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COMBINED NEURAL NETWORKS AND PREDICTIVE CONTROL FOR HEAT EXCHANGER NETWORKS OPERATION

Article Highlights
• An artificial neural network model is trained and validated to represent a heat exchanger network
• A predictive controller is designed and tuned based on the neural network for temperature control
• The results are compared to conventional controller approaches, providing good accurate outcomes

Abstract
Optimal operation of integrated heat exchangers is a challenging 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 were compared to a traditional controller, and the control performance was improved when compared to the Ziegler-Nichols tuning method.

Keywords: heat exchanger networks, artificial neural networks, model predictive control.

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 [1]. 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 [2].

Analysis that evaluates the ability of the plant to deal with disturbances, controllability indexes and the design of proper control structure have 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 developing strategies for bypass selection to incorporate control decisions [3], optimal synthesis and control structure design for flexible
HENs [4] and advanced control strategies to increase energy savings [5].

In a recent study, a thermodynamically based approach proposed by León et al. [6] 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. In this context, Jäschke and Skogestad [7] presented an approach for optimizing the stream split in a parallel heat exchanger system. In their method, only temperature measurements are required.

Among the control techniques available, the proportional-integral-derivative (PID) controller is one of the most used in the industries [8]. However, it may not be suitable for all purposes dynamics, leading to poor quality control indexes, such as high overshoot, settling and rising times [9].

The model predictive control (MPC) is worth highlighting due to its proven ability to handle heat integrated process [5]. The MPC relies on a dynamic model of the process to predict output trajectories performed by an online optimization [2]. 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 [10]

Regarding model identification, new developments in machine learning have seen the re-emergence of artificial intelligence (AI) and, among them, artificial neural networks (ANN) have been used in thermal systems for heat transfer analysis, performance prediction and dynamic control [11], appearing as an advanced alternative to conventional models that apply ordinary or partial differential equations and numerical methods.

If well-trained, an ANN can represent a thermal process and in a quick and reliable way predict future performance, as demonstrated by several works in neural computational field. Other applications are based on pattern identification and fault diagnosis, that was also applied for highly integrated process optimization [12].

With regard to industrial applications, ANN was used to predict the dynamic behavior of heat exchangers in the pioneering work of Diaz et al. [13]. The methodology included training the neural network with mass flow rate and temperature database as inputs to predict the total heat transferred (steady-state and time dependent data sets). Then, standard PI and PID controllers were compared with an ANN controller. Although the proposed technique showed higher overshoot than the standard ones, its overall performance was better.

Ni and Ma [14] developed a multi-input approach that relied on a neural network model to predict the power generation of an energy converter. The algorithm proposed by the authors was able to detect changes and possible fault diagnosis due to the presence of anomalies that conventional models would not be able to detect.

Trong and Duc [15] implemented a neural network controller with online learning weights for a sliding mode control. Numerical simulations showed that stability and robustness were assured against parameters uncertainties. In another recent work, Katic et al. [16] applied a neural network predictive control (NNPC) to personalize a heating system that directly predicts individual settings of a heating chair. Results showed that the model can provide a quality substitute for user’s control.

Regarding heat exchangers themselves, Lalot et al. [17] compared neural network to Kalman filters to detect fouling. It was possible to conclude that the neural model performed better when dealing with fast drifts.

In the field of advanced controlling techniques, Oravec et al. [18] successfully implemented a robust model predictive system to optimize the control performance of heat exchangers.

Vasickaninová et al. [19] controlled a tubular heat exchanger with a control structure composed by two controllers based on neural networks, also comparing the results with conventional PID controllers and analyzing set point tracking and disturbance rejection. The authors confirmed the superiority of the neural network-based controller for a single heat exchanger, suggesting the proposed approach to be applied in different types of heat exchangers and processes.

Despite the successful applications of this control strategy in the heat exchanger literature, there are still few works that take into account more complex plant dynamics, as heat exchanger networks [20]. Based on the above achievements, the present 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, performing simulations combining the neural
network with a predictive controller to assess its performance regarding set point tracking. The performance of this strategy is compared to traditional controlling approaches.

HEAT EXCHANGER NETWORK MATHEMATICAL MODEL

System description

The heat exchanger network simulated in this work is illustrated in Figure 1.

Three oil streams are available at different temperatures. The cold stream C1 (light oil) is passed through 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.

Dynamic modelling

Lumped models introduce the concept of a modelling cell, defined as perfectly mixed tanks that exchange heat with each other through a dividing wall. This approach leads to ordinary differential equations with respect to time only, instead of partial differential equations with respect to time and space [21].

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 there are 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 [22].

Figure 2a shows in detail the hot and cold cells inlet and outlet conditions as well as the dividing wall and the heat exchanged through it. In Figure 2b, an entire heat exchanger with a countercurrent configuration is depicted.

The mathematical model based on cells was first proposed by Varga et al. [23] and then validated by Markowski et al. [24]. Simulation results have shown that lumped models are able to satisfactorily predict heat exchanger dynamic behavior allied to computational simplicity when using an adequate number of cells [25].

Considering fully developed turbulent flows, some simplifications are made [21]:

- Fluid and tube wall physical properties are constant in each cell due to the perfect mixing assumption and, thus, the temperature is constant in each cell;
- Wall resistance to heat transfer is negligible in comparison with convective resistance;
- There is no heat loss to the environment or heat conduction between cells.

For each cell, there are three equations derived from the energy balances (Eqs. (1), (4) and (7)), for the hot fluid, wall and cold fluid, respectively. The energy balances are defined in terms of volume instead of mass holdups. As one cell will not represent accordingly the dynamics of the whole heat exchanger, it is more convenient to present the energy balances by using the volume of each cell. Defining 3N as the number of modelling cells, with n = 1,...,N, the energy balances for the hot side (subscript h) is written as follows:

\[
\frac{dT_h^{n+1}}{dt} = \alpha_h (T_h^0 - T_h^m) + \beta_h (T_w^0 - T_h^m)
\]

where

\[
\alpha_h = \frac{m_h}{\rho_h V_h^0}
\]

Figure 1. Heat exchanger network case study topology.
For the dividing wall:

$$\frac{d T_w^n}{dt} = \alpha_w \left( T_h^{n-1} - T_w^n \right) + \beta_w \left( T_c^n - T_w^n \right)$$

(4)

where

$$\alpha_w = \frac{h_n A_n}{\rho_n C_p V_n}$$

(5)

$$\beta_w = \frac{h_n A_n}{\rho_n C_p V_n}$$

(6)

And, then, for the cold fluid:

$$\frac{d T_c^{n+1}}{dt} = \alpha_c \left( T_c^{n-1} - T_c^n \right) + \beta_c \left( T_w^n - T_c^n \right)$$

(7)

where

$$\alpha_c = \frac{m_c}{\rho_c C_c}$$

(8)

$$\beta_c = \frac{h_n A_n}{\rho_n C_p V_n}$$

(9)

In Eqs. (1)-(9), $h$ is the heat transfer coefficient, $V$ is the cell volume, $C_p$ is the heat capacity, $\rho$ is the density, $m$ is the mass flow rate and $A_n$ and $A_i$ are the shell and tube areas for each cell, respectively. In this work, the HEN model was implemented considering $N=10$ in all the heat exchangers.

Tables 1 and 2 describe the geometric characteristics of each heat exchanger in the network and the properties regarding each process stream available. The physical properties were obtained using the Aspen EDR database for steady-state simulation of each heat exchanger.

| Table 1. Heat exchanger geometric characteristics |
| --- | --- | --- |
| Type | Area (m²) | $V_t$ (m³) | $V_s$ (m³) |
| E-2 | 264 | 1.4 | 1.38 |
| E-3 | 77 | 0.45 | 0.67 |
| E-4 | 233 | 1.15 | 2.06 |

| Table 2. Hot and cold streams availability |
| --- | --- | --- |
| Stream | $m$ (kg/s) | $T_{in}$ (°C) |
| C1 | 210 | 135 |
| H1 | 280 | 205 |
| H2 | 75 | 253 |

Following the work of Mathisen et al. [26], the derived state equations previously defined from energy balances were set for each cell $n$, respecting the interdependences regarding the flow configuration of each heat exchanger. Therefore, the computation of physical values (density, heat capacity and heat transfer coefficients) is made in each fluid cell as a function of temperature.

Matlab offers an interactive environment through Simulink, which was used in this work. A useful tool in Simulink to solve state equations are the S-functions, which enable the interaction with Simulink equation solvers. It can be defined as a computer language description of a Simulink block that, in this work, is written in Matlab.
By being given an input and state variables vectors, Simulink repeatedly invokes the s-function using a flag argument to indicate the task to be performed. This flag corresponds to the actions regarding the following:

- Initialization of the block, including initial conditions and sample times;
- Calculation of the derivatives of the state variables;
- Updating the discrete states and sample times;
- Calculation of the output of the function.

Figure 3 shows a block diagram of the solution process. The system of differential equations is solved using the Runge-Kutta method throughout the ode45 solver in Simulink.

![Block diagram of the simulation steps using Simulink.](image)

**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 using the plant model and an optimization algorithm computes the control signals that optimizes future plant performance at each time step.

**Artificial neural network model**

An artificial neural network is inspired by the human neural network, consisting of 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 [27].

The training process consists in adjusting the weights between the neurons to be handled 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 dataset as the teaching method to continuously update the weight and bias until the algorithm achieves the desired performance. Figure 4 illustrates the learning process of an artificial neural network.

Regarding the supervised algorithms, the Levenberg-Marquardt is one of the most popular and fastest backpropagation 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. A sampling interval of 1 second, generating 1500 samples of data series was considered.

**MPC design formulation**

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

$$J(i) = \sum_{j=1}^{N_1} \left( y_r(i+j) - y_m(i+j) \right)^2 +$$

$$+ \lambda \sum_{j=1}^{N_2} \left( u'(i+j+1) - u'(i+j-2) \right)^2$$

where $N_i$ 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), $\lambda$ 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 sequence of future control increments.

The model obtained by the neural network is used by the MPC to predict future control actions over a predefined horizon. All the simulations were performed using Matlab/Simulink.

The analysis was made in the servo problem, aiming to test the controller ability to track the set point (cold stream outlet temperature) as it changes
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 in 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 $2.70 \times 10^{-6}$ at epoch 38, which indicates a good performance.

The optimum number of hidden neurons is given by the smallest network that provides an acceptable accuracy. In that case, a maximum MSE was set to $1 \times 10^{-5}$. As expected, if the number of neurons in the hidden layer increases, lower MSE values are obtained. However, the number of epochs needed to achieve the required MSE also increases for a slight improvement of predicted values. Then, after testing neural networks with 1 to 15 neurons in the hidden layer, the smallest one that attended the MSE requirement in an acceptable number of epochs was composed by 8 neurons.

In addition, it is worth considering the network overfitting. Overfitting occurs when the network has memorized instead of learned to generalize the training set for new inputs. To overcome this issue, the validation step was included. After the training step, that is used to update the weights and biases of the network, a smaller set of data are used to validate the network and stop the training when it begins to overfit the data.

As can be seen in Figure 5, 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 the training can be considered successful.

Among the 1500 data set generated by the mathematical model, 80% were used for the training procedure and 20% were selected for the validation step. Figure 6 depicts the plant and neural network output for the same input values during the training step, as well as the associated errors. During all the time series, the error between plant and neural network response was less than 1%, confirming that the neural network is well trained for this heat exchanger network model.

Figure 7 depicts the validation results for the neural network model. The comparison between the plant and the neural network model indicates that the validation procedure was successful, with associated error less than 0.5%, and, therefore, the neural network can represent the heat exchanger network.

Heat exchanger network simulation

Following the neural network training, the predictive control starts. The parameters for the predictive controller in the cost function described in Eq. (10) are $N_p = 6$ (maximum predicted horizon), $N_c = 2$ (control horizon) and the smoothness factor $\lambda$ is 0.001. Table 3 shows all information about the neural network and MPC parameters.

In addition, the control input constraints were $240 \leq m \leq 280 \text{ kg/s}$ and the control output constraint $183 \leq T_{co} \leq 189 \text{ °C}$. 

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Figure 5. Training, validation and test performances at each epoch for the neural network model.

Figure 6. Training results for neural network predictive control and the associated errors.

Figure 7. Validating results for neural network predictive control and the associated errors.
Table 3. Parameters of the ANN and MPC

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<th>Name</th>
<th>Value</th>
<th>Name</th>
<th>Value</th>
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</thead>
<tbody>
<tr>
<td>Cost horizon ((N_2))</td>
<td>6</td>
<td>Training samples</td>
<td>1200</td>
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<tr>
<td>Control horizon ((N_u))</td>
<td>2</td>
<td>Validation samples</td>
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<td>Control weight factor ((\tau))</td>
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<td>Size of hidden layer</td>
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<td>Iteration per sample time</td>
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<td>Training function</td>
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</table>

In order to compare the NNPC efficiency in set point tracking, a conventional PID controller was tuned by the Ziegler-Nichols method and simulated for the same conditions as NNPC.

Figure 8 shows NNPC and PID response curves to a positive and negative step changes in the set point (dotted line).

At the first 100 s of simulation, it is worth noting that despite the PID overshoot being bigger, its settling time is considerably smaller when compared to the NNPC. However, during the steady-state period, the PID controller showed noisy values in all three set points simulations. Analyzing the 300 and 700 s (set point steps), it is clear the ability of the NNPC in tracking the set point, with small values of overshoot and settling times. This is possible by balancing the control and predicted horizon of the predictive controller \((N\_u \text{ and } N\_2, \text{ respectively})\). The adjustment of those horizons in the NNPC avoids aggressive actions and contributes to anticipating violations early enough to maintain good performance.

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. Comparison with the well-known PID controller showed that the overall performance can be improved 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 predictive 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 and, then, the strategy can be applied as an industrial decision-making tool related to the operation of heat exchanger networks.

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Nomenclature

\( A \)  
Area

\( N_u \)  
Control horizon

\( u' \)  
Control signal

\( N_T \)  
Cost horizon

\( C_p \)  
Heat capacity

\( h \)  
Heat transfer coefficient

\( m \)  
Mass flow rate

\( N \)  
Number of cells

\( y_m \)  
Predicted output

\( y_r \)  
Reference value

\( T \)  
Temperature

\( V \)  
Volume

Greek letters

\( \rho \)  
Density

\( \alpha, \beta \)  
Geometric parameters

\( \lambda \)  
Weighting factor

Subscripts

\( c \)  
Cold side

\( h \)  
Hot side

\( s \)  
Related to shell

\( t \)  
Related to tube

\( w \)  
Wall side

REFERENCES

KOMBINOVANJE NEURONSKIH MREŽA I PREDIKTIVNE KONTROLE U RADU MREŽA RAZMENJIVAČA TOPLOTE

Optimalan rad integriranih razmenjivača toplote je izazovan zadatak na polju kontrole procesa zbog nelinearnosti sistema, poremećaja i odgovarajuće identifikacije modela. Ovaj rad opisuje razvoj napredne neuronske mreže za prediktivnu kontrolu i njenu primenu na mrežu razmenjivača toplote. Za testiranje predložene strategije korišćena je studija slučaja sa dva topla i jednog hladnog toka, kroz tri protivstrujna razmenjivača toplote. Zbirni dinamički model razvijen je na osnovu koncepcije višećelijske topologije (mešani sudovi), gde su tople i hladne čelije povezane zidnim elementom po celoj dužini razmenjivača toplote. Pretpostavlja se da je svaka čelija idealno izmešana i da su sva fizička svojstva konstantna. Distribirano ponašanje postiže se povećanjem broja čelija. Glavne pretpostavke modela su konstantna temperatura u svakoj čeliji, ravnomerno distribuirana zapremina i površina razmenjivača toplote između čelija i zanemarljivi gubici toplote u okolini. Prediktivni regulator se zasniva na neuronskom modelu postrojenja koji se koristi za identifikaciju sistema i predviđanje budućih performansi tokom unapred definisanog horizonta. Rezultati su upoređeni sa tradicionalnim regulatorom, a performanse kontrole poboljšane su u poređenju sa Ziegler-Nicholsovom metodom podešavanja.

Ključne reči: mreže razmenjivača toplote, veštačke neuronske mreže, model predviđanja.