO chemical processes have been reported.

A multivariable neural network modeling and neural network model predictive control (NNMPC) technique are investigated in this paper for application to a steel pickling process which is commonly found in the steel industries of Thailand. The process involves removal of surface oxides (scales) and other contaminants out of metals by an immersion of the metals into an aqueous acid solution, which consists of three acid baths in series. The highly nonlinear dynamic behavior, multivariable in nature and interaction between baths cause this process to be difficult to control by conventional controllers. It is, therefore, the aim and contribution of this work to apply an iterative multistep neural network prediction model in a predictive control strategy for controlling such a nonlinear system. To demonstrate the robustness of the proposed control strategy, tests involving set point tracking with introduction of various disturbances including model mismatch and noise are performed in these studies.

## 2. Process description

The steel pickling process consists of two major steps: pickling and rinsing steps [14,15]. The purpose of the pickling step is to remove surface oxides (scales) and other contaminants on the metals by an immersion of the metals into an aqueous acid solution. Metals are immersed in pickling baths, containing 5%, 10% and 15% by weight of hydrochloric acid (HCl), respectively, in order to remove the scales from the metals. The metals move counter current to the

acid stream. The reaction occurring in the pickling baths is as follows:



Drag in–out pickling solution is removed from the metal surface using rinsing water during the rinsing step, which consists of three pure water baths. Here, the amount of drag out solution of each bath is assumed to be equal to the amount of drag in solution. The following assumptions are made for the purpose of this study.

- The system is supposed to be perfectly mixed and isothermal.
- All state variables are measurable directly.
- Density of liquid is assumed to be constant.
- The deterioration of pickling efficiency resulting from iron concentration is considered negligible.

Based on the above assumptions, the mathematical model of the continuous steel pickling process (see Fig. 1) for the change in volume and concentration can be derived for the pickling step as follows:

Pickling step (occurring in the 5%, 10% and 15% HCl baths)

$$A \frac{dh_1}{dt} = F_2 - F_1 - q \quad (2)$$

$$A \frac{dh_2}{dt} = F_3 - F_2 - F_{11} \quad (3)$$

$$A \frac{dh_3}{dt} = F_5 - F_3 - F_{10} \quad (4)$$

$$\frac{d(V_1 C_1)}{dt} = F_2 C_2 - C_1(F_1 + q) - V_1 r_1 \quad (5)$$

$$\frac{d(V_2 C_2)}{dt} = q C_1 + F_3 C_3 - C_2(F_2 + F_{11} + q) - V_2 r_2 \quad (6)$$

$$\frac{d(V_3 C_3)}{dt} = q C_2 + F_5 C_{20} - C_3(F_3 + F_{10} + q) - V_3 r_3 \quad (7)$$

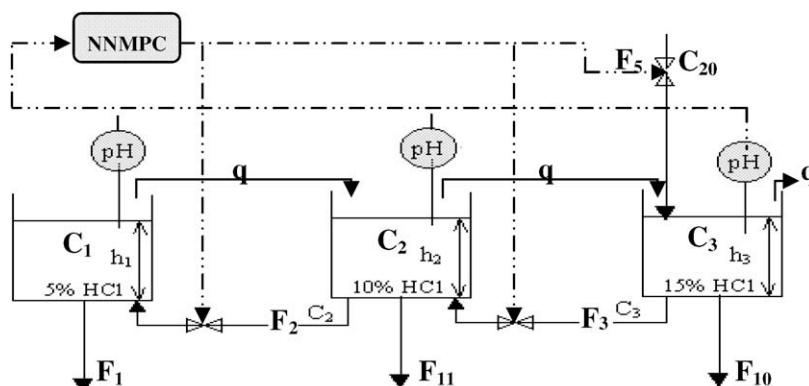


Fig. 1. Flow diagram of pickling baths control system.

**Table 1**  
Nominal operating conditions of the steel pickling process

$A = 0.0729 \text{ (m}^2\text{)}$
$k = 3.267 \times 10^{-4} \text{ (mol/(l min))}$
$C_{20} = 6.034 \text{ (mol/l)}$
$q = 5 \times 10^{-3} \text{ (l/min)}$
$F_2 = 4.65 \times 10^{-2} \text{ (l/min)}$
$F_3 = 9.16 \times 10^{-2} \text{ (l/min)}$
$F_5 = 1.328 \times 10^{-1} \text{ (l/min)}$
$h_{1i}, h_{2i}, h_{3i} = 0.205 \text{ (m)}$
$C_{1i} = 1.35 \text{ (mol/l)}$
$C_{2i} = 2.8 \text{ (mol/l)}$
$C_{3i} = 4.35 \text{ (mol/l)}$

The meanings of all these variables are specified in the nomenclature.

To complete the mathematical modeling of this continuous process, the expression of the reaction rate (Eq. (1)) in the pickling baths needs to be imposed. The reaction is assumed to be first order neglecting the deterioration of pickling efficiency. Therefore, the rate of reaction studied here solely depends upon acid concentration as shown below:

$$r_i = kC_i, \quad i = 1, \dots, 3 \quad (8)$$

where  $k$  is the reaction rate constant.

The normal operating conditions of the process used in our case study can be seen in Table 1.

The objective of this work is to control the concentration of HCl in all the pickling baths ( $C_1$ ,  $C_2$  and  $C_3$ ) to a desired set point by manipulating inlet flows  $F_2$ ,  $F_3$  and  $F_5$  as illustrated in Fig. 1. Since a neural network based model is used for the control, we will first

describe the procedure for neural network modeling and its use for control in the next section.

### 3. Neural network modeling

Neural networks have the advantages of distributed information processing and the inherent potential for parallel computation. In many cases, when sufficiently rich data are available, they can provide fairly accurate models for nonlinear controls when model equations are not known or only partial state information is available [16,17]. Due to their parallel processing capability, nonlinearity in nature and their ability to model without a priori knowledge, neural networks can be used successfully to capture the dynamics of nonlinear and complex, multivariable systems. They, therefore, offer potential benefits in MPC strategies.

Although various types of neural network exist such as multi-layer perceptron (MLP), radial basis function (RBF) network and recurrent neural network (RNN), they consist of the same basic features: nodes, layers and connection. In this work, multi-layered feedforward network is used for the neural network since it is one of the most popular and successful neural network architectures suited to a wide range of applications in prediction, process modeling and control. Since multiple output predictions are required, we have used the neural network in an iterative method to predict the multiple future values to be used in the MPC strategy.

#### 3.1. Procedure for obtaining feedforward neural network models

The detailed procedures to find the feedforward neural network models for the various baths are summarized in Fig. 2. In the data

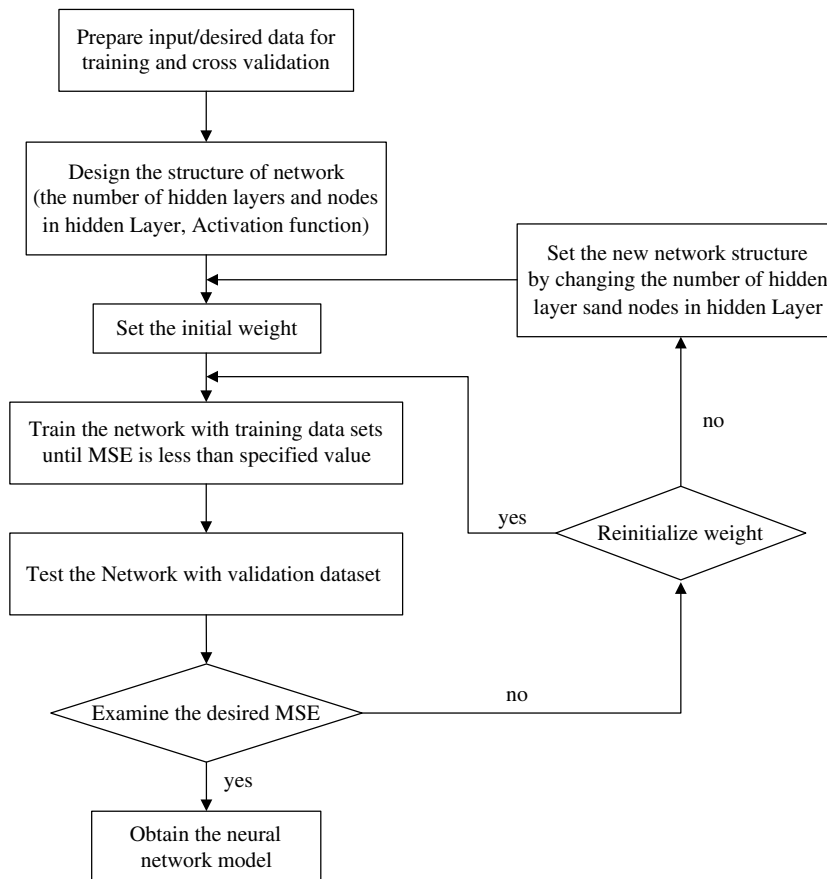


Fig. 2. Procedure for obtaining feedforward neural network models.

preparation, training and validation data sets are obtained by selecting appropriate excitation signals from the simulation of the steel pickling process models by solving Eqs. (2)–(7). These equations are solved to obtain the process states according to various step changes in the manipulated variables, i.e., flow rates ( $F_2$ ,  $F_3$  and  $F_5$ ). The excitation signals used to generate the testing data sets for the neural network modeling are the manipulated variables that are changed with multilevel pseudorandom steps of varying frequencies within the range of the operating conditions of the process, with a sampling time of 0.5 min. These step perturbations have to be of sufficient excitation to predict the nonlinear dynamics of the system. Details of the training procedure to model nonlinear systems are explained in [18,19]. Various data sets are then selected as the training data set (to design the neural network model) and as the validation data set (data sets use to validate these networks after training). Mathematically, these RNN models can be expressed as the function of inputs as shown below:

NN model for the pickling baths:

5% HCl bath:

$$C_1(k+1) = f(F_2(k-1), F_2(k), C_2(k-1), C_2(k), C_1(k)) \quad (9)$$

10% HCl bath:

$$C_2(k+1) = f(F_2(k-1), F_2(k), F_3(k-1), F_3(k), C_1(k-1), \times C_1(k), C_3(k-1), C_3(k), C_2(k)) \quad (10)$$

15% HCl bath:

$$C_3(k+1) = f(F_3(k-1), F_3(k), F_5(k-1), F_5(k), C_2(k-1), \times C_2(k), C_3(k)) \quad (11)$$

The inputs to the neural network selected are the previous and current value of the input variables which effect the output state variable in each bath. The data sets need to be scaled in order to overcome the significant minimum and maximum values used in the training process. Raw process data generated earlier are scaled down linearly to between 0.05 and 0.95 to avoid obtaining zero outputs and an infinite gain network.

In the neural network design, suitable neural network structure or configuration needs to be selected. The important aspects to consider are the number of hidden nodes, layers and transfer function used in the neural network. In this work, we use the sigmoidal function as the activation function of the nodes in the hidden layer and linear function neurons in its output layer. The defined neural

networks are trained with the Levenberg–Marquardt algorithm in the MATLAB neural network toolbox where the common objective is to reduce the error between the neural network predicted value and the actual targeted value. The training is switched between the train and test data and the training stops when the desired mean squared error (MSE) reaches the specified value of  $10^{-6}$  for both cases. The MSE is expressed mathematically as

$$MSE = \frac{1}{n} \sum_{k=1}^n (F_{tg}(k) - F_N(K))^2 \quad (12)$$

where  $n$  is the number of data,  $F_{tg}$  is the target/desired flow value and  $F_N$  is the neural network output.

After training, the trained neural networks are validated by use of the validation data sets. If the validation routine is not satisfactory, the neural network is not properly trained and requires more training. This can be done first by re-initializing the weights and biases and to re-train the neural network for the next loop. Reconfiguring the neural network architecture can also help to increase the quality of the neural network simply by increasing or decreasing the number of hidden nodes.

In this work, the optimum structures are selected by the minimum MSE method. The hidden nodes are varied in various quantities. The MSE error is then monitored and the one that corresponds to the minimum MSE value is selected for determining the final number of hidden nodes. The number of hidden nodes selected for each model are 4, 4 and 8, respectively, and therefore, the structure of the neural network models for the 5% HCl bath, 10% HCl bath and 15% HCl bath are 5:4:1 (inputs:hidden layer nodes:output), 9:4:1 and 7:8:1, respectively. The validation of the neural network model (7-8-1 configuration) for the 15% HCL bath can be seen in Fig. 3 which shows excellent accuracy. Only one bath is shown since the others are of similar accuracy.

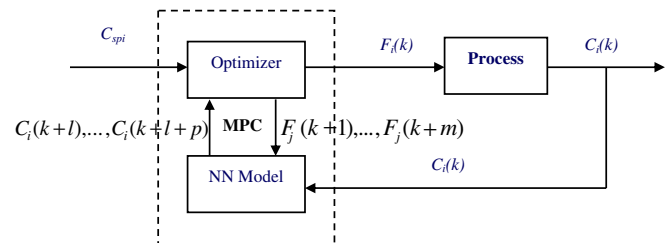


Fig. 4. Multivariable NN MPC strategy.

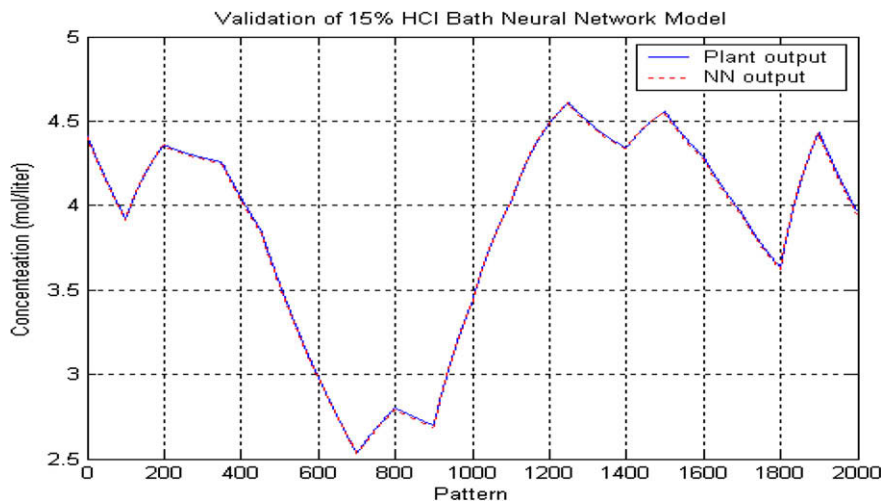


Fig. 3. Validation of the 15% HCL bath using the neural network model (7-8-1 network).

#### 4. Neural network model based predictive control

The neural network MPC strategy developed in this work is shown in Fig. 4. In this approach the neural network model is used

to predict future outputs several steps in future over the prediction horizon ( $p$ ). The output from the first prediction,  $C(k+1)$  will be used as inputs for the next prediction in predicting  $C(k+2)$ . With this iterative procedure, we can predict the multiple output  $P$  steps

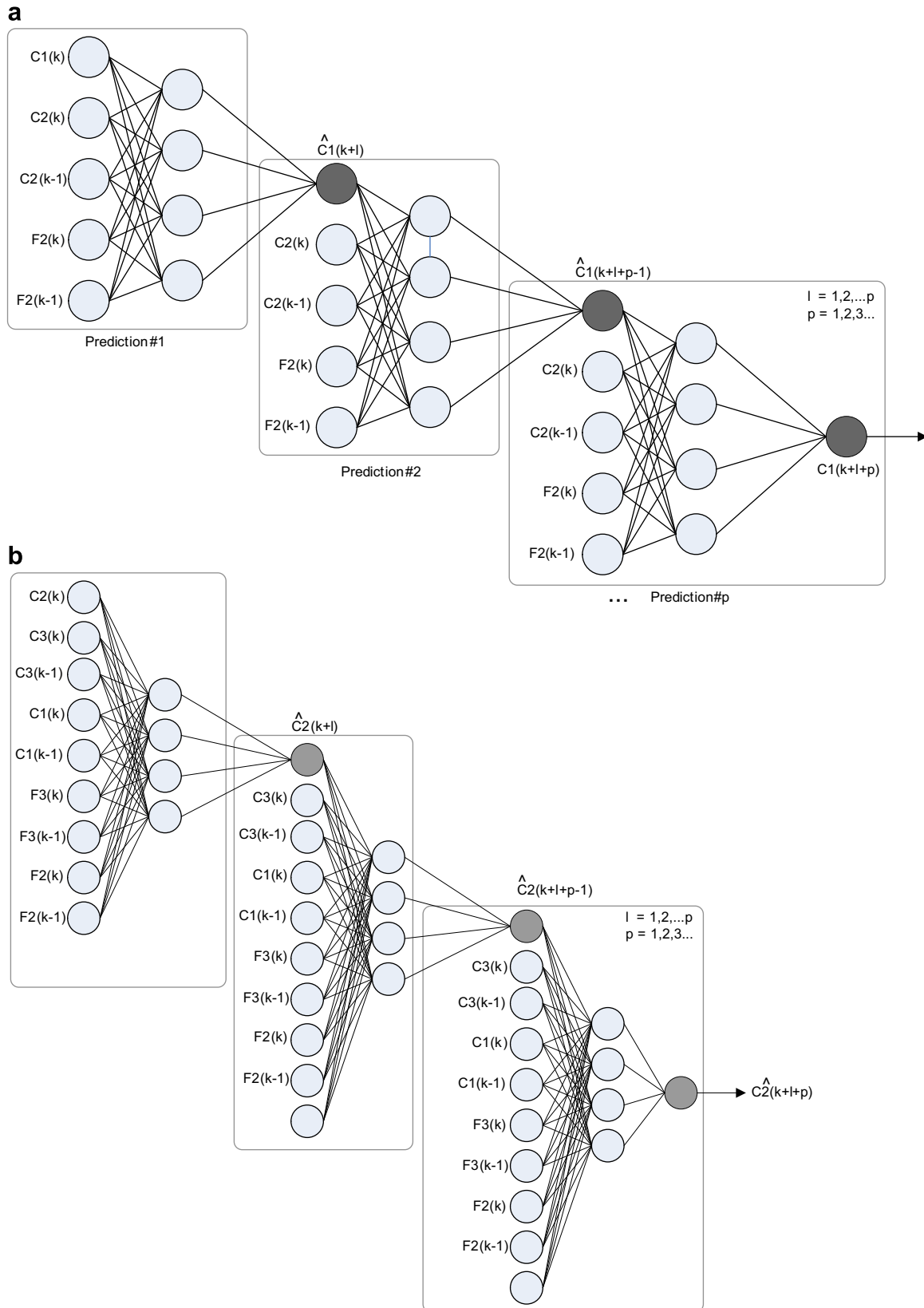


Fig. 5. (a) Iterative method using neural network to obtain  $C_1$ , (b) iterative method using neural network to obtain  $C_2$  and (c) iterative method using neural network to obtain  $C_3$ .

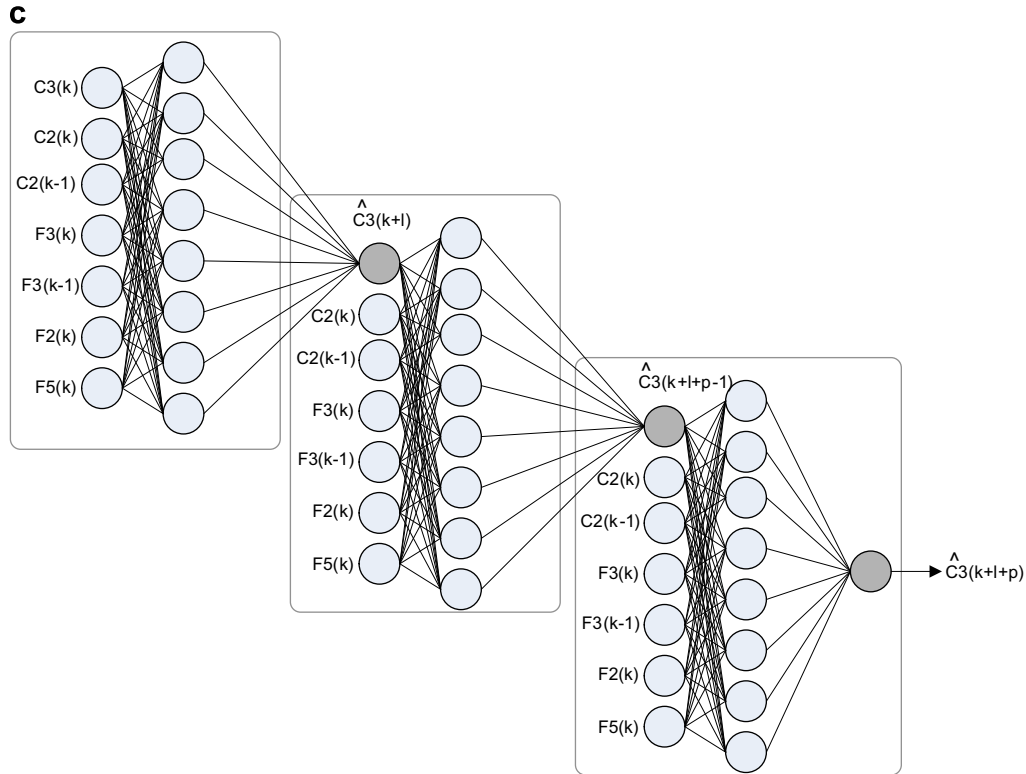


Fig. 5 (continued)

in the future as shown in Fig. 5a–c. Other inputs are obtained as from the previous values. This iterative method for predicting the future values is considered more stable than utilizing multiple neural networks to perform these predictions [7,18]. After that the predicted outputs are passed to an optimization routine which produce the present and future control signals

$$[F_j(k+1), \dots, F_j(k+m)] \quad (13)$$

They are selected by ensuring that the sum of squares of the errors between the predicted outputs and the setpoint values evaluated over the prediction horizon (objective function, Eq. (14)) will be minimized. The objective function of the predictive control strategy has the form as follows:

$$\min_{F_j(k+1), \dots, F_j(k+m)} \sum_{C_i=1}^3 \sum_{l=1}^p W_i \| (C_{spi}(k+1) - C_i(k+l)|k) \|^2 \quad (14)$$

Subject to

$$(F_j)_{\min} \leq F_j(k+l) \leq (F_j)_{\max}, \quad l = 1, \dots, m \quad j = 2, 3 \text{ and } 5$$

where  $p$  is a parameter specifying the prediction horizon;  $C_{spi}$  is the required set point of each bath,  $C_i$  is the concentration in each bath, with the  $i$ th element specifying the parameter for the corresponding bath and  $W_i$  is weighting parameter used to give different weights to different squared tracking errors. If all variables in Eq. (14) are in a similar range, then the choice of identity parameters may suffice.

Various trials have been done through simulations to find the set of suitable control parameters, i.e., values for the parameters,  $p$ ;  $m$  (control horizon) and  $W_i$  for this strategy. The choice of  $p$  includes an equal number of future predictions of each output in the objective function where  $p$  is set at eight in this case.  $W_i$  is chosen as the identity vector because the outputs of process are scaled before they are use in the network process model. The control hori-

zon ( $m$ ) is set as two. Sequential quadratic programming is used to solve the multivariable optimization problem by minimizing the objective function in Eq. (14) with respect to  $F_j$  and to produce a solution constrained within the process input operating ranges. Similar objective function and approach has been used in other nonlinear multivariable systems [20].

At each sample interval, although the solution of Eq. (14) yields a vector of future control moves ( $F_j(k+m)$ ), only the first one ( $F_j(k+1)$ ) is implemented. The other elements of the solution vector are disregarded as in a receding horizon method. A summary of the operation of the NNMPC algorithm, which was implemented in MATLAB and used to control the steel pickling process simulation, is given below. At each sample interval (Fig. 4)

- (1) Sample the process outputs,  $C_i(k)$ ,  $i = 1, \dots, 3$ .
- (2) Use the NN process models which are developed in Section 3 to predict the next  $P$  values of the process outputs,  $C_i(k+1), \dots, C_i(k+1+p)$  (iterative prediction).
- (3) Use the process outputs,  $C_i(k+1), \dots, C_i(k+1+p)$  which are predicted in step 2 to calculate the set of manipulated variables  $[F_j(k+1), \dots, F_j(k+m)]$ , using the sequential quadratic programming procedure (SQP). In SQP procedure, the steps 2 and 3 are iterative at each sample time.
- (4) Implement  $F_j(k+1)$ ,  $j = 2, 3$  and 5 to adjust the concentration of HCl in the baths to the desired set points.

## 5. Simulation results

The multivariable NNMPC strategy is initially applied to control the concentration of HCl in the 5% HCl, 10% HCl and 15% HCl bath to the normal values of 1.40 (5% by weight HCl), 2.87 (10% by weight HCl) and 4.41 (15% by weight HCl) mol/l by adjusting the manipulated variables  $F_2$ ,  $F_3$  and  $F_5$ , respectively. The simulations are divided into four cases of control studies, which are the set

point tracking case, disturbance case, model mismatch case and noise case, respectively.

For the set point tracking case, the controllers are designed to bring the concentration of HCl in each bath to the desired value from initial values of pH 1.2, pH 2.7 and pH 4.2 for the 5%, 10%, and 15% baths, respectively. The desired set points are set at 1.40, 2.87 and 4.41 mol/l and changed to 1.35 and back to 1.4 mol/l for the 5% HCl bath, 2.77 and back to 2.87 mol/l for the 10% HCl bath and 4.35 and back to 4.41 mol/l for 15% HCl bath at the 10th and 25th minutes, respectively. The control results as in Fig. 6 show that, although there exists effects among input and output variables of the acid baths, suitable control has been found to drive the process response to follow the set points without overshoot and oscillations. The satisfactory performance obtained is

due to the accurate representation of the nonlinear dynamics of the process by these neural network models. For comparison, three PI controllers have been designed for the three loops within the process. The controllers are designed using the Ziegler–Nichols closed loop method around one operating point and with subsequent fine tuning. The maximum and manipulated flow rate is limited to a value of 2 l/min, which is based on the pump flow rate limit. The control of HCl concentration in the three baths using PI show poor performances as displayed in Fig. 7 because of the nonlinear dynamics exhibited by these baths. They show overshoot of the controlled variables and sluggish adjustment of the manipulated variables. The control of the 15% bath using the conventional MPC method ( $m = 2$ ,  $p = 8$ ) can be seen in Fig. 8 for a single set point. It can be seen that the MPC provided slow response and

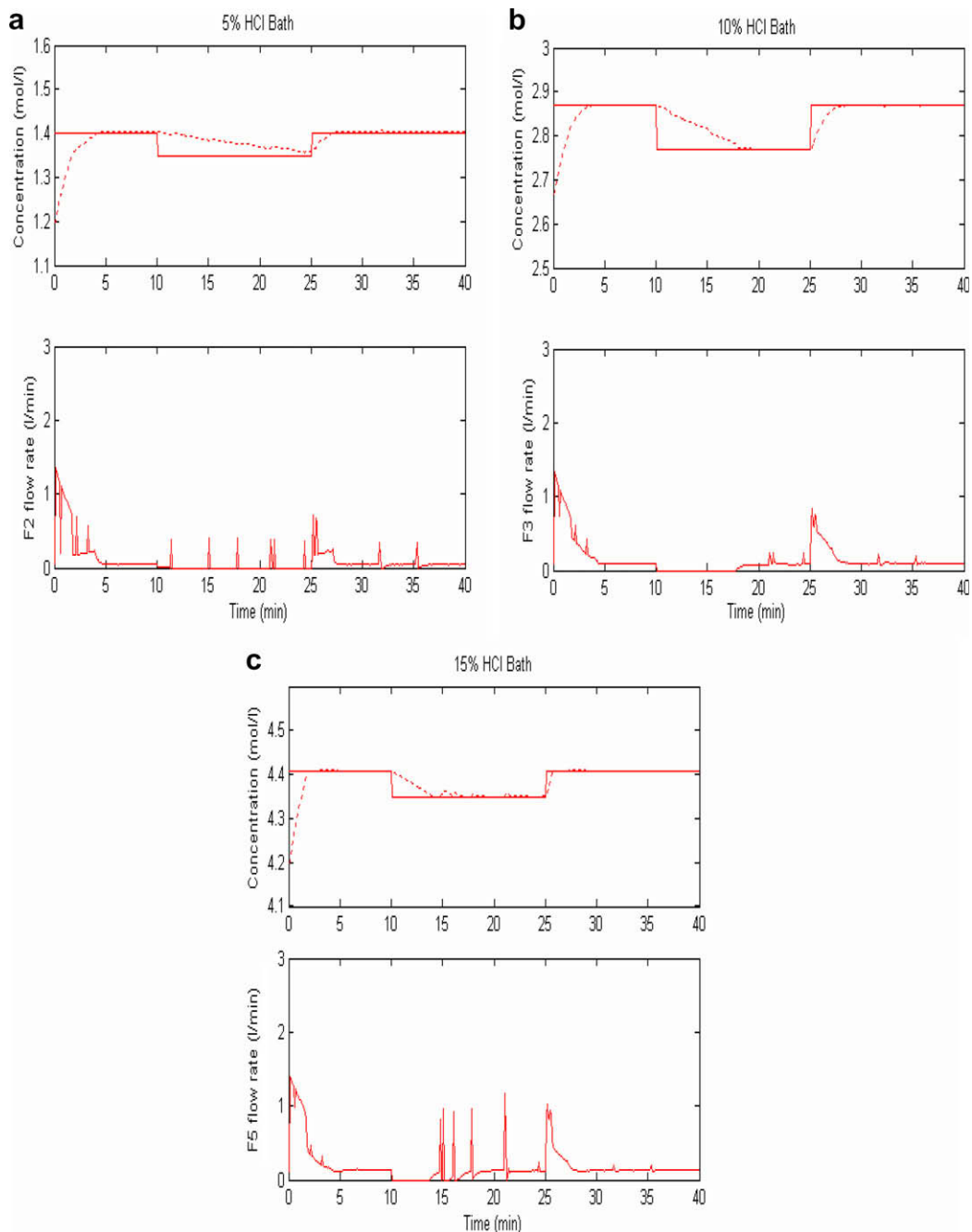


Fig. 6. Set point tracking with NNMPC control for HCl acid concentration, under normal conditions ( $m = 2$ ,  $p = 8$ ); (a) 5% HCl bath, (b) 10% HCl bath and (c) 15% HCl bath.

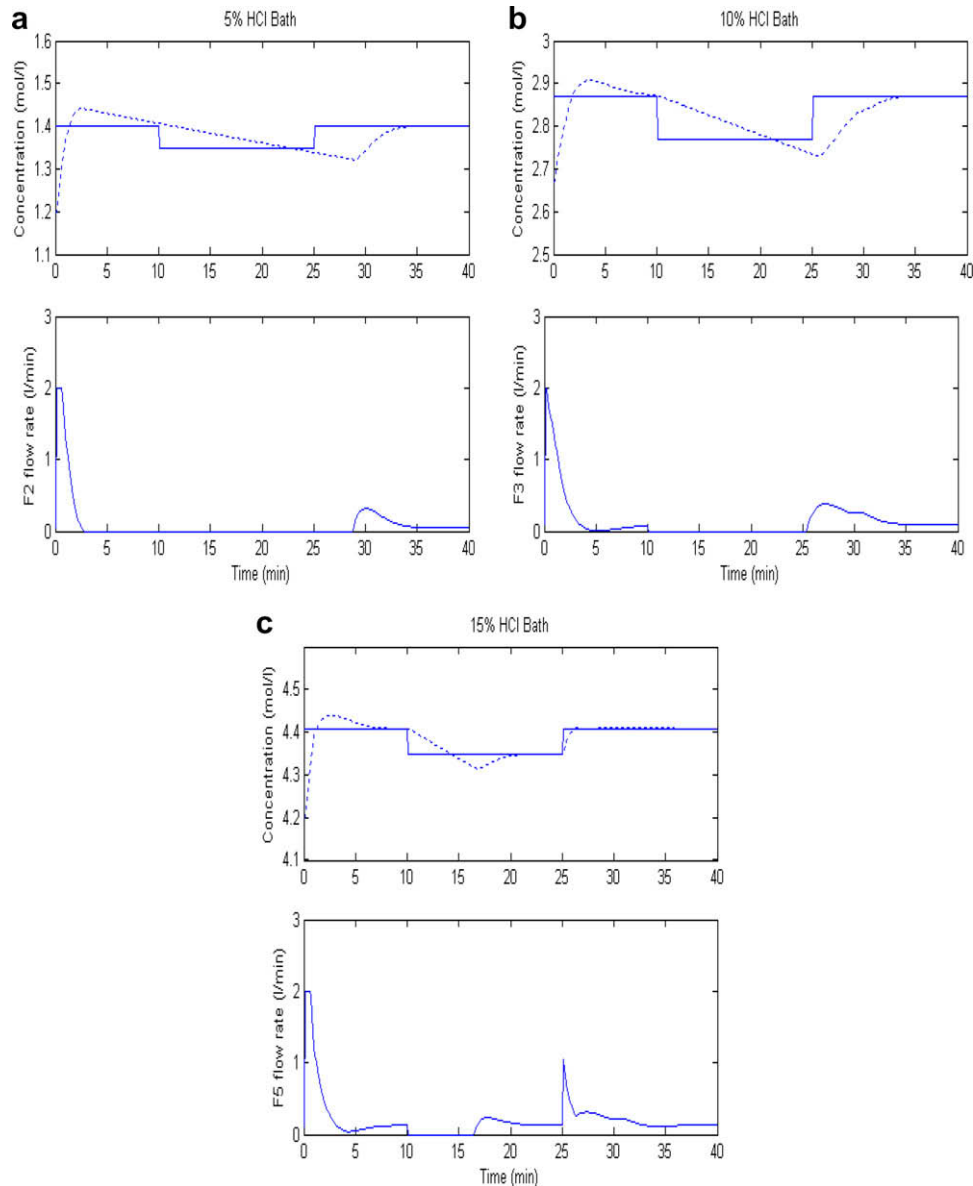


Fig. 7. Set point tracking with PI control for HCl acid concentration: (a) 5% HCl bath, (b) 10% HCl bath and (c) 15% HCl bath.

overshoot due to its heavy dependence on the accuracy of the conventional model used.

For the disturbance case, a change in the concentration of the stream  $F_5$ ,  $C_{20}$  is introduced by randomly increasing and reducing its nominal operation values by 15%. Fig. 9 shows the results of the NNMPC and PI control for the 15% HCl bath with the introduction of these disturbances. It can be seen from Fig. 9 that the NNMPC strategy brought the concentration to the required value by gradually increasing the flow rate of  $F_5$ , while the PI control bring the concentration to the set point by sudden adjustment of the  $F_5$  flow rate which in turn cause overshoot in the process response. Relatively, similar results are obtained in the 5% and 10% HCl bath. Table 2 summarizes the IAE values using the NNMPC and PI control for the three baths. They indicate that the NNMPC give smoother and better control performance than the PI controllers with smaller IAE error values, when disturbances are introduced into the system.

For the model mismatch case, the rate of reaction in the acid bath is considered as the model mismatch in parameter. The model

mismatch is introduced by randomly increasing and reducing the kinetic rate constant from its nominal value by 15%. Fig. 10 shows the results of the NNMPC and PI control in this case. The figures illustrate that the NNMPC strategy brought the concentrations to the set points by gradual increase of the flow rate of  $F_5$  which give smooth control response. The PI control in turn brought the concentration to the set point by rigorous adjustment of the  $F_5$  flow rate causing overshoot in the process response with a long response time. Relatively, similar results are obtained for the 5% and 10% HCl bath and are not shown here. Table 3 shows the IAE values of NNMPC and PI control for the three baths. They indicate that NNMPC gives less error and gives better control performances than the PI controllers, similar to the disturbance case study.

For the case in the presence of noise, noises accounting to 2% random values from the output measurement are introduced into the system to further test its robustness and performance of the NNMPC approach under real situations. The results in Fig. 11 show that the NNMPC strategy can control the system and bring the concentration to the desired value, while the PI control can only bring



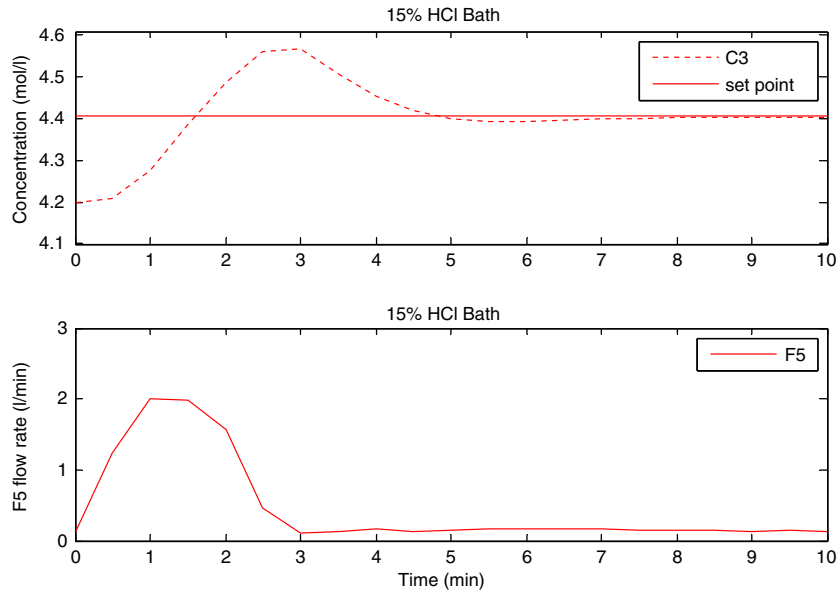


Fig. 8. Control of 15% HCl bath using conventional MPC controller ( $m = 2, p = 8$ ).

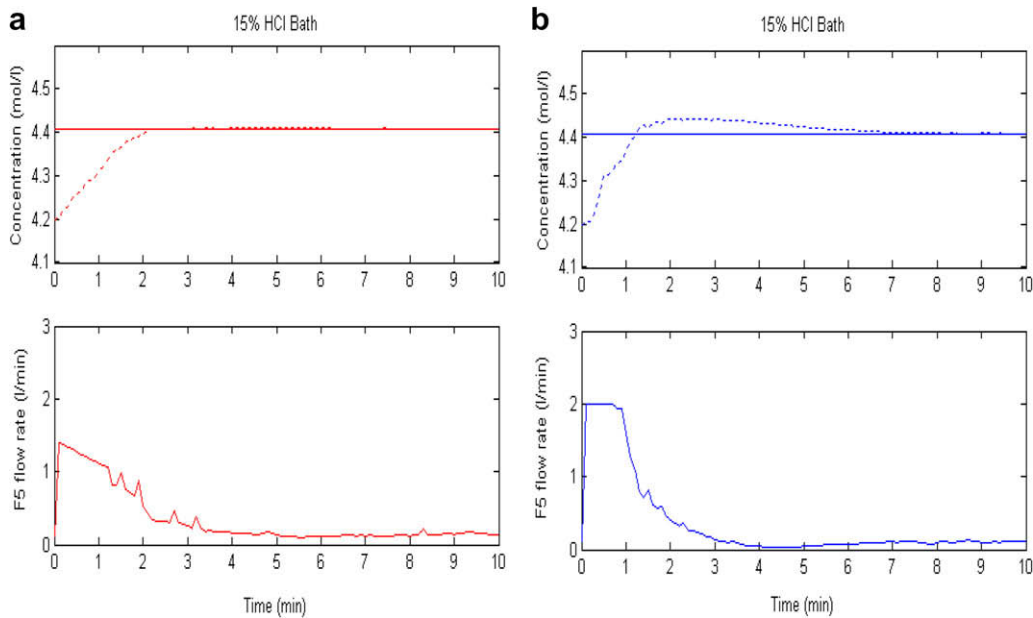


Fig. 9. Concentration control in 15% HCl bath under the disturbance case: (a) NNMPC control and (b) PI control.

**Table 2**  
Performance comparison between NNMPC and PI control under the disturbance case

Bath	IAE values	
	NNMPC	PI
5% HCl bath	0.223	0.355
10% HCl bath	0.266	0.332
15% HCl bath	0.220	0.421

the concentration to the set point by rigorously adjusting the  $F_5$  flow rate causing overshoot in the process response and large deviations and oscillations in the controlled variable. Table 4 shows the

IAE values of NNMPC and PI control for the three baths under noise effects. These results show that the NNMPC model method has less perturbations and oscillations when dealing with noise as compared to the PI controllers. These results also show the robustness of the neural network models in dealing with disturbances and noises not encountered by it during training of the models.

Comparison is also made for the NNMPC using different control and prediction horizons for set point tracking under nominal conditions. It can be seen in Fig. 12 that increasing the control horizon increases the overshoot with more drastic control actions. However as seen in Fig. 13 decreasing the prediction horizon will smoothen the response with more sluggish control actions.

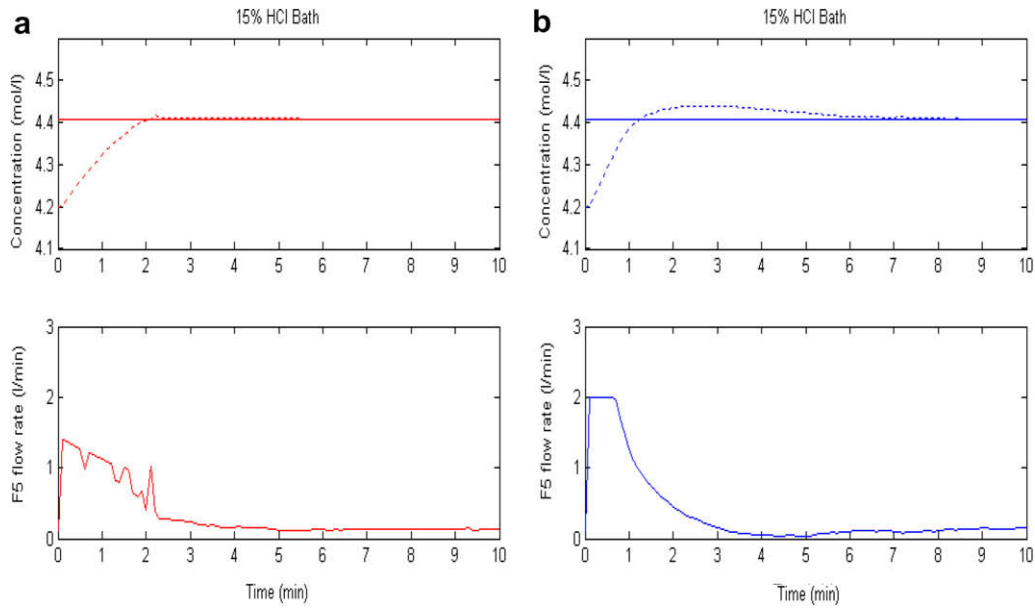


Fig. 10. Concentration control in 15% HCl bath under the model mismatch case: (a) NNMPC control and (b) PI control.

**Table 3**  
Performance comparison between NNMPC and PI control under the model mismatch case

Bath	IAE values	
	NNMPC	PI
5% HCl bath	0.218	0.356
10% HCl bath	0.266	0.331
15% HCl bath	0.130	0.420

**Table 4**  
Performance comparison between NNMPC and PI control under presence of noises

Bath	IAE values	
	NNMPC	PI
5% HCl bath	0.350	0.410
10% HCl bath	0.304	0.471
15% HCl bath	0.278	0.375

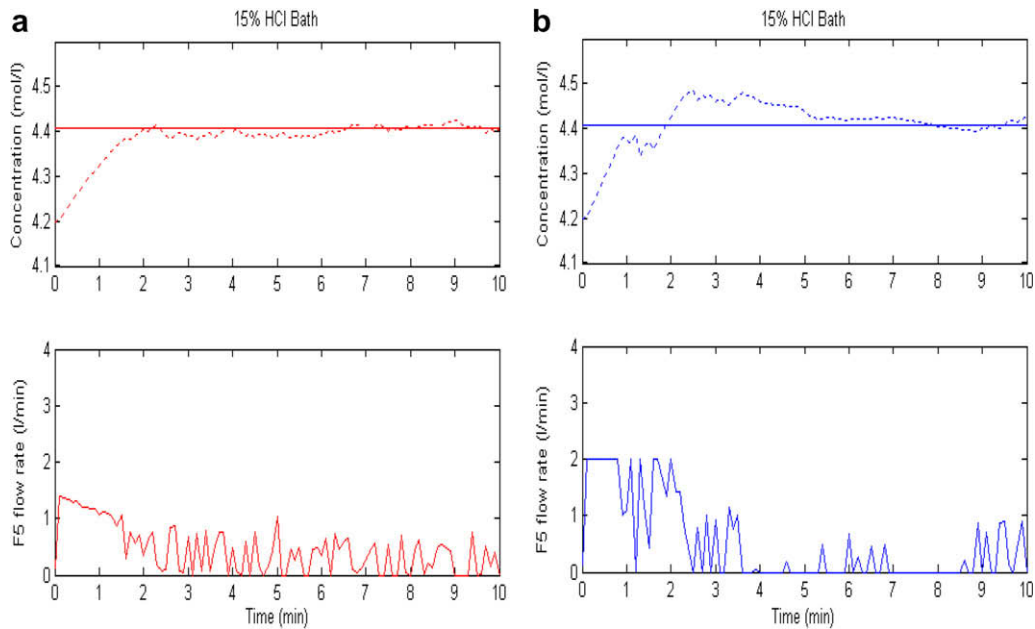


Fig. 11. Concentration control in 15% HCl bath under presence of noise: (a) NNMPC control and (b) PI control.

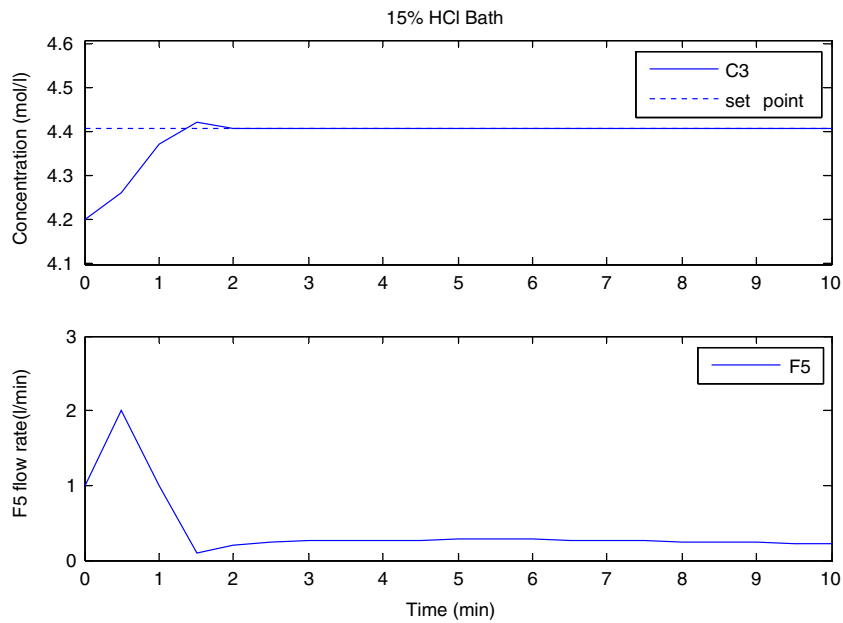


Fig. 12. Concentration control in 15% HCL bath for NN MPC control with  $m = 4$  and  $p = 8$ .

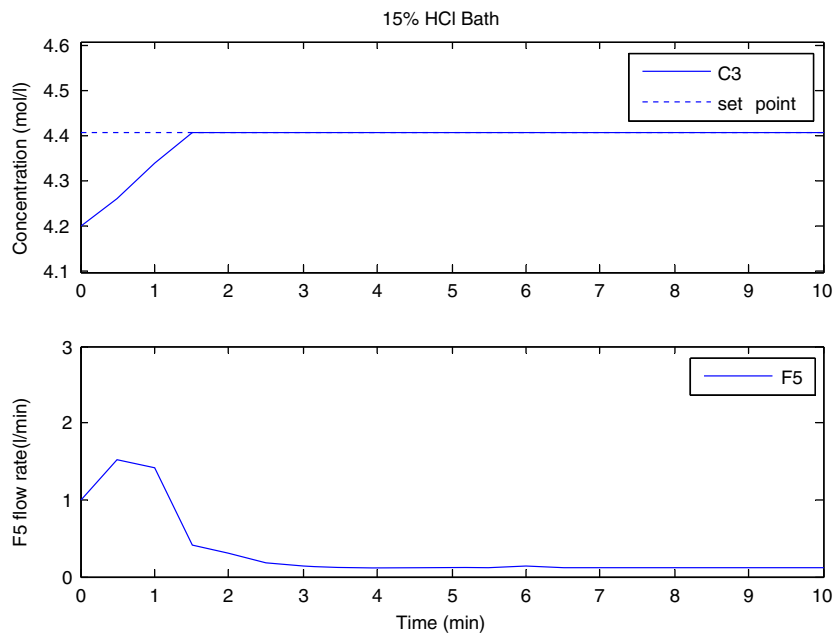


Fig. 13. Concentration control in 15% HCL bath for NN MPC control with  $m = 2$  and  $p = 4$ .

## 6. Conclusions

The application of a neural network model based predictive controller to a nonlinear multivariable chemical process is investigated. Since the real chemical processes are nonlinear and multivariable interacting systems, which make them difficult to control by using conventional controllers, model based advance control techniques are then required to obtain tighter control. However, in many cases it is even impossible to obtain a suitable process model due to the complexity of the underlying processes or the lack of knowledge of critical parameters of the models. So in this work, the multi-layer feedforward neural network is used

to model the steel pickling process which is highly nonlinear and involves multivariable interactions in nature. The neural network models are used to predict the future process response in the MPC algorithm for controlling the concentrations of pickling in a steel pickling process. It was observed that NN MPC can bring the control variables to their set points without oscillations in all cases studies, i.e., set point tracking case, disturbance case, model mismatch case and noise case. Comparison of performance with the conventional PI controller indicated that NN MPC was more robust than the PI controller and gave better results in cases involving disturbances, model mismatches and noise. These results validate the robustness of the NN MPC controllers which make them highly

promising to be implemented in nonlinear multivariable interacting systems such as this steel pickling process.

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