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Neural network predictive control of a heat exchanger

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Possibility to use a neural network predictive control (NNPC) strategy for control of a heat exchanger is studied. The heat exchanger is a tubular one and it is used for pre-heating of petroleum by hot water. The control objective is to keep the output temperature of the heated stream at a desired value and minimize the energy consumption. The advantage of the NNPC is that it is not a linear-model-based strategy and the control input constraints are directly included into the synthesis. The NNPC of the heat exchanger is compared with classical PID control by simulations experiments. Comparison of the simulation results obtained using NNPC and those obtained by classical PID control demonstrates the effectiveness and superiority of the NNPC because of smaller consumption of heating medium.

1. Introduction

Predictive control is recently the most widely implemented advanced process control technology in industrial applications (Qin and Badgwell, 2003; Darby et al., 2009). The predictive control algorithms use an explicit process model to predict the future behavior of a plant and so, the term model predictive control (MPC) is utilized. Although industrial processes usually contain complex nonlinearities, most of the MPC algorithms are based on a linear model of the process. Recently, neural networks have become an attractive tool in the construction of models for complex nonlinear systems (Subhra et al., 2010). When a neural network is combined with MPC approach, it is used as a feed-forward process model for the prediction of process outputs (Ponton and Klemeš, 1993; Huang and Lewis, 2003; Kittisupakorn et al., 2009). Inclusion of constraints is the other feature that most clearly distinguishes MPC from other process control techniques, leading to a tighter control and a more reliable controller.
Heat exchangers are key devices used in a wide variety of industrial applications. Control of a heat exchanger is a complex process due to its non-linear behaviour and complexity caused by many phenomena such as leakage, friction, temperature-dependent flow properties, contact resistance, unknown fluid properties, etc. (Dugdale et al., 2002; Álvarez et al., 2007). Therefore, neural network model based control is expected to be a better alternative to the PID control (Varshney and Panigrahi, 2005),

although many industrial applications use PID control to maintain constant process variables.

2. Process description

Consider a tubular heat exchanger, where petroleum (subscript 1) is heated by hot water (subscript 3) through a copper tube (subscript 2). The controlled variable is the outlet petroleum temperature $\vartheta_{1out}(t)$. Among the input variables, the water flow rate $q_3(t)$, is selected as the control variable, whereas the other inlet variables are constant. The tubes are described by a linear coordinate z, which measures the distance of a generic section from the inlet. Assume that the petroleum, tube and water temperatures $\vartheta_1(z,t)$, $\vartheta_2(z,t)$, $\vartheta_3(z,t)$ are functions of time t and the axial coordinate z, whereas water flow rate $q_3(t)$ is function of time t only. The petroleum, water and tube material densities ρ as well as specific heats C_P are assumed to be uniform in the heat exchanger. The simplified nonlinear dynamic mathematical model of the heat exchanger can be described by three partial differential equations

$$T_1 \frac{\partial \vartheta_1(z,t)}{\partial t} + T_1 w_1 \frac{\partial \vartheta_1(z,t)}{\partial z} = -\vartheta_1(z,t) + \vartheta_2(z,t) \tag{1}$$

$$T_2 \frac{\partial \vartheta_2(z,t)}{\partial t} = Z_1 \vartheta_1(z,t) - \vartheta_2(z,t) + Z_2 \vartheta_3(z,t) \tag{2}$$

$$T_3 \frac{\partial \vartheta_3(z,t)}{\partial t} + T_3 w_3(t) \frac{\partial \vartheta_3(z,t)}{\partial z} = \vartheta_2(z,t) - \vartheta_3(z,t) \tag{3}$$

where time constants T, liquid velocities w and gains Z are calculated as follows:

$$T_1 = \frac{D_1 \rho_1 C_{P1}}{4\alpha_1}, \quad w_1 = \frac{q_1}{\pi D_1^2}, \quad T_2 = \frac{(D_2^2 - D_1^2)\rho_2 C_{P2}}{4(D_1\alpha_1 + D_2\alpha_2)}, \quad Z_1 = \frac{D_1\alpha_1}{D_1\alpha_1 + D_2\alpha_2},$$

$$Z_2 = \frac{D_2\alpha_2}{D_1\alpha_1 + D_2\alpha_2}, \; T_3 = \frac{(D_3^2 - D_2^2)\rho_3 C_{P3}}{4 D_2 \alpha_2}, \; w_3(t) = \frac{q_3(t)}{\pi(D_3^2 - D_2^2)}.$$

Here, ϑ is the temperature, D is the tube diameter, ρ is the density, C_P is the specific heat capacity, α *is* the heat transfer coefficient, q is the volumetric flow rate. Parameters and steady-state inputs of the heat exchanger are enumerated in Table 1.

3. Predictive Control Using Neural Network Predictor

Objectives of the predictive control strategy are to estimate the future output of the plant and to minimize a cost function based on the error between the predicted output of the processes and the reference trajectory.

Table 1: Heat exchanger parameters and steady-state inputs

Variable	Unit	Value	Variable	Unit	Value
l	m	12	ρ_1	kg m^{-3}	810
D_3	m	0.5	ρ_2	kg m^{-3}	8960
D_2	m	0.28	ρ_3	kg m^{-3}	1000
D_1	m	0.25	C_{P1}	J kg^{-1} K^{-1}	2100
α_1	W m^{-2} K^{-1}	750	C_{P2}	J kg^{-1} K^{-1}	418
α_2	W m^{-2} K^{-1}	1480	C_{P3}	J kg^{-1} K^{-1}	4186
q_1	m^3 s^{-1}	3.7723×10^{-4}	ϑ^s_{1in}	K	308.5
q_{3in}^s	m^3 s^{-1}	1.1111×10^{-4}	ϑ^s_{3in}	K	317.8

The cost function 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 cost function is utilizes

$$J(k) = \sum_{j=N_1}^{N_2} \left(\hat{y}(k+j) - y_r(k+j)\right)^2 + \lambda \sum_{j=1}^{N_u} \Delta u(k+j-1)^2 \tag{4}$$

where N_u is the control horizon, N_1 and N_2 are the minimum and maximum prediction horizons respectively, y_r is the reference trajectory, $\hat{y}$ is the predicted controlled output, λ is the weight factor, and Δ is the differentiation operator. The control input u may be constrained: $u_{min} \le u(k+i) \le u_{max}$, $i = 1, 2, \ldots, N_u$. The length of the control horizon N_u must satisfy the constraints $0 < N_u \le N_2$. The value of N_2 should cover the important part of the step response curve. The role of the coefficient λ is to scale the second sum of squared control increments against the first sum representing squared predicted control errors. The output sequence of the optimal controller is obtained over the prediction horizon by minimizing the cost function J with respect to the vector of control inputs.

When the future output of the plant in predictive control strategy is predicted using neural network plant model, the neural network predictive control (NNPC) is established. The general control structure for the NNPC is shown in Figure 1. The neural network model of the controlled plant is the important component of the NNPC methodology.

Two-layer network with sigmoid transfer functions in the hidden layer and linear transfer functions in the output layer is used in our NNPC design. The prediction error between the plant output and the neural network (NN) output is used as the NN training signal. The NN plant model uses previous inputs and previous plant outputs to predict future values of the plant output. The structure of the neural network plant model is shown in Figure 2, where $u(t)$ is the system input, $y_p(t)$ is the plant output, $y_m(t)$ is the neural network model plant output, the blocks TDL are tapped delay lines that store previous values of the input signal, $\boldsymbol{IW}^{i,j}$ is the weight matrix from input number j to layer number i, $\boldsymbol{LW}^{i,j}$ is the weight matrix from layer number j to layer number i.

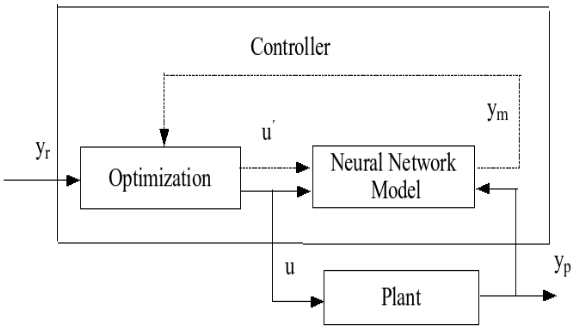

Figure 1: Neural Network Predictive Control

This network can be trained off-line in batch mode, using data collected from the operation of the plant. The procedure for selecting the network parameters is called training the network. The Levenberg-Marquardt (LM) algorithm is very efficient for training. The LM algorithm is an iterative technique that locates the minimum of a function that is expressed as the sum of squares of nonlinear functions (Lera and Pinzolas, 2002; Madsen et al, 2004).

4. Control of the heat exchanger

1.1 4.1 Neural Network Predictive Control of the heat exchanger

The designed controller uses a neural network model to predict future heat exchanger responses to potential control signals. An optimization algorithm then computes the control signals that optimize future plant performance. The neural network plant model was trained using the Levenberg-Marquardt algorithm. The training data were obtained from the nonlinear model of the heat exchanger (1) – (3).

The used neural network predictive control method was based on the receding horizon technique. The neural network model predicted the plant response over a specified time horizon. The predictions were used by a numerical optimization program to determine the control signal that minimized the cost function (4) over the specified horizon.

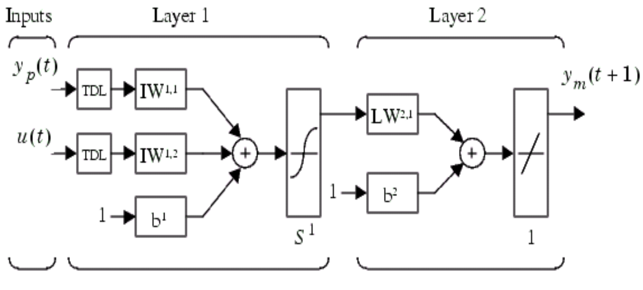

Figure 2: Structure of the neural network plant model

The controller block was implemented in MATLAB-Simulink with following values: N_1=1, N_2=*8*, N_u=*2*, λ=0.5, the number of neurons in the first layer of the plant model network was 6, the number of delayed plant inputs was 3, the number of delayed plant outputs was 2, sampling interval – interval at which the program collects data from the Simulink plant model was 2. One hundred of training samples was used. The plant input constraints were: $1.5\times10^{-4} \le q_3(t) \le 3.1\times10^{-4}$ m^3s^{-1} and the plant output constraints were: $309.15 \le \vartheta_{1out}(t) \le 316.15$ K . Number of plant training iterations was 500 and the training function for training the plant model was Levenberg-Marquardt one with the number of training epochs = 41.

1.2 4.2 PID Control

The PID controllers were tuned using Cohen-Coon and Strejc methods (Ogunnaike and Ray, 1994; Mikleš and Fikar, 2007) on the basis of linear model of the plant. The model was identified from the step response of the heat exchanger in the form of the 3rd order plus time delay transfer function. The transfer function parameters are: the gain $K = 3.7\times10^4$, the time constant $T = 18$ s and the time delay $D = 2.4$ s. The PID controller parameters obtained using Cohen-Coon method were $k_p = 1.7\times10^{-4}$, T_i = 32.7, T_d = 5 and those obtained using Strejc method were $k_p = 6.2\times10^{-5}$, T_i = 44.4, T_d = 14.6, where k_p is the proportional gain, T_i is the integral time and T_d is the derivative time.

Simulation results obtained using designed neural network predictive controller and two PID controllers are shown in Figures. 3(a) and 3(b). Figure 3(a) compares controlled output in the task of set-point tracking. The control response obtained by NNPC is the best one, it has the smallest overshoots and the shortest settling times. The energy consumption is measured by the total amount of hot water consumed during the control process. The situation for NNPC and PID control is presented in Figure 3(b), and it can be stated that the smallest energy consumption is assured using NNPC .

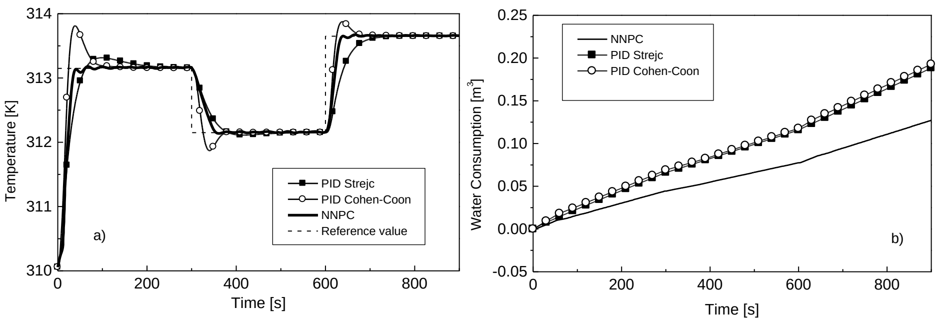

Figure 3: Comparison of the neural network predictive control and PID control: a) outlet temperature, b) hot water consumption

5. Conclusion

In this paper, an application of a neural network model based predictive control strategy to a heat exchanger is presented. The simulation results confirm that NNPC is one of the possibilities for successful control of heat exchangers. The advantage of this approach is that it is not linear-model-based strategy and the control input constraints are directly included to the synthesis. Comparison to classical PID control demonstrates the superiority of the NNPC. Implementation of NNPC in industrial application can lead to significant energy savings.

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