NN-Based MPC for Heat Exchanger System in Hard Chrome Electroplating

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ABSTRACT

To develop an accurate and precise detector, a sensor needs to be coated by metals to protect any corrosion caused by pH or chemicals. Regarding a biodetector, a sensor is mostly in the condition of acid with corresponding to the pH of a human. The process of sensor's plating is then requested to handle this issue. In this work, the temperature control of a heat exchanger in an electroplating process is studied to present the applicability of a control strategy. A hard chrome electroplating process, a complex process and multivariable interacting system, is considered to be one of difficult control problems by conventional controllers. In a plating step, the heat generated by electric current, is accumulated in a plating bath and affects on the quality of surface layers, physical and mechanical properties. In order to achieve good plating, the temperature of plating solution have to be controlled in a desired range. A neural network model based model predictive control (MPC) is proposed in this study to handle the control problem. The multiple input-output feedforward neural network models are developed and used to predict the state variables over a prediction horizon incorporating in the model predictive control algorithm for searching optimal control actions via sequential quadratic programming. The proposed algorithm is tested for control of a hard chrome electroplating process in both nominal and plant/model mismatches. Simulation results for the proposed algorithm show good control performances in keeping the plating solution temperature at the desired set point without any oscillation and overshoot compared to that of the conventional PI controller and NNDIC strategy in all cases.

Keywords: neural network based model predictive control, neural network direct inverse control, optimal neural network structure

1. INTRODUCTION

Nowadays, chromium plating has widely used both in industry and everyday life. The hard chrome plating is used for fairly heavy coating or work pieces repairing. The property of chromium plated work pieces depends on the operating conditions of the plating: concentrations of chromic acid and sulfuric acid, a DC power voltage and current requirements. A major problem in hard chrome electroplating manufactory is the increase in the temperature of plating solution while the work pieces are being chromium plated. Generally, an operating temperature of plating solution is about 50°C and a heat exchanger is used to reduce temperature of bath. However, due to the accumulated heat from the high current density and chemical reactions in the plating bath as well as poor control of the heat exchanger, the temperature of the solution is raised to be higher than 60°C or more. Therefore, it requires a suitable method for controlling the plating solution temperature as desired.

Recently, neural network control techniques, one of advanced control strategies, have been developed for precise control of such chemical manufacturing processes that have many challenging control problems such as non-linear dynamic behavior, unmeasured state variables, high-order and etc. have been popular extensively and handle the above situation. It can be important in the modelling and control process. For examples, Daosud et al. [1] presented the neural network for inverse model to be a controller for a steel pickling process. Charoenniyom et al. [2] applied neural network to be a modelling for the methyl methacrylate production process in a batch reactor and Thampasato et al. [3] proposed neural network modelling for a batch crystallizer. Kittisupakorn et al. [4] presented a multi-layer feedforward neural network based model predictive control for a steel pickling process. Furthermore, the neural network is applied to control in many researches [5-7].

The aim of this research is to improve the plating solution temperature in a hard chrome plating process. Therefore, this work has proposed the use of a neural network forward model to predict the dynamics behavior and a neural network inverse model to perform the control of the process. The Lenvenberg-Marquardt training algorithm is applied to train the neural network model. Optimal neural network structures for forward and inverse models are chosen based on mean square error (MSE). The obtained optimal neural network structure for forward model has been employed to predict the plating solution temperature over a predictive horizon within a model predictive control (MPC) framework for searching optimal control actions via successive quadratic programming (SQP). Performance and robustness tests of the model predictive control based on the neural network

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model have been carried out and compared with the conventional PI and NNDIC approaches.

2. PROCESS DESCRIPTION

The hard chrome plating process consists of an electroplating bath, an internal heat exchanger, a receiver tank of cooling water (tank 1) and a cooling tower (tank 2) as shown in Fig. 1. Each unit can be represented by and mathematical model in the form of ordinary differential equations. The meaning of letters and symbols are given in nomenclature and Table 1. The physical properties, geometry characteristics and process data are summarized in Table 1. Assumptions made in this work are as follows.

- The volume of the plating solution in the bath and the water in two tanks are constant.
- The physical and chemical properties, density and heat capacity of the plating solution are constant.
- The electroplating bath condition is well mixed.
- The heat transfer from water in piping to surrounding is negligible.
- The water temperatures at any points in the tanks are identical.

2.1 Electroplating bath

Based on the assumptions above, the mathematical models of the electroplating bath can be written as follows:

$$\frac{d(\rho_p V_p)}{dt} = 0 \tag{1}$$

$$\frac{dT_p}{dt} = \frac{IV - Q_{ploss} - UA_{ht} \triangle T_{lm} + Q_{re}}{\rho_p C_{pp} V_p} \tag{2}$$

$$Q_{re} = \triangle HrV_p \tag{3}$$

When $r = kC_a$ and $\triangle T_{lm} = \frac{T_{wout} - T_{win}}{In[(T_p - T_{win})/(T_p - T_{wout})]}$ The energy balance (2) is shown that the change of plating solution temperature depends on load shown on terms of the current load multiplied by electrical voltage (IV), heat transfer out of the plating solutions $UA_{ht} \triangle T_{lm}$, heat loss out of the environment Q_{ploss} and heat released from reaction Q_{re} .

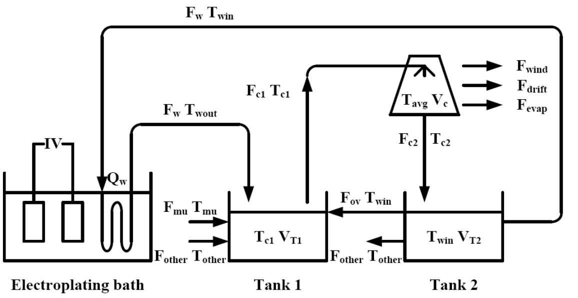


Fig.1:: A hard chrome electroplating process.

2.2 Heat exchanger

The mathematical models of heat exchanger can be written as follows:

$$\frac{d(\rho_w V_{tube})}{dt} = 0 \tag{4}$$

$$\frac{dT_{wout}}{dt} = \frac{F_w(T_{win} - T_{wout})}{LA_0} + \frac{UA_{ht} \triangle T_{lm}}{\rho_w C_{pw} LA_0} \tag{5}$$

As shown in (2) and (5), the average temperature different between the plating solution and water using the log mean temperature different is used. U is the overall ability of a series of conductive and convective barriers to transfer heat across the heat exchanger tube.

2.3 Cooling System

Based on the above assumptions, the mathematical models of the cooling system are:

$$F_{mu} = F_{wind} + F_{evap} + F_{drift} \tag{6}$$

When $F_{evap} = 0.00085 F_{c1}(T_{c1} - T_{c2})$ and $F_{wind} = \frac{F_{evap}}{(cycles-1)}$; $3 < cycles < 5$

$$F_{c2} = F_{c1} - F_{mu} \tag{7}$$

$$F_{ov} = F_{c2} - F_w - F_{other} \tag{8}$$

$$\frac{dT_{c1}}{dt} = \frac{F_w T_{wout} + F_{mu} T_{mu} + F_{other} T_{other} + F_{ov} T_{win} - F_{cl} T_{cl}}{V_{t1}} \tag{9}$$

$$\frac{dT_{win}}{dt} = \frac{F_{c2} T_{c2} - (F_w + F_{ov} + F_{other}) T_{win}}{V_{t2}} \tag{10}$$

$$\frac{dT_{c2}}{dt} = \frac{F_{c1} T_{c1} - F_{mu} T_{avg} - F_{c2} T_{c2}}{V_c} - \frac{\frac{h_A A_s (T_{avg} - T_{air})}{\rho_w C_{pw}} + \frac{F_{evap} C_{evap}}{C_{pw}}}{V_c} \tag{11}$$

When $T_{avg} = \frac{T_{c1} + T_{c2}}{2}$ The energy conservation equations of the cooling tower consist of 2 parts: heat transfer by convection between water and air, and heat transfer due to evaporation as studied by Khan and Zubair [8].

Table 1:: The chemical and physical properties of the hard chrome plating process

Area (m^2)		Heat transfer coefficient of convection between water and air (kW/°C); h_A	2.0250
- cross sectional area of heat exchanger pipe; A0	1.2668×10^{-4}		
- heat exchanger area of pipe; A_{ht}	0.9975	Reaction rate constant ($mol^{-1}.s^{-1}$); k	6.371×10^{-7}
Concentration of chromic acid (mol/l); C_a	2.554	Length of heat exchanger pipe (m); L	30.00
		Temperature(°C)	
Water latent heat of vaporization (kJ/kg); C_{evap}	2,260	- Air; T_{air}	28.00
		- Water makes up; T_{mu}	28.00
Heat capacity(kJ/kg°C)		- Outlet water;T_{other}	45.00
- Plating solution; C_{pp}	4.9172	Overall heat transfer coefficient (kW.m^2.°C); U	0.7239
- Water; C_{pw}	4.1810		
Flow rate (m^3/sec)		Volume (m^3)	
- Drift loss; F_{drift}	2.3550×10^{-6}	- Bottom of the cooling tower water; V_c	0.3771
- Evaporation; F_{evap}	4.3238×10^{-6}		
- Make up water; F_{mu}	7.7597×10^{-6}	- Plating bath; V_p	9.3062
- Other plating bath; F_{other}	4.3364×10^{-4}	- Water of tank 1; V_{t1}	2.1155
- Water flow rate; F_w	5.34×10^{-4}	- Water of tank 1; V_{t2}	2.5663
Density (kg/m3)			
- Plating solution; ρ_p	1,174.4		
- Water; ρ_w	992.25		

3. NEURAL NETWORK

Neural network has the ability to resemble human characteristics in problem solving that are difficult to simulate and complex system using the logical, analytical techniques of expert system and standard software technologies [1]. Neural networks consist of input layer, hidden layer and output layer. Input and output data have to be provided to the network so that it can be trained by an algorithm to properly adjust its internal weights and biases. Basic steps of the neural network has been reported by Daosud [9].

3.1 Neural Network Modelling

In this part, the neural networks modelling have been applied to give predictions of plating solution temperature and inlet water temperature corresponding to pipe heat exchanger profile in a hard chrome electroplating process. In order to develop the neural networks modelling for the heat exchanger system in hard chrome electroplating, available data sets from the experimental work cooperated with the mathematical models are divided into training set (60 % of the total data), validation set (30 % of the total data), and test set (10 % of the total data). The input-output map for the neural networks modelling is shown in Fig. 2. The input layer of the neural networks of the electroplating bath consists of past and present values of the plating solution temperature ($T_p(k-1)$, $T_p(k)$), inlet water temperature in pipe heat exchanger ($T_{win}(k-1), T_{win}(k)$), and water flow rate ($F_w(k-1), F_w(k)$) respectively. The output layer provides the future value of the plating solution temperature (T_p) and the inlet water temperature in pipe heat exchanger (T_{win}) at time interval $k+1$.

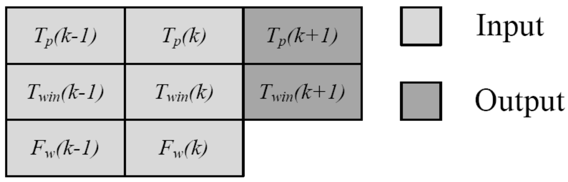


Fig.2:: Input/output map of the neural network forward model.

The networks structure selected consists of two hidden layers with six neurons along with each input and output layer with two neurons. The activation function in the hidden layer is chosen as the sigmoid function. The neural networks are trained with the LevenbergMarquardt method. The training stops when the desired mean squared error (MSE) reaches the specified value of 1×10^{-06}. The MSE is expressed mathematically below:

$$MSE = \frac{1}{n}\sum_{k=1}^{n}(T_{tg}(k) - T_N(k))^2 \qquad (12)$$

In this work, the optimal structure is selected based on a minimum MSE method [10]. It has been found that the optimal structure of the neural network models for the hard chrome electroplating bath is 6-4-6-2 (inputs layer nodes-1$^\sharp$ hidden layer nodes-2$^\sharp$ hidden layer nodes-output layer nodes). Fig. 3 shows good prediction performance of the neural model for the prediction of the plating solution temperature and the inlet water temperature in the pipe heat exchanger of the hard chrome electroplating process.

3.2 Neural Network Direct Inverse Control (NNDIC)

In this part, NNDIC has been applied to control the process as shown in Fig. 4. The neural network inverse models trained as described in the previous sections are utilized to predict the manipulated flow rates of the electroplating bath to manage the process to desired conditions. The NNDIC controller determines the control action, $F_w(k)$, based on current and past values of the process model state variables and the past control action as well as the required set point. The input-output map for the NNDIC is shown in Fig. 5. The input layers of the neural networks used consist of past and present values of the plating solution temperature ($T_p(k-1)$, $T_p(k)$), set point of plating solution temperature ($T_{psp}(k+1)$), and water flow rate ($F_w(k-1)$,$F_w(k)$), respectively. The output layer estimates the present value of the water flow rate, F_w at time interval k. The optimal structure is selected based on the minimum MSE method. It has been found that [6-8-4-1] structure gives the least MSE for the electroplating bath inverse model, then it is selected and used as a controller in the control strategy. This control strategy is then implemented in the hard chrome electroplating process to control the plating solution temperature in the electroplating bath by manipulating the water flow rate (F_w). The control performances are tested under the nominal case and plant/model mismatch. The simulation results and discussion of these control studies are described in the next section.

4. NEURAL NETWORK BASED MODEL PREDICTIVE CONTROL (NNMPC)

The basic concept of the MPC is that it calculates future control profile based on current measurements via the solution of predictive control strategy, but only the first element of controls is applied to the process. For the predictive control part of NNMPC strategy, the obtained neural network forward model in the neural network modelling part is applied as a predictor to predict the future values of outputs over a prediction horizon (p). An optimal manipulated variable (F_w) is determined by solving the optimization problem using a successive quadratic programming (SQP) algorithm to minimize a specified objective function subject to the neural network model and lower and upper bounds of the manipulated variable as represented by (14). Moreover, (15) is included to ensure that the controlled variables are forced to desired set points at the terminal time. The objective function of the NNMPC strategy has been formed as follows:

$$\min_{F_w} \sum_{i=1}^{p} [W_1 \{T_{psp}(k+i) - T_p(k+i)\}^2 + W_2 \{\triangle F_w\}^2] \tag{13}$$

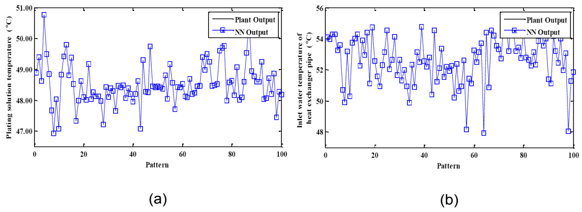


Fig.3:: The validating result of temperature for the neural network forward model [Structure 6-4-6-2] (a) plating solution temperature (T_p), (b) inlet water temperature of heat exchanger pipe (T_{win}).

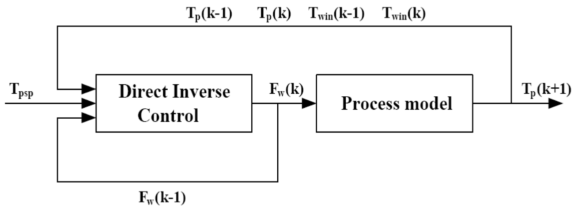


Fig.4:: The NNDIC strategy.

Subject to neural network forward model

$$(F_w)_{min} \leq F_w(k+i) \leq (F_w)_{max}; i = 1, 2, 3, ..., p \tag{14}$$

$$T_p(k+p) = T_{psp} \tag{15}$$

Fig. 6 shows the information flowchart of the NN-MPC strategy. A control trajectory $F_w(k)$ referring to set point *(k)* for an entire horizon is computed based on current state but only the first one is implemented. This means that the control action at time $(k+1)$ is the control $F_w(1)$ referring to temperature set point (1) of future controls calculate at time k.

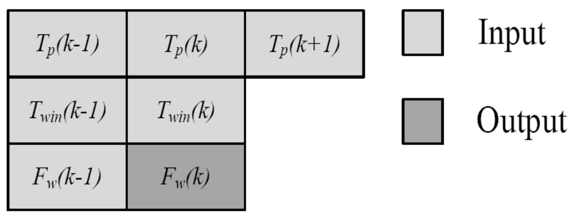


Fig.5:: Input/output map of the neural network inverse model.

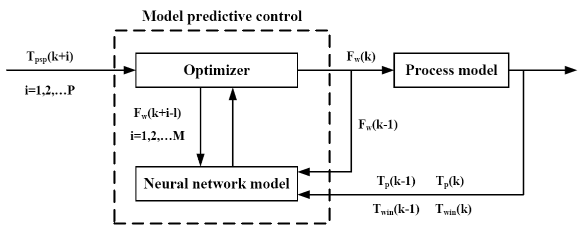


Fig.6:: The NNMPC strategy.

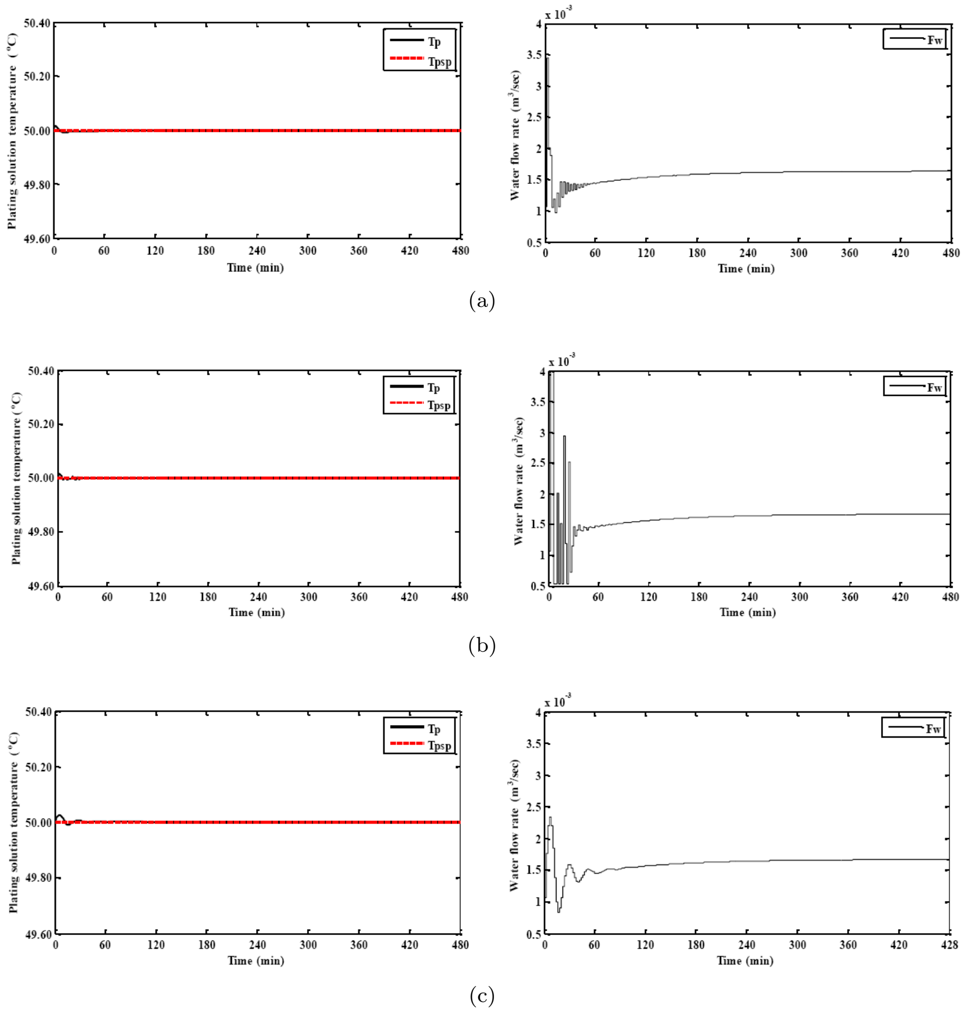


Fig.7:: The plating solution temperature control under the nominal case using (a) NNMPC, (b) NNDIC, and (c) PI controller.

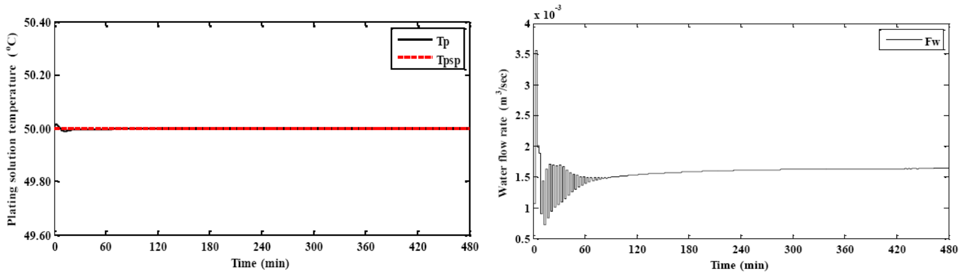
Various trials have been carried out through simulations to find set of suitable control parameters, i.e., values for the parameters, *p; m* (control horizon) and W_i for this strategy. The choice of p includes an equal number of future predictions of each output in the objective function where p is tuned as four times of the sampling time. W_i is chosen as the identity vector because the outputs of process are scaled before they are used in the network process model. The control horizon *(m)* is selected as three times of sampling time. Nevertheless, the higher of both control horizon and prediction horizon, the less drastic control action gives [11].

5. SIMULATION RESULT

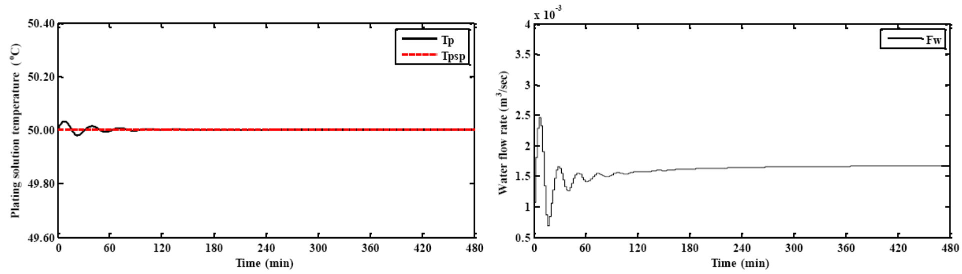
This section demonstrates the neural network based controllers to control the plating solution temperature (T_p) for the hard chrome plating process by adjusting the water flow rate (F_w). In this work, the control performance is compared with a conventional PI control, which is indicated by the integral of absolute value of the error (IAE). For the simulation study, two cases: nominal case and parameter mismatch cases are considered.

5.1 Nominal Case

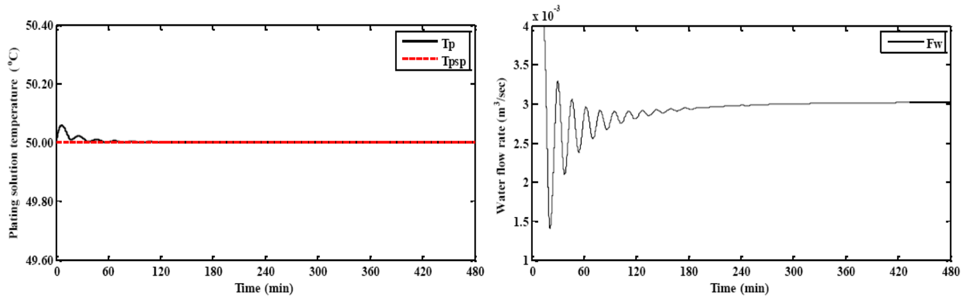
In this case, the controllers are applied to bring the plating solution temperature in an electroplating bath to the desired value. Fig. 7(a), (b) and (c) show the plating solution temperature in the electroplating bath using NNMPC, NNDIC and PI control respectively. The results in these figures indicate that NNMPC and NNDIC can bring the plating solution temperature to the set point without overshoot and offset while PI controller provides slow response of controlled variable with a bit overshoot. In addition, drastic change of the manipulated variable and oscillation at the initial state of the NNDIC affects low effectiveness of the controller leading to long time to control the temperature to the desired set point. Their performances are evaluated using the integral absolute error (IAE). The IAE results for the nominal case of the controllers are summarized in Table 2. It can be seen that the NNMPC strategy gives the best control performance with the least IAE values.



(a)



(b)



(c)

Fig.8:: The plating solution temperature control under the parameter mismatch case (+30% IV, -30% h_A and -30%U) using (a) NNMPC, (b) NNDIC, and (c) PI controller.

Table 2:: Performance Indices of the Controllers under the Nominal and the Parameter Mismatch Cases

Cases	IAE values		
	NNMPC	NNDIC	PI
Nominal	1.1592	1.1739	1.1642
+30% IV	2.6937	2.7478	2.9092
-30% hA	2.1268	2.1435	2.1562
-30% U	2.5142	2.7790	2.9857
+30% IV, -30% hA, -30%U	7.9273	8.3175	8.4521

5.2 Model Mismatch Case

In this case, IV, h_A and U are considered as parameter mismatches. The model mismatches are introduced by increasing and decreasing these parameters from their nominal values by 30%. Therefore, the model mismatch test is divided into four cases consisting of 30% increasing of IV, 30% decreasing of h_A, 30% decreasing of U and summation of previously mismatch parameters from their nominal values. Fig. 8(a), (b) and (c) show the plating solution temperature in the electroplating bath using NNMPC, NNDIC strategy and the conventional PI controller respectively in the last case. Fig. 8(a) illustrates that the NNMPC can still bring the plating solution temperature to the desired set point with smooth and without oscillated control response by rapidly adjusting the water flow rate. As illustrated in Fig. 8(b) and (c), the NNDIC and PI controller bring the plating solution temperature to the desired set point with oscillatory adjustment of the water flow rate causing slow and overshoot in the process response. Relatively, similar results are obtained for the 30% increasing of IV, 30% decreasing of h_A and 30% decreasing of U and are not shown here. Table 2 shows the IAE values of NNMPC, NNDIC and PI control for the electroplating bath. They indicate that the NNMPC gives the least error and the best control performances among the others, when the model mismatches are introduced into the system. These results also show the robustness of the NNMPC strategy in dealing with model mismatches.

Table 3:: Nomenclature

A_s	surface area of plating solution exposed to air (m^2)
F_{c1}, F_{c2}	inlet and outlet water flow rate of cooling tower (m^3/sec)
F_{ov}, F_{wind}	overflow rate of water from tank 2 to tank 1 and water flow rate of blow down (m^3/sec)
I	electric current (amp)
Q_{ploss}, Q_{re}	heat loss between plating bath and surrounding and heat released from reaction (W)
t_f, t_f^*	final time and batch time (min)
T_{c1}, T_2, T_{c2}	water temperature in tank 1, tank 2, cooling tower (°C)
T_{tg}, T_N	target/desired temperature and neural network output temperature (°C)
T_p, T_{psp}	plating solution temperature and set point of the plating solution temperature (°C)
T_{win}, T_{wout}	inlet and outlet water temperature of heat exchanger pipe (°C)
V	electric voltage (volt)
V_{tube}	volume of heat exchanger pipe (m^3)
$\triangle$H	heat of reaction (kJ)

6. CONCLUSION

The neural network modelling and neural network based controls are proposed to provide effective control performance for the electroplating bath in a hard chrome electroplating process. Since, the hard chrome electroplating process is a multivariable interacting system and nonlinear dynamic behaviour which makes it difficultly to control by the conventional control system. Then, a model based advance control techniques are 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. In this work, the multi-layer feed-forward neural network is used to model the hard chrome electroplating process which is implemented to predict the future process response in the MPC algorithm for controlling the plating solution temperature of the electroplating bath. The proposed controller, NNMPC provides good control and can maintain the plating solution temperature at the desired set point without any oscillation, overshoot and offset in all cases studies, i.e., nominal case and model mismatch case. Comparison of performance with the conventional PI controller indicates that the NNMPC is more robust than the conventional PI controller and gives the better control results in all cases. These results show the robustness and applicability of the NNMPC controller to control the temperature in the hard chrome electroplating process.

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