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Neural Network Predictive Controller Design for Counter-Current Tubular Heat Exchangers in Series

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This paper aims at showing the application of neural network predictive control (NNPC) to counter-current heat exchangers (HEs) in series for water savings. The controlled process unit is composed of five counter-current shell-and-tube heat exchangers in series in which petroleum, coming from a distillation unit in a refinery is cooled.
Neural network predictive control (NNPC) of the HEs for water savings was studied by simulations. The neural network (NN) plant model of the heat exchangers in series was obtained off-line. The two-layer network with sigmoid transfer functions in the hidden layer and linear transfer functions in the output layer was trained using the Levenberg-Marquardt (LM) algorithm. The neural network predictive control (NNPC) combines the advantages of neural-network-based modelling and model-based predictive control (MPC). Neural-network modelling is suitable for modelling non-linear processes, processes with asymmetric dynamics and processes with uncertainty. MPC is a model-based strategy and usually linear models of controlled processes are used. This fact can cause problems when strongly non-linear processes, processes with asymmetric dynamics or uncertainty have to be controlled. Using neural-network plant model in MPC is one of the ways to overcome these problems. Moreover, MPC can handle boundaries on control inputs and controlled outputs. As the calculated control inputs are obtained as a result of an optimisation procedure, MPC can lead to water savings. Results obtained using NNPC for the HEs were compared with those by the classical PID control. They confirm that using the advanced control strategy leads to water savings.

1. Introduction

Shell-and-tube heat exchangers (HEs) belong to the basic thermal equipment which are frequently used in the chemical, polymer, rubber and energy industry.
In (Inchaurregui-Méndez et al., 2016), a new MINLP model for heat exchanger network synthesis considering streams with phase change and their geographical allocation based on safety is proposed. The paper (González et al., 2006) discusses the online optimization and control of a heat-exchanger network through a two-level control structure. The low level is a constrained predictive control model and the high level is a supervisory online optimiser. The study (Oravec et al., 2016) investigates using robust model based predictive control algorithms for optimal operating of heat exchangers in series from the stability and economic viewpoints. The aim of the paper (Vasičkaninová et al., 2016) is to show the benefits of two advanced control strategies in heat exchanger control. The designed controllers were verified on a real-time control of a laboratory heat exchanger. In the work (Trafczynski et al., 2016), to improve the quality indices of the heat exchanger control under fouling conditions, a more advanced method of the optimization of controller tuning is presented. The work (Rohani et al., 2016) considers improving the heat recovery of an existing heat exchanger network while minimizing the total annualized cost of the retrofit design. In the paper (Yong et al., 2015), the problems in retrofitting a heat exchanger network for utility usage reduction are discussed. The paper (Vasičkaninová and Bakošová, 2015a) investigates a predictive control algorithm to regulate the output petroleum temperature of the tubular heat exchanger. The work (Vasičkaninová and Bakošová, 2015b) presents an advanced control strategy that uses a neural network predictive controller and a fuzzy controller in the complex control structure with an auxiliary manipulated variable. The goal of the contribution (Barna et al., 2016) was to develop an object oriented model

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and a prototype file storage format primarily for HEs related tasks. The alternative robust model predictive control strategy was implemented to find the optimal control actions taking into account the boundaries on control inputs in (Oravec et al., 2015). Advanced control of heat exchangers is able to ensure high energy efficiency and to minimize energy losses. NNPC is one of the advanced control strategies that combines the advantages of neural-network-based modelling and model-based predictive control. Neural-network modelling is suitable for the modelling of non-linear processes, processes with asymmetric dynamics and processes with uncertainty. The control inputs calculated in MPC are the result of an optimisation procedure and MPC can handle boundaries on control inputs and controlled outputs. As the control inputs are the result of an optimisation procedure, MPC can lead to energy savings. The aim of this research is to show that NNPC can be attractive for HEs operation because of increasing energy efficiency and water savings that are very important for sustainable management the natural resource fresh water, to protect the water environment, and to meet the current and future human demand.

2. Process description

A heat exchanger (HE) is a device for the heat transfer from one fluid to another. The most common heat exchangers in industrial applications are the shell-and-tube heat exchangers. These exchangers consist of a shell and a large number of tubes packed in a shell with their axes parallel to that of the shell (Figure 1).

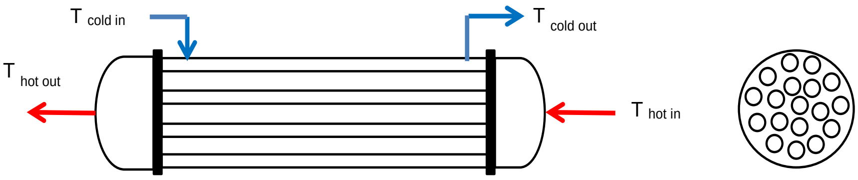

Figure 1: Counter- current flow.

Consider five identical counter-current shell-and-tube HEs in series (Figure 2). Petroleum flows in the inner tubes and cooling water in the shell of each heat exchanger. The tubes of the heat exchangers are made from steel. The controlled output is the temperature of the outlet stream of petroleum from the 5th heat exchanger and the control input is the volumetric flow rate of the inlet stream of cold water into the 5th heat exchanger. The objective is to cool down the outlet temperature of the petroleum to the reference values and to minimize the cold water consumption.

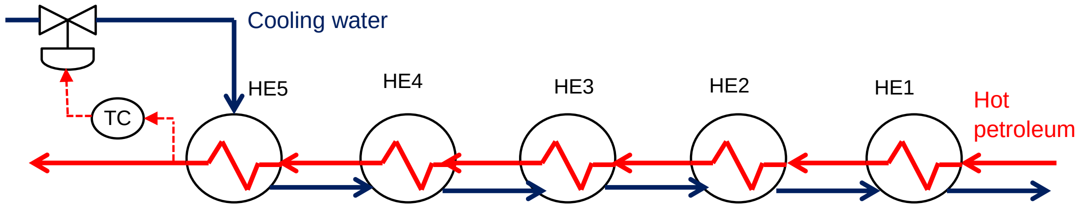

Figure 2: Schematic of a counter- current shell-and-tube heat exchangers in series.

The simplified nonlinear dynamic mathematical model of the HEs can have the form of ten first-order ordinary differential equations (Oravec et al., 2016).

$$\frac{dT_1^j(t)}{dt} = \frac{AU}{2V_1\rho_1 c_{p1}}\left(\left(T_2^j(t) - T_1^{j+1}(t)\right) + \left(T_2^{j-1}(t) - T_1^j(t)\right)\right) + \frac{q_1}{V_1}\left(T_2^j(t) - T_1^{j+1}(t)\right) \quad (1)$$

$$\frac{dT_2^j(t)}{dt} = \frac{AU}{2V_2\rho_2 c_{p2}}\left(\left(T_2^j(t) - T_1^{j+1}(t)\right) + \left(T_2^{j-1}(t) - T_1^j(t)\right)\right) + \frac{q_2}{V_2}\left(T_2^j(t) - T_1^{j+1}(t)\right) \quad (2)$$

where the subscripts 1, 2 indicate the cold and the hot stream. The superscript j = 1, …, 5 stands for the 1st, …, 5th heat exchanger, $T_1^j(0) = T_{1,0}^j$, $T_2^j(0) = T_{2,0}^j$ are initial conditions. In Eqs(1)–(2), t is the time, $T(t)$ is the time-varying temperature, n is the number of the HE's tubes, l is the length of the HE, d_{1in} is the inner diameter of the tube, d_{1out} is the outer diameter of the tube, d_{2in}, is the inner diameter of the shell, V is the volume, ρ is the density, c_p is the specific heat capacity, q is the volumetric flow rate, A is the heat transfer area and U is the overall heat transfer coefficient. The steady-state temperatures T_{1j}^s and T_{2j}^s, j = 1, …, 5, were computed for the inlet temperature T_{1in} = 293.15 K, T_{2in} = 503.15 K from the steady-state model represented by Eqs(1)–(2) with zero derivatives. Parameters of the heat exchangers are presented in Table 1. To demonstrate the robustness of the controllers used, two interval parametric uncertainties are considered. The heat-transfer coefficient U changes as the flow rate of the cooling medium changes, and the petroleum density ρ_2 depends on the temperature in the HE (Table 1).

Table 1: Parameters of heat exchangers

Variable	Unit	Value	Variable	Unit	Value
n	1	40	q_1	$m^3\ s^{-1}$	0.0048
l	m	6	q_2	$m^3\ s^{-1}$	0.0058
d_{1in}	m	0.019	ρ_1	$kg\ m^{-3}$	980
d_{2in}	m	0.414	c_{p1}	$J\ kg^{-1}\ K^{-1}$	4,186
d_{1out}	m	0.025	c_{p2}	$J\ kg^{-1}\ K^{-1}$	2,140
A	m^2	16.6	U	$J\ s^{-1}\ m^{-2}\ K^{-1}$	482.17±20
V_1	m^3	0.0912	ρ_2	$kg\ m^{-3}$	810±16.2
V_2	m^3	0.7165			

3. Neural network-based model predictive control

The objective of the model-based predictive control (MPC) is to predict the future behaviour of the process over a certain time horizon using the dynamic model and to obtain the control actions minimizing a cost function. At each sampling period, only the first control input of the calculated sequence of control inputs is applied to the controlled process. At the next sampling time, the procedure is repeated. This is known as the receding horizon concept. So, the controller is composed from a plant model and an optimization block. The basic implementation of the model-based predictive control (MPC) was mainly for linear systems. Recently, great effort is devoted to the development and implementation of nonlinear versions of this algorithm. One of these implementations is the use of neural networks for controller design. Neural networks are capable of capturing the system nonlinear dynamics and can be used to approximate the process as well as to design the model predictive controller. The neural network-based predictive controller (NNMPC) uses a neural network model of a nonlinear plant to predict future plant performance (Figure 3). Then the controller calculates the predicted control input that will optimize plant performance over a specified future time horizon. This control method is based on the receding horizon technique (Soloway and Haley, 1996). The NNMPC structure is composed of four components in addition to the plant. These components are two neural networks, one for the plant and the other for the controller, an optimizer and a performance function. For a selected time horizon, the controller optimizes the plant output using the neural network plant model for calculating controller moves and predicting plant output. The neural network controller is trained in order to produce the correct controller moves generated by the optimization algorithm (Hunt et al., 1992).

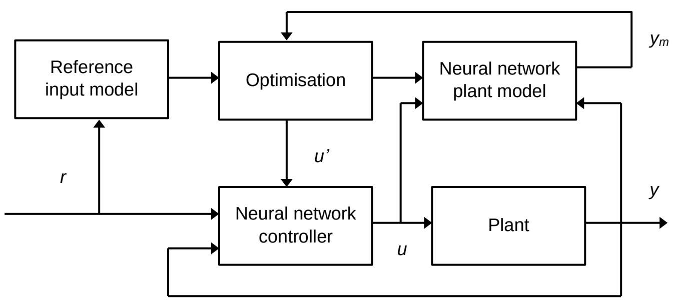

Figure 3: The neural network-based MPC structure.

The neural network model predicts the plant response over a specified time horizon. The predictions are used by a numerical optimization program to determine the control signal that minimizes the following performance criterion over the specified horizon:

$$J = \sum_{j=N_1}^{N_2} \left(r(t+j) - y_m(t+j) \right)^2 + \lambda \sum_{j=N_1}^{N_2} \left(u'(t+j-1) - u'(t+j-2) \right)^2 \tag{3}$$

where N_1, N_2, and N_u define the horizons over which the tracking error and the control increments are evaluated. The u' variable is the tentative control signal, r is the reference response, and y_m is the network model response. The λ value determines the contribution that the sum of the squares of the control increments has on the performance index (Beale et al., 2015). The optimization block determines the values of u' that minimize J, and then the optimal u is input to the plant.

4. Simulations and results

4.1 NNPC of the heat exchangers

The neural network predictive controller uses a neural network model to predict future HEs responses to potential control signals. An optimization algorithm then computes the control signals that optimize future plant performance. The neural network (NN) plant model of the HEs was obtained off-line. The two-layer network with sigmoid transfer functions in the hidden layer and the linear transfer functions in the output layer was trained using the Levenberg-Marquardt (LM) algorithm (Figure 4). 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. The LM algorithm can be thought of as a combination of the steepest descent and the Gauss-Newton method. The training data was obtained from the nonlinear model of the HEs.

Constraints and parameters values used for NNPC design were: the controller horizons N_1 = 1, N_2 = 5, N_u = 2, the weighting parameter λ = 0.05. The number of neurons in the first layer of the plant model network was 6, the number of delayed plant inputs was 4, the number of delayed plant outputs was 3, the sampling interval was 3 s, training samples = 1,500 (number of data points generated for training, validation, and test sets). The constraints on control inputs were chosen: the minimum control input q_{1min} = 1.6667×10^{-4} m^3 s^{-1}, the maximum control input q_{1max} = 0.0086 m^3 s^{-1}.

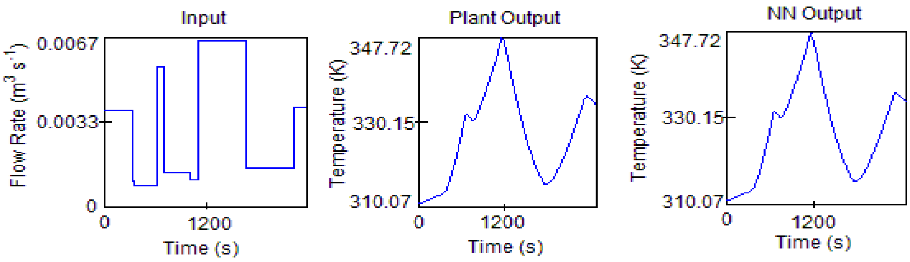

Figure 4: Training data for NNPC.

4.2 PID control of the heat exchangers

PID controllers are described by the transfer function

$$C = k_p \left(1 + \frac{1}{t_i s} + t_d s \right) \tag{4}$$

where k_p is the proportional gain, t_i the integral time and t_d the derivative time, were tuned using Cohen-Coon and Rivera-Morari methods (Ogunnaike and Ray, 1994). The model was identified from the step response of the HEs in the form of the nth order plus time delay transfer function (Mikleš and Fikar, 2007).

$$S = \frac{K}{(\tau s + 1)^2}^{-Ds} \tag{5}$$

The transfer function parameters are: the gain K = - 62.6 K s m^{-3}, the time constant τ = 96 s and the time delay D = 6 s. The PID controller parameters obtained using the Cohen-Coon formulas are k_p = – 0.21 K^{-1} s^{-1} m^3, t_i = 64 s, t_d = 9.6 s and those obtained using the Rivera-Morari formulas are k_p = – 0.1077 K^{-1} s^{-1} m^3, t_i = 274 s, t_d = 12.6 s.

Simulation results obtained using designed NNPC and two PID controllers in the set-point tracking and in the disturbance rejection are shown in Figures 5 – 7 for the nominal system, for the system with maximal changes of the uncertain parameters and for the system with minimal changes of the uncertain parameters. The disturbances were represented by changes of the volumetric flow rate of the hot stream by $+8.33\times10^{-4}$ m^3 s^{-1} at 600 s, -12×10^{-4} m^3 s^{-1} at 1800 s, $+15\times10^{-4}$ m^3 s^{-1} at 3,000 s.

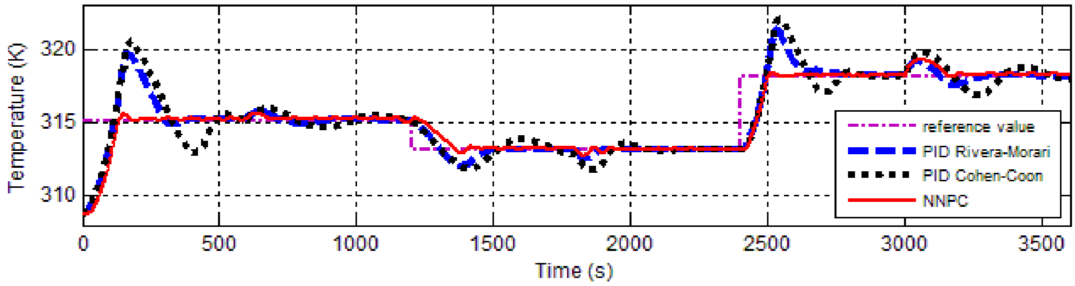

Figure 5: Comparison of NNPC and PID control for the nominal system.

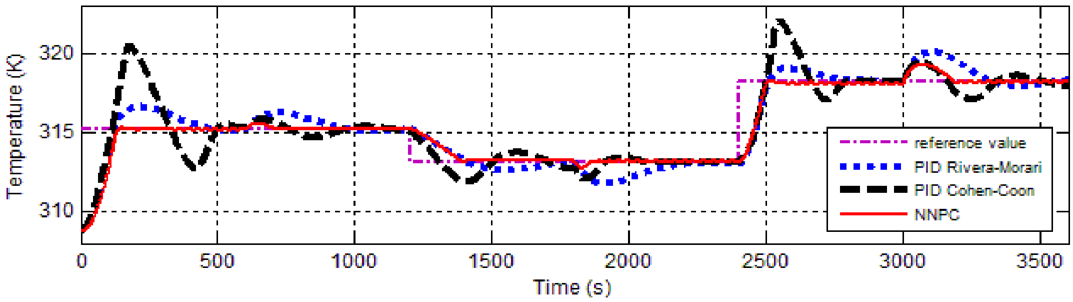

Figure 6: Comparison of NNPC and PID control for the system with minimal changes of the uncertain parameters.

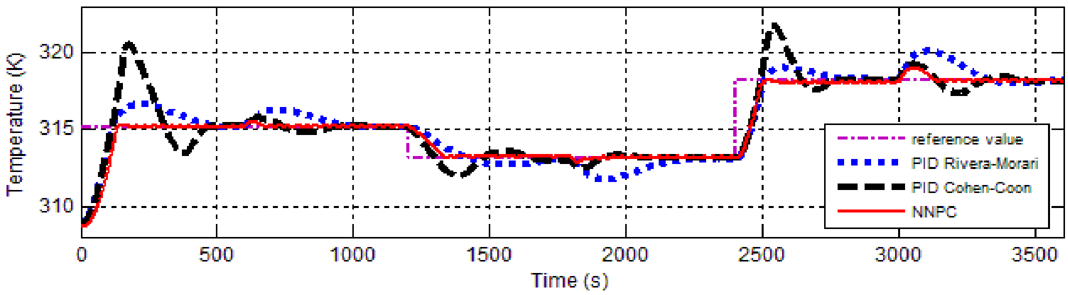

Figure 7: Comparison of NNPC and PID control for the system with maximal changes of the uncertain parameters.

Table 2: Values of IAE and V_2

Controller	IAE (–)			V_2 (m^3)		
	minimal changes	nominal system	maximal changes	minimal changes	nominal system	maximal changes
PID Cohen-Coon	51.68	54.06	43.02	20.30	17.64	17.54
PID Rivera-Morari	43.95	33.63	44.76	17.45	17.07	18.24
NNPC	22.23	24.57	21.65	16.19	16.24	16.06

The control performance achieved using the NNPC was better in both cases (namely the set-point tracking and the disturbance rejection) than the performance achieved by PID control. The control response using the NNPC controller was fast and without big overshoots and undershoots in all studied situations. The simulation results were compared using the integral quality criterion IAE (integrated absolute error) (Ogunnaike and Ray, 1994), see Table 2. The NNPC achieves the best results also in accordance to the IAE. The total volume of cooling water V_2 consumed during the control was also followed. The results are compared in Table 2 and it can be stated that the lowest water consumption was obtained using the NNPC structure.

5. Conclusions

Neural-network-based predictive control of five counter-current heat exchangers in series was studied. The simulation results confirm that the advanced control strategies such as neural-network-based predictive control can be used for efficient control of heat exchangers in series. The advantage of this approach is that it is not a linear-model-based strategy and the neural-network plant model is suitable for modelling the HEs with uncertainty and asymmetric dynamics. The other advantage is that the control input constraints are directly included into the controller synthesis. Moreover, the simulation results showed that NNPC leads to water savings in comparison to the conventional PID control.

Further research will be focused to the improvement of the neural-network-based predictive control algorithm and to the extension of the studied process model to a heat recovery network as the coolant outlet stream of the HEs can be used for heating in another process unit.

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References

Barna B., Varbanov P.S., Klemeš J.J., Yong J.Y., 2015, Object-oriented model and file format for heat exchanger network computations, Chemical Engineering Transactions, 45, 319-324.

Beale M.H., Hagan M.T., Demuth H.B, 2015, Neural Network Toolbox™, User's Guide, MATLAB® R2015a, The MathWorks, Inc., Natick, MA, USA, 410 ps. ISBN: 0-9717321-0-8.

González A.H., Odloak D., Marchetti J.L., 2006, Predictive control applied to heat-exchanger networks, Chemical Engineering and Processing: Process Intensification, 45(8), 661-671.

Hunt K.J., Sbarbaro D., Zbikowski R., Gawthrop P.J., 1992, Neural networks for control system - a survey, Automatica 28, 1083–1112.

Inchaurregui-Méndez J.A., Vázquez-Román R., Ponce-Ortega J.M., Mannan M.S., 2016, Optimal safe layouts with heat exchanger networks synthesis having isothermal process streams, Chemical Engineering Transactions, 48, 655-660.

Mikleš J., Fikar M., 2007, Process Modeling, Identification, and Control, Springer, Berlin/Heidelberg, Germany, 480 ps. ISBN: 978-3-540-71969-4.

Ogunnaike B.A., Ray W.H., 1994, Process Dynamics, Modelling, and Control, Oxford University Press, New York, USA, 1260 ps. ISBN: 978-0195091199.

Oravec J., Bakošová M., Mészáros A., 2015, Comparison of robust model-based control strategies used for a heat exchanger network, Chemical Engineering Transactions, 45, 397-402.

Oravec J., Bakošová M., Meszáros A., 2016, Robust model predictive control of heat exchangers in series, Chemical Engineering Transactions, 52, 253-258.

Rohani N., Ayotte-Sauvé E., Ashrafi O., Bédard S., 2016, Multiple modifications in stepwise retrofit of heat exchanger networks, Chemical Engineering Transactions, 52, 313-318.

Soloway D., Haley P.J., 1996. Neural generalized predictive control, Proceedings of the 1996 IEEE International Symposium on Intelligent Control, Dearborn, MI, USA, 277–281.

Trafczynski M., Markowski M., Alabrudzinski S., Urbaniec K., 2016, Tuning parameters of PID controllers for the operation of heat exchangers under fouling conditions, Chemical Engineering Transactions, 52, 1237-1242.

Vasičkaninová A., Bakošová M., 2015a, Fuzzy model-based neural network predictive control of a heat exchanger, Chemical Engineering Transactions, 45, 313-318.

Vasičkaninová A., Bakošová M., 2015b, Control of a heat exchanger using neural network predictive controller combined with auxiliary fuzzy controller, Applied Thermal Engineering, 89, 1046-1053.

Vasičkaninová A., Bakošová M., Čirka L., Kalúz M., 2016, Robust controller design for a heat exchanger, Chemical Engineering Transactions, 52, 247-252.

Yong J.Y., Nemet A., Varbanov P.S., Klemeš J.J., Čuček L., Kravanja Z., Mantelli V., 2015, Heat exchanger network modification for waste heat utilisation under varying feed conditions, Chemical Engineering Transactions, 43, 1279-1284.