Proceeding Series of the Brazilian Society of Computational and Applied Mathematics, v. 7, n. 1, 2020.

Trabalho apresentado no XXXIX CNMAC, Uberlândia - MG, 2019.

Proceeding Series of the Brazilian Society of Computational and Applied Mathematics

---

Model predictive control based on neural networks for heat exchanger networks operation

Carolina B. Carvalho[1]
Department of Chemical Engineering, State University of Maringá (UEM), Brazil
Esdras P. Carvalho [2]
Department of Mathematics, State University of Maringá (UEM), Brazil
Mauro A. S. S. Ravagnani[3]
Department of Chemical Engineering, State University of Maringá (UEM), Brazil

Abstract. Optimal operation of integrated heat exchangers is a challenge task in the field of process control due to system nonlinearities, disturbances and adequate model identification. This paper describes the design of an advanced neural network predictive control (NNPC) applied to a heat exchanger network. A case study with two hot and one cold streams, through three counter-current heat exchangers is used to test the proposed strategy. A lumped dynamic model is built based on the concept of multi-cells topology (mixed tanks), where the hot and cold cells are connected by a wall element throughout the heat exchanger length. Each cell is assumed perfectly mixed and all physical properties are constant. A distributed behavior is achieved by increasing the number of cells. The main assumptions of the lumped model are constant temperature in each cell, heat exchanger volume and area equally distributed between cells and negligible heat loss to the environment. The predictive controller relies on a neural-based model of the plant that is used to identify the system and to predict future performance over a predefined horizon. Results showed good control output regarding set point tracking.

Palavras-chave. Chemical engineering, Heat exchangers networks, Process control

1 Introduction

Heat exchanger networks (HEN) are a recurrent subject in process systems engineering due to their capability to recover energy from hot and cold process streams and, thus, maintain the operation at a competitive economic level. However, heat integration also often results in more complex and less operable plants [6]. In the majority of the cases, the thermal outlet condition is frequently a controlled variable that must attend products specification, environmental restrictions and safety constraints without reducing the operation efficiency [4].

---

[1]carolinabcarvalho@outlook.com
[2]epcarvalho@uem.br
[3]massravagnani@uem.br

Analysis that evaluate the ability of the plant to deal with disturbances, controllability indexes and the design of proper control structure has become an important part in the literature regarding operation and control of integrated systems. Early contributions addressed structural and flexible design approaches for HEN control and optimal operation. Those topics contributed to develop strategies for bypass selection to incorporate control decisions [8] optimal synthesis and control structure design for flexible HENs [2] and advanced control strategies to increase energy savings [1].

In a recent study, a thermodynamically based approach proposed by [7] described a methodology to relate process control and process design stage, analyzing the disturbance cost and the relative gain array aiming to obtain the best balance between integration and control. On the other hand, the design of the control system itself is often considered as an independent task. Compared to the well-developed HEN design literature, much less effort has been dedicated to its control and operation.

Among control techniques available, the proportional-integral-derivative (PID) controller is one of the most used in the industries. However, it may not be suitable for all purposes dynamics, leading to poor quality control indexes, such as overshoot, settling and rising time, as presented by [3].

The model predictive control (MPC) is worth highlighting due to its proven ability to handle heat integrated process. The MPC relies on a dynamic model of the process to predict output trajectories performed by an online optimization [4]. Furthermore, the possibility to include constraints on the process variables in the optimization model is an important feature that distinguishes the MPC from the other conventional control approaches. They enforce bounds of these variables within physical and safety limits, if a feasible solution to the optimization problem exists [5].

Regarding model identification, a well-trained artificial neural network (ANN) can represent thermal process with a quick and reliable way to predict future performance, as demonstrated by several works in neural computational field [9].

Therefore, this work aims to develop a multi-layer neural network model trained by a back-propagation algorithm to represent the nonlinear behavior of the heat exchanger network. Then, perform simulations combining the neural network with a predictive controller to assess its performance regarding set point tracking.

2 Heat exchanger network mathematical model

2.1 System description

The heat exchanger network simulated in this work is branch of a pre-heat train from a refinery composed by three shell and tube heat exchangers in series. Also, three oil streams are available at different temperatures.

The cold stream C1 (light oil) is passed through the three counter-current heat exchangers. Hot streams H1 and H2 (heavy oils) are used to increase C1 outlet temperature (controlled variable). In this case, only the mass flow rate of H1 can be manipulated to keep the cold stream outlet temperature at the desired set-point. For all heat exchangers, the hot fluid is located inside the tubes.

Table 1: Heat exchanger geometric characteristics.

	Area (m^2)	V_t (m^3)	V_s (m^3)	M (kg)
E-2	264	1.4	1.38	5480
E-3	77	0.45	0.67	2420
E-4	233	1.15	2.06	4830

Table 1 describes the geometric characteristics of each heat exchanger in the network. Physical properties, such as density, heat capacity and heat transfer coefficients, were obtained using the Aspen EDR database for steady-state simulation of each heat exchanger.

2.2 Dynamic modeling

Lumped models introduce the concept of a modeling cell, defined as a perfectly mixed tank that exchanges heat with each other through a dividing wall. This approach leads to ordinary differential equations regarding to time only, instead of partial differential equations regarding to time and space [3].

Heat is transferred from one mixing tank in the hot side to the corresponding one in the cold side, resulting in as many energy balances as the number of tanks (or cells). The numeric linearization of the dynamic system is made around the steady-state operating point, leading to a state-space description of the HEN. Ref. [3] presents the detailed dynamic model.

For each cell, there are three equations derived from the energy balances, for hot fluid, wall and cold fluid, respectively. Defining $3N$ as the number of modeling cells, which $n = 1, \ldots, N$, the energy balances for the hot side (subscript h) is written as follows:

$$\frac{dT_h^{n+1}}{dt} = \frac{m_h}{\rho_h^n\ V_h^n}\left(T_h^n - T_h^{n+1}\right) + \frac{h_h^n\ A_t^n}{\rho_h^n\ V_h^n\ C_{p_h}^n}\left(T_w^n - T_h^{n+1}\right). \tag{1}$$

For the dividing wall:

$$\frac{dT_w}{dt} = \frac{h_h^n A_t^n}{\rho_w^n\ V_w^n\ C_{p_w}^n}\left(T_h^{n+1} - T_w^n\right) + \frac{h_c^n A_s^n}{\rho_w^n\ V_w^n\ C_{p_w}^n}\left(T_c^n - T_w^n\right). \tag{2}$$

And, then, for the cold fluid:

$$\frac{dT_c^{n+1}}{dt} = \frac{m_c}{\rho_c^n\ V_c^n}\left(T_c^{n-1} - T_c^n\right) + \frac{h_c^n\ A_s^n}{\rho_c^n\ V_c^n\ C_{pc}^n}\left(T_w^n - T_c^n\right). \tag{3}$$

In Equations (1) - (3), h is the heat transfer coefficient (W/m^2K), V is the cell volume (m^3), C_p is the heat capacity (J/kgK), ρ is the density (kg/m^3), m is the mass flow rate (kg/s) and A_s and A_t are the shell and tube areas for each cell (m^2), respectively. The HEN model was implemented in Matlab R2018a considering $N = 10$ in all the heat exchangers.

3 Neural network model predictive controller

Two typical steps are involved when using neural networks for control: system identification and control design. First, the neural network is developed (or trained) to represent the plant. Then, for model predictive control, the control design is performed by using the plant model and an optimization algorithm computes the control signals that optimizes future plant performance at each time step.

3.1 Artificial neural network model

An artificial neural network is inspired by the human neural network, consisting in a set of neurons and nodes, that try to establish a relationship between input and output information. The neurons carry out the task of processing information, transmitting it as a weight in a relationship between them and, thus, predicting the output values.(Omrani et al., 2018) The training process consists in adjust the weights between the neurons and may be handle by supervised or non-supervised learning algorithms. Supervised machine learning is the most commonly used and is applied in this work. It consists in using the data set as the teaching method to continuously update the weight and bias until the algorithm achieves the desired performance. Figure 1 illustrates the learning process of an artificial neural network.

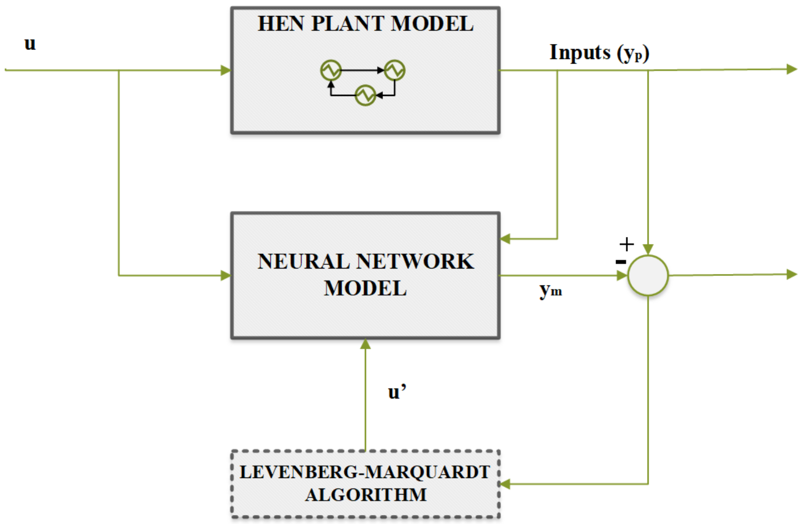

Figure 1: Schematic diagram of an artificial neural network learning process.

Regarding the supervised algorithms, the Levenberg-Marquardt is one of the most popular and fastest back propagation methods and was chosen as the training function for this work. The aim of the Levenberg-Marquardt is to minimize the mean square error between the targets and the outputs. A multi-layer (input, hidden and output layers) was implemented and the training procedure updated the weight and bias of the neural network in the batch mode until the stop criterion was achieved. The dynamic model was used to generate the training data for the neural network model. There were considered a sampling interval of 1 second, generating 1500 samples of data series.

3.2 MPC design formulation

The cost function for optimal control is defined as for the i-th step can be written as:

$$J(i) = \sum_{j=1}^{N_2} \left(y_r(i+j) - y_m(i+j)\right)^2 + \lambda \sum_{j=1}^{N_u} \Delta u'(i+j-1)^2 \tag{4}$$

where N_u is the horizon over which the deviation in control action is minimized (control horizon), N_2 is the horizon over which the set-point error is minimized (cost horizon), λ is the control weighting factor multiplying the deviation in control action, y_r is the reference value, y_m is the predicted controlled output and u' is the optimal input to the plant. The control output and input variables are box constrained. The model obtained by the neural network is used by the MPC to predict future control actions over a predefined horizon. The minimization routine *csrchbac* was used to solve the optimization problem. All the simulations were performed using Matlab/Simulink. The analysis was made by applying a noise in the manipulated variable and the cold outlet temperature behavior was observed.

4 Results

4.1 Neural network training and validation

Neural network training performance was assessed by the mean square error (MSE). Low MSE indicates that the predicted data are closer to the true values. For the case study presented by this work, a two-layer network with 8 neurons in the hidden layer and one neuron in the output layer was created and the value of MSE was 2.70×10^{-6} at epoch 38, which indicates a good performance.

In addition, six validation tests were performed after the achievement of the best validation performance (from epoch 38 to 44) and the validation performance did not improve, indicating that the network is not overfitted and, thus, the training can be considered successful.

4.2 Heat exchanger network simulation

Following the neural network training, the predictive control starts. The parameters for the predictive controller was obtained after extensive simulations and are $N_2 = 6$ (maximum predicted horizon), $N_u = 2$ (control horizon) and the smoothness factor λ is 0.001. In addition, the control input constraints were $240 \leq \dot{m} \leq 280$ kg/s and the control output constraint $183 \leq T_{co} \leq 189.5$ ^oC. Figure 3 shows NNPC response curve to a positive and negative step changes in the set point. In order to compare the output responses, a PID controller tuned by Ziegler-Nichols method was also simulated.

The steady-state was achieved after the first 100 s of simulation for the first step change. However, analyzing the 300 s and 700 s (set point steps), it is clear the ability of

DOI: 10.5540/03.2020.007.01.0400

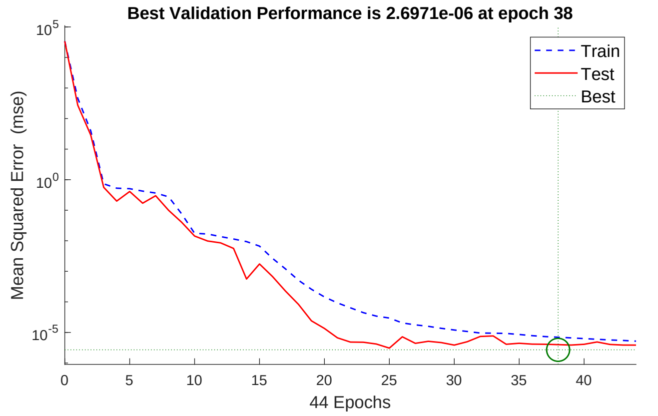

Figure 2: Train, validation and test performances at each epoch for the neural network model.

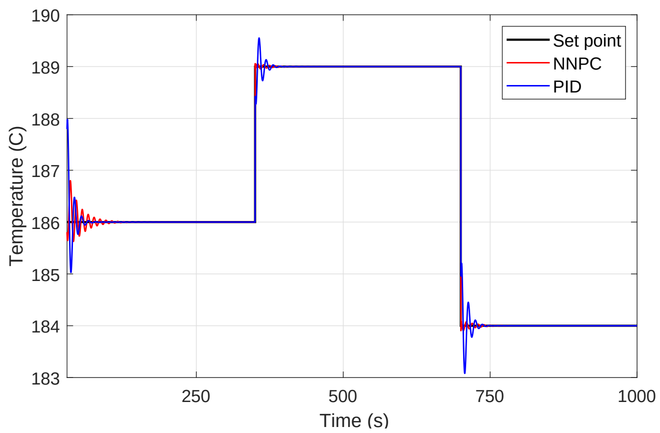

Figure 3: Step response set point tracking for NNPC and PID.

the NNPC in track the set point, with small values of overshoot and settling times. This was possible by balancing the control and predicted horizon of the predictive controller. If the predicted horizon was bigger, the controller would not be able to act during set point changes in enough time to maintain good performance.

5 Conclusions

Improvements in control performance regarding set point tracking are presented in this work by the application of a neural based predictive controller in a heat exchanger network plant. A lumped parameter model was implemented to generate the training data for the neural network. Simulation showed that the overall performance was satisfactory when a NNPC is applied as the control system for plants with complex dynamics. The controller system requires a well-trained network and adequate parameters for the predic-

DOI: 10.5540/03.2020.007.01.0400

tive controller, however an important advantage of this approach is that the output and input constraints can be directly included in the controller optimization problem. The case study showed that overshoot and settling time can be improved with a more sophisticated controller and the performance can be even more significant in bigger heat exchanger networks. Also, this simulation can be extended for real plants by using measured values of plant operation in the neural network training and validation procedures.

Acknowledgments

The authors would like to acknowledge the financial support from the Coordination for the Improvement of Higher Education Personnel - Process 88881.171419/2018-01- CAPES (Brazil) and CNPq (Brazil).

References

[1] M. Bakosova, J. Oravec. Robust model predictive control for heat exchanger network, *Applied Thermal Engineering*, 73(1):924–930, 2014.

[2] L. Braccia, P. A. Marchetti, P. Luppi, D. Zumoffen. A Sequential Integration between Optimal Flexible Heat Exchanger Network Synthesis and Control Structure Design, *Industrial & Engineering Chemistry Research* 57:11094–11111, 2018.

[3] C. B. Carvalho, E. P. Carvalho, M. A. S. S. Ravagnani. Tuning Strategies for Overcoming Fouling Effects in Proportional Integral Derivative Controlled Heat Exchangers, *Industrial & Engineering Chemistry Research* 57(31):10518–10527, 2018.

[4] A. H. Gonzalez, D. Odloak, J. L. Marchetti. Predictive control applied to heat exchanger networks, *Chemical Engineering and Processing: Process Intensification*, 45(8):661–671, 2006.

[5] J. K. Huusom. Challenges and opportunities in integration of design and control, *Computers & Chemical Engineering* 81:138–146, 2015.

[6] D. Leitold, A. Vathy-Fogarassy, J. Abonyi. Evaluation of the Complexity, Controllability and Observability of Heat Exchanger Networks Based on Structural Analysis of Network Representations, *Energies*, 12(3):513–535, 2019.

[7] C. de Leon, C. B. Miranda, C. M. G. Andrade, M. A. S. S. Ravagnani. Thermodynamically-based response time as controllability indicator in heat exchanger networks, *The Canadian Journal of Chemical Engineering*, 95(7):1305–1312, 2017.

[8] L. Sun, X. Zha, X. Leo, Coordination between bypass control and economic optimization for heat exchanger network, *Energy*, 160:318–329, 2018.

[9] T. N. Trong, M. N. Duc. Sliding Surface in Consensus Problem of Multi-Agent Rigid Manipulators with Neural Network Controller, *Energies* 10(12):2127–2141, 2017.

