Accepted Manuscript

Title: Neural network predictive control of a heat exchanger

Authors: Anna Vasičkaninová, Monika Bakošová, Alojz Mészáros, Jiří Jaromír Klemeš

PII: S1359-4311(11)00035-4
DOI: 10.1016/j.applthermaleng.2011.01.026
Reference: ATE 3390

To appear in: Applied Thermal Engineering

Received Date: 15 November 2010
Revised Date: 14 January 2011
Accepted Date: 15 January 2011


This is a PDF file of an unedited manuscript that has been accepted for publication. As a service to our customers we are providing this early version of the manuscript. The manuscript will undergo copyediting, typesetting, and review of the resulting proof before it is published in its final form. Please note that during the production process errors may be discovered which could affect the content, and all legal disclaimers that apply to the journal pertain.
Neural network predictive control of a heat exchanger

Anna Vasičkaninová, Monika Bakošová, Alojz Mészáros, Jiří Jaromír Klemes

Institute of Information Engineering, Automation, and Mathematics, Faculty of Chemical and Food Technology, Slovak University of Technology in Bratislava, Radlinského 9, 812 37 Bratislava, Slovakia
anna.vasicikaninova@stuba.sk, monika.bakosova@stuba.sk
Institute of Engineering Studies of the Slovak University of Technology, Vazovova 5, 812 43 Bratislava, Slovakia
aloj.meszaros@stuba.sk
Centre for Process Integration and Intensification – CPI, Research Institute of Chemical and Process Engineering, Faculty of Information Technology, University of Pannonia, Egyetem u. 10, 8200 Veszprém, Hungary
klemes@cpi.uni-pannon.hu

Corresponding author: Monika Bakošová, Institute of Information Engineering, Automation and Mathematics, Faculty of Chemical and Food Technology, Slovak University of Technology in Bratislava, Radlinského 9, 812 37 Bratislava, Slovakia, monika.bakosova@stuba.sk

Abstract

The study attempts to show that using the neural network predictive control (NNPC) structure for control of thermal processes can lead to energy savings. 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. In the designed approach, the neural network is used as a nonlinear process model to predict the future behaviour of the controlled process with distributed parameters. The predictive control strategy is used to calculate optimal control inputs. The efficiency of the described control approach is verified by simulation experiments and a tubular heat exchanger is chosen as a controlled process. The control objective is to keep the temperature of the heated outlet stream at a desired value and minimize the energy consumption. The NNPC of the heat exchanger is compared with classical PID control. 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.

Keywords

Neural network, predictive control, PID control, tubular heat exchanger, energy saving

1. Introduction

As energy costs are permanently increasing, energy saving is becoming very important in industrial processes and they have to be improved in terms of efficiency. Nowadays, various approaches are applied to reduce energy consumption and implementation of advanced modelling and control methods can reduce the energy costs down [1, 2, 3, 4]. Predictive control is recently the most widely implemented advanced process control technology in industrial applications [5, 6]. The predictive control algorithms use an explicit process model to predict the future behaviour of a plant and so, the term model predictive control (MPC) or model-based predictive control (MBPC) is utilized. Although industrial processes usually contain complex nonlinearities, most of the MPC strategies are based on a linear model of the process [7]. To overcome difficulties connected with nonlinearity of the controlled process, model reduction methodology has been exploited to enable the efficient application of linear MPC [8]. Recently, neural networks have become an attractive tool in the construction of models for various types of complex nonlinear systems [9, 10] and heat exchangers play important role between them [11, 12]. When a neural network (NN) is combined with MPC approach, it is used as a feed-forward process model for the prediction of process outputs. The implementation of the NN MPC varies, a neural-network-based controller is designed for a class of nonlinear systems with constant input and state-feedback delays in [13], an iterative multistep neural network prediction model in a predictive control strategy for controlling a nonlinear system is described in [14], a NNMPC method for a class of discrete-time multi-input multi-output systems is given in [15]. 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. [16, 17]. Therefore, neural network model based predictive control is expected to be a better alternative to the PID control [18], although many industrial applications use PID control to maintain constant process variables.

In this paper, the neural network is used as a nonlinear process model to predict the future behaviour of the tubular heat exchanger as a system with distributed parameters. The neural network model with one hidden layer with 6 neurons is trained off line. The predictive control strategy is used to calculate optimal control inputs so that the demanded temperature of the heated outlet stream is assured. The energy consumption measured by heating water consumption is also followed. The NN MPC of the heat exchanger is compared with classical PID control.

2. Controlled process
Consider a co-current tubular heat exchanger, where petroleum is heated by hot water through a copper tube (Fig. 1). The controlled variable is the outlet petroleum temperature \( \theta_{1\text{out}} \). Among the input variables, the water volume flow rate \( q_{w3}(t) \) is selected as the control variable, whereas the other inlet variables are constant.

Fig. 1 Scheme of the tubular heat exchanger

The mathematical model of the heat exchanger is derived under several simplifying assumptions. The tubes are described by a linear coordinate \( z \), which measures the distance of a generic section from the inlet. The fluids move in a plug velocity profile and the petroleum, tube and water temperatures \( \theta_i(z,t) \) and \( \theta_j(z,t) \) are functions of the axial coordinate \( z \) and time \( t \). The petroleum flow rate is constant, whereas the water flow rate \( q_{w3}(t) \) is a function of time \( t \) only, i.e. it can change in time, but it is the same along the whole heat exchanger. The petroleum, water and tube material densities \( \rho \) as well as the specific heat capacities \( C_p, i = 1, 2, 3 \), are assumed to be constant. The simplified nonlinear dynamic mathematical model of the heat exchanger is described by three partial differential equations

\[
\begin{align*}
\tau_1 \frac{\partial \theta_1(z,t)}{\partial t} + \tau_1 w_1 \frac{\partial \theta_1(z,t)}{\partial z} &= -\theta_1(z,t) + \theta_2(z,t) \\
\tau_2 \frac{\partial \theta_2(z,t)}{\partial t} &= K_1 \theta_1(z,t) - \theta_2(z,t) + K_2 \theta_3(z,t) \\
\tau_3 \frac{\partial \theta_3(z,t)}{\partial t} + \tau_3 w_3(t) \frac{\partial \theta_3(z,t)}{\partial z} &= \theta_2(z,t) - \theta_3(z,t)
\end{align*}
\]

(1)

(2)

(3)

where time constants \( \tau_1, \tau_2, \tau_3 \), velocities of liquids \( w_1, w_3 \) and gains \( K_1, K_2 \) are calculated as follows

\[
\tau_1 = \frac{d_1 \rho_1 C_{p1}}{4 h_{21}}, \quad \tau_2 = \frac{4q_1}{\pi d_1^2}, \quad \tau_3 = \frac{4q_3(t)}{\pi (d_3^2 - d_2^2)} \frac{C_{p3}}{4d_2 h_{32}}
\]

\[
K_1 = \frac{d_1 h_{21}}{d_1 h_{21} + d_2 h_{32}}, \quad K_2 = \frac{d_2 h_{32}}{d_1 h_{21} + d_2 h_{32}}
\]

Here, \( d \) is the tube diameter, \( \rho \) is the density, \( C_p \) is the specific heat capacity, \( h \) is the heat transfer coefficient, \( q_v \) is the volume flow rate. Parameters and steady-state inputs of the heat exchanger are enumerated in Table 1, where the superscript \( s \) denotes the steady state and the subscript \( \text{in} \) denotes the inlet.

Table 1 Heat exchanger parameters and steady-state inputs

<table>
<thead>
<tr>
<th>Variable</th>
<th>Unit</th>
<th>Value</th>
<th>Variable</th>
<th>Unit</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>( l )</td>
<td>m</td>
<td>10</td>
<td>( \rho_1 )</td>
<td>kg ( \text{m}^{-3} )</td>
<td>810</td>
</tr>
<tr>
<td>( d_1 )</td>
<td>m</td>
<td>0.025</td>
<td>( \rho_2 )</td>
<td>kg ( \text{m}^{-3} )</td>
<td>8960</td>
</tr>
<tr>
<td>( d_2 )</td>
<td>m</td>
<td>0.028</td>
<td>( \rho_3 )</td>
<td>kg ( \text{m}^{-3} )</td>
<td>1000</td>
</tr>
<tr>
<td>( d_3 )</td>
<td>m</td>
<td>0.05</td>
<td>( C_{p1} )</td>
<td>J ( \text{kg}^{-1} \text{K}^{-1} )</td>
<td>2100</td>
</tr>
<tr>
<td>( h_{21} )</td>
<td>W ( \text{m}^{-2} \text{K}^{-1} )</td>
<td>750</td>
<td>( C_{p2} )</td>
<td>J ( \text{kg}^{-1} \text{K}^{-1} )</td>
<td>418</td>
</tr>
<tr>
<td>( h_{32} )</td>
<td>W ( \text{m}^{-2} \text{K}^{-1} )</td>
<td>1480</td>
<td>( C_{p3} )</td>
<td>J ( \text{kg}^{-1} \text{K}^{-1} )</td>
<td>4186</td>
</tr>
<tr>
<td>( q_{w1} )</td>
<td>m( ^3 ) s(^{-1} )</td>
<td>3.7723\times10^4</td>
<td>( \theta_{1\text{in}}^s )</td>
<td>°C</td>
<td>20</td>
</tr>
<tr>
<td>( q_{w3} )</td>
<td>m( ^3 ) s(^{-1} )</td>
<td>1.1111\times10^4</td>
<td>( \theta_{3\text{in}}^s )</td>
<td>°C</td>
<td>75</td>
</tr>
</tbody>
</table>

The steady-state analysis of the heat exchanger was done at first and the steady-state dependence of the petroleum outlet temperature \( \theta_{1\text{out}}^s \) on the water flow rate \( q_{w3} \) was obtained (Fig. 2). It confirmed the nonlinearity of the heat exchanger.

Fig. 2 Steady-state analysis of the heat exchanger

3. Predictive control using neural network predictor

Model-based predictive control (MBPC) includes a broad variety of control methods that comprise certain common ideas [19]. A process model is explicitly used to predict the process output \( \hat{y} \) for a fixed number \( N \) of steps into future and the predictions are calculated based on information up to time \( k \) and on the future control actions. A future reference trajectory is known. A future control trajectory is calculated as a solution of an optimisation problem consisting of a cost function and possibly some constraints. A receding strategy is used, i.e. only the first control signal \( u(k) \) of the calculated sequence is applied to a controlled process. A useful feature of MBPC is that the process constraints can easily be incorporated into the design and therefore MBPC is very interesting for industrial application. MBPC algorithms are also very versatile and robust in process control applications and they usually outperform PID controllers.
The cost function in MBPC comprises future output predictions, future reference trajectory, and future control actions. The standard cost function used in MBPC contains quadratic terms of control error and control increments on a finite horizon into the future and can have the form (4)

$$J(k) = \sum_{j=N_{\text{min}}}^{N_{\text{max}}} [P\dot{y}(k + j) - y_r(k + j)]^2 + \lambda \sum_{j=1}^{N_y} [\Delta u(k + j - 1)]^2$$

where $N_y$ is the control horizon, $N_{\text{min}}$ and $N_{\text{max}}$ are the minimum and maximum prediction horizons respectively, $y_r$ is the reference trajectory, $\dot{y}$ is the predicted controlled output, $\lambda$, $P$ are the weight factors, and $\Delta u$ is the sequence of the future control increments that have to be calculated. The cost function is minimized in order to obtain the optimum control input that is applied to the nonlinear plant. The control input $u$ may be constrained: $u_{\text{min}} \leq u(k + j) \leq u_{\text{max}}, \quad j = 1, \ldots, N_y$.

The length of the control horizon $N_u$ must satisfy following constraints: $0 < N_u \leq N_{u_{\text{max}}}$. The value of $N_{u_{\text{max}}}$ should cover the important part of the step response curve. The role of the coefficient $\lambda$ is to scale the second sum of squared control increments against the first sum representing squared predicted control errors and $P$ scales the predicted controlled output against the reference signal. 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.

The reference trajectory is assumed to be known. If it is not the case, several approaches are possible. The simplest way is to assume that the future reference is constant and equal to the desired set point: $y_r(k) = y_r(\infty)$. The preferred approach is to use smooth reference trajectory that begins in the actual output value and approaches asymptotically via the first order filter to the desired set point $y_r(\infty)$: $y_r(k) = y_r(\infty) + (1 - \alpha) y_r(k - 1)$. The parameter $\alpha$ determines smoothness of the trajectory with $\alpha \to 0$ being the fastest and $\alpha \to 1$ being the slowest trajectory.

### 3.1 Neural network predictive control

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 Fig. 3.

Fig. 3 Neural network predictive control

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 presented 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 Fig. 4, where $u(k)$ is the system input, $y(k)$ is the plant output, $\dot{y}(k)$ is the NN plant model output, the blocks TDL are the tapped delay lines that store previous values of the input signals, $IW^{ij}$ is the weight matrix from the input number $j$ to the layer number $i$, $LW^{ij}$ is the weight matrix from the layer number $j$ to the layer number $i$.

Fig. 4 Neural network plant model

The first stage in NNPC is the system identification. The identification means to train a neural network to represent the feed-forward dynamics of the plant. The 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 [20, 21].

### 4. Control of the heat exchanger

#### 4.1 Neural network predictive control of the heat exchanger

The controlled process is the tubular heat exchanger described in Section 2. The neural network predictive controller uses a neural network model (Fig. 4) to predict future heat exchanger responses to potential control signals. The first step in NNPC is training the network. The parameters of the NN model and the parameters for identification are chosen as follows. The NN model has 3 delayed plant inputs, 2 delayed plant outputs and 6 neurons in the hidden layer. The Levenberg-Marquardt algorithm is chosen for network training and the name of the training function in MATLAB is \texttt{trainlm}.

The training data were obtained from the controlled process with distributed parameters represented by the nonlinear model of the heat exchanger (1) – (3) with the sampling interval 2 s. 600 training samples were used for the neural network training and the number of realised plant training epochs was 6. The NN model was trained off-line. The results of training are shown in Fig. 5 for the training data and in Fig. 6 for the validation data. In both cases, the prediction error is sufficiently small and the process output and the NN model output fit well. It is possible to state that the NN training was successful.

Fig. 5 Training data for NN model
After the NN model is trained, the NNPC starts. The parameters for NNPC of the described heat exchanger are chosen as follows: minimum prediction horizon $N_{\text{min}} = 1$, maximum prediction horizon $N_{\text{max}} = 8$, control horizon $N_u = 2$, weight coefficients in the cost function $\lambda = 0.5$, $P = 1$, and the parameter for the reference trajectory calculation $\alpha = 0.0022$. For computing the control signals that optimise future plant performance, the minimization routine csrchbac was chosen. It is in fact one-dimensional minimization using the backtracking method. The control input constraints were set: $1.5 \times 10^{-4} \leq q_{V3} \leq 3.1 \times 10^{-4} \text{ m}^3 \text{s}^{-1}$ and control output constraints: $36 \leq \theta_{\text{out}} \leq 43 \, ^\circ \text{C}$. The controller block was implemented in MATLAB-Simulink.

### 4.2 PID Control of the heat exchanger

PID controllers described by the transfer function

$$C = K_p \left(1 + \frac{1}{t_i s} + t_d s\right)$$

with $K_p$, the proportional gain, $t_i$ the integral time and $t_d$ the derivative time, were tuned using Cohen-Coon and Strejc methods [19, 22] on the basis of a linear model of the plant. The model was identified from the step response of the heat exchanger in the form of the $n$th order plus time delay transfer function

$$S = \frac{K}{(s + 1)^n} e^{-Ds}$$

The transfer function parameters are: the gain $K = 3.7 \times 10^4$, the order $n = 3$, the time constant $\tau = 18$ s and the time delay $D = 2.4$ s. The other two parameters obtained from identification are $t_u = 14.5$ s, $t_n = 66.4$ s. Here, $t_u$ represents the effective time delay, i.e. the time when the tangent line drawn at the inflection point on the step response curve intersects the initial value of the step response. Analogically, $t_n$ represents the effective time constant, i.e. the time from $t_u$ to the time when the tangent line intersects the final value of the step response.

The Cohen-Coon formulas given e.g. in [22] are for the PID controller parameters

$$K_p = \frac{1}{K} \frac{t_n}{t_u} \left(\frac{4 + 1}{3 + 4 \frac{t_u}{t_n}}\right),$$

$$t_i = t_u \left(\frac{32 + 6 \frac{t_u}{t_n}}{13 + 8 \frac{t_u}{t_n}}\right), \quad t_d = t_u \left(\frac{4}{11 + 2 \frac{t_u}{t_n}}\right).$$

The Strejc formulas given e.g. in [19] are for the PID parameters

$$K_p = \frac{1}{K} \frac{16n + 1}{16(n - 2)}, \quad t_i = \tau \frac{7n + 16}{15}, \quad t_d = \tau \frac{(n+1)(n+3)}{7n + 16}.$$

The PID controller parameters obtained using the Cohen-Coon formulas are $K_p = 1.7 \times 10^4$, $t_i = 32.7$ s, $t_d = 5$ s and those obtained using the Strejc formulas are $K_p = 6.2 \times 10^5$, $t_i = 44.4$ s, $t_d = 11.7$ s.

### 4.3 Results

Simulation results obtained using designed neural network predictive controller and two PID controllers are shown in Figs. 7, 8. Fig. 7 compares controlled outputs in the task of set point tracking. The set point changes from $40 \, ^\circ \text{C}$ to $39 \, ^\circ \text{C}$ at time $300$ s, and then to $40.5 \, ^\circ \text{C}$ at time $600$ s. The control response obtained by NNPC is the best one; it has the smallest overshoots and the shortest settling times. The simulation results were compared also using integral criteria ISE (integrated squared error) and IAE (integrated absolute error) defined e.g. in [19] as follows

$$\text{ISE} = \int_0^\infty (e(t))^2 \, dt, \quad \text{IAE} = \int_0^\infty |e(t)| \, dt$$

Here, $e(t)$ is the error between the reference value $y_r(t)$ and the actual process output $y(t)$. The values of ISE and IAE are enumerated in Table 2. The smallest values of ISE and IAE are assured using NNPC.
Table 2 Values of ISE and IAE

<table>
<thead>
<tr>
<th>Method</th>
<th>ISE</th>
<th>IAE</th>
</tr>
</thead>
<tbody>
<tr>
<td>NNPC</td>
<td>279.35</td>
<td>159.90</td>
</tr>
<tr>
<td>PID Cohen-Coon</td>
<td>304.71</td>
<td>212.23</td>
</tr>
<tr>
<td>PID Strejc</td>
<td>297.42</td>
<td>232.96</td>
</tr>
</tbody>
</table>

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 Fig. 8, and it can be stated that the smallest energy consumption is assured using NNPC structure.

Fig. 7 Comparison of the outlet temperature of the heat exchanger received using the neural network predictive control and PID control: —◊— NNPC, —○— Strejc PID controller, —∇— Cohen-Coon PID controller

Fig. 8 Comparison of the neural network predictive control and PID control by hot water consumption: —◊— NNPC, —○— Strejc PID controller, —∇— Cohen-Coon PID controller

5. Conclusion

In this paper, the application of a neural network model based predictive control strategy to a tubular heat exchanger as a system with distributed parameters is presented. The simulation results confirm that NNPC as a non-linear-model-based strategy is a good tool for successful control of heat exchangers. The NNPC is able to assure less oscillating control responses with shorter settling times in comparison to classical PID control. The other advantage of this approach is that the control input constraints and the controlled outputs constraints are directly included into the synthesis. Because of the optimisation procedure used for the control input calculations, the NNPC is also a tool for ensuring an optimal or a nearly optimal behaviour of the controlled process. This fact leads to smaller consumption of hot water used for heating of petroleum in comparison to classical PID control, and it is also confirmed by simulation results. The energy savings would be more significant if the NNPC would be implemented in the frame of the heat exchanger network. The NNPC approach can be used also for practical application. Implementation of NNPC into industrial applications is straightforward. The real process is used instead of the process model and the training data for NN model training are obtained by measuring corresponding input and output process. Comparison to classical PID control shows the superiority of the NNPC in both problems, the problem of the set point tracking, as well as the problem of energy savings.

Nomenclature

Symbols

- \( d \) diameter (m)
- \( D \) time delay (s)
- \( C_p \) specific heat capacity (J kg\(^{-1}\) K\(^{-1}\))
- \( h \) coefficient of heat transfer (W m\(^{-2}\) K\(^{-1}\))
- \( J \) cost function
- \( k \) discrete time (s)
- \( K \) gain (1)
- \( l \) length (m)
- \( n \) system order (1)
- \( N \) number of steps (1)
- \( q_v \) volume flow rate (m\(^3\) s\(^{-1}\))
- \( t \) time (s)
- \( t_e \) effective time delay (s)
- \( t_r \) effective time constant (s)
- \( w \) velocity (m s\(^{-1}\))
- \( u \) control input
- \( y \) controlled output
- \( y_r \) set point, reference trajectory
- \( \hat{y} \) predicted output
- \( z \) space coordinate (m)

Greek letters

- \( \rho \) density (kg m\(^{-3}\))
- \( \tau \) time constant (s)
- \( \theta \) temperature (°C)

Subscripts
1 petroleum
copper tube
2 from copper tube to petroleum
3 water
32 from water to copper tube
d derivative
i integral
in inlet
min minimum
max maximum
out outlet
p proportional

Subscript
s steady state

Acknowledgments

The authors gratefully acknowledge the contribution of the Scientific Grant Agency of the Slovak Republic - grants 1/0537/10, 1/0071/09, the Slovak Research and Development Agency - VV-0029-07 and the bilateral SK-HU 0023-08 (OMFB-01457/2009) Advanced Optimisation and Control Strategies in Energy Saving Systems.

References


Neural network predictive control is used for control of a tubular heat exchanger.

The neural network represents a model of the nonlinear process.

The predictive control strategy calculates optimal control inputs.

Neural network predictive control is compared with classical PID control.

Neural network predictive control leads to smaller consumption of heating water.
hot water
$q_{V_3} \theta_{3_{in}}$

inlet petroleum
$q_{V_1} \theta_{1_{in}}$

$\theta_2(z,t)$

$\theta_1(z,t)$

$\theta_3(z,t)$

$z$ $z+dz$

$\text{outlet petroleum}$
$q_{V_1} \theta_{1_{out}}$

$\text{hot water}$
$q_{V_3} \theta_{3_{out}}$

$\text{Fig. 1}$
Fig. 3
Inputs $y(k)$  

Layer 1  

$\mathbf{y}^{(k)}$  

Layer 2  

$\mathbf{y}^{(k+1)}$  

Fig. 4
**Input**

Flow Rate ($\text{m}^3\text{s}^{-1}$)

**Plant Output**

Temperature ($^\circ\text{C}$)

**Error**

Temperature ($^\circ\text{C}$)

**NN Output**

Temperature ($^\circ\text{C}$)

*Fig. 5*
Fig. 6
Fig. 7