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Fuzzy Model-based Neural Network Predictive Control of a Heat Exchanger

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The paper investigates a predictive control algorithm to regulate the output petroleum temperature of the tubular heat exchanger. In the controller design, a Takagi–Sugeno fuzzy model is applied in combination with the model predictive control algorithm. The process model in form of the Takagi–Sugeno fuzzy model is obtained via subtractive clustering from the plant's data set. The neural network is used to predict the system outputs and trained on the fuzzy model by the Levenberg-Marquardt algorithm. The simulation results show that the proposed control strategy has good set-point tracking and adequate disturbance rejection ability.

1. Introduction

Predictive control is an advanced control strategy which attracts interest of most of the industries. The model predictive control (MPC) scheme is based on the use of a process model and process measurements to generate values for process input as a solution of an optimisation problem. MPC has found a wide range of industrial applications, showing good performance and a certain degree of robustness (Keshavarz et al., 2010). There have been a number of contributions in the field of model-based predictive control dealing with issues like stability, efficient computation, optimisation, constraints, and others. Vozák and Veselý (2014) present a stable predictive controller design based on solving a linear matrix inequality. Moon (2015) suggested an indoor temperature control method that can provide a comfortable thermal environment through the integrated control of the cooling system and the surface openings. In Santos et al. (2013) an application of artificial neural networks to the identification of a polymerisation system was presented.

The modelling and control of fuzzy systems is a very active research area. Takagi-Sugeno (TS) fuzzy models were first proposed by Takagi and Sugeno (1985). Tanaka and Wang (2001) proved that any smooth nonlinear control system can be approximated by a TS fuzzy model with linear rule consequence as a set of flat linear segments. In Bello et al. (2014), a fuzzy model predictive control strategy is proposed to regulate the output variables of a coagulation chemical dosing unit. In Zhang et al. (2009), the robust stability of a networked control system via a fuzzy estimator is studied, where the controlled plant is a class of nonlinear systems with external disturbances, which can be represented by a Takagi–Sugeno fuzzy model. The fuzzy logic controller for an unstable bioprocess was designed and used for controlling the biomass concentration in Galluzzo and Cirino (2013). In Liew et al. (2013), fuzzy optimisation was applied as the multiple objectives optimisation approach to determine the most sustainable biodiesel production pathway screening. Abu-Siada and Hmood (2013) introduced a fuzzy logic approach for standardising dissolved gas analysis interpretation techniques. A fuzzy logic model was obtained to predict the recoveries of copper and iron from a chalcopyrite copper concentrate by conventional and electrochemical bioleaching processes in Ahmadi and Hosseini (2015). In Mendes et al. (2014) a new method for automatic extracting all fuzzy parameters of a fuzzy logic controller in order to control nonlinear industrial processes is proposed.

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2. Process description

Based on the previous work (Vasičkaninová et al., 2011) consider a co-current tubular heat exchanger, where petroleum is heated by hot water through a copper tube (Figure 1).

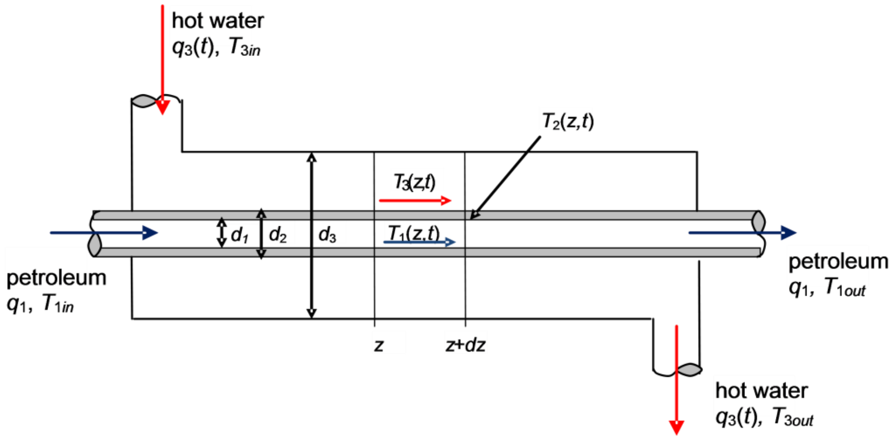

Figure 1: Scheme of the tubular heat exchanger.

The controlled variable is the outlet petroleum temperature T_{1out}. Among the input variables, the hot water flow rate $q_3(t)$ is selected as the control variable. The mathematical model of the heat exchanger is derived under some simplifying assumptions and parameters and steady-state inputs of the heat exchanger are given in (Vasičkaninová and Bakošová, 2012).

3. Fuzzy modelling based on subtractive clustering

Subtractive clustering method is a method which extracts rules from supplied input-output training data. The idea of fuzzy clustering is to divide the data space into fuzzy clusters, each representing one specific part of the system behaviour. After projecting the clusters onto the input space, the antecedent parts of the fuzzy rules can be found. The consequent parts of the rules can be simple functions. One cluster corresponds to one rule of the TS model (Kim et al., 2005).
Let us consider a collection of n data points $\{x_1, x_2, ..., x_n\}$ in an M dimensional space. Each data point is a candidate for cluster center. The density measure at data point $\mathbf{x}_i$ is defined as

$$P_k = \sum_{j=1}^{N} exp\left(-\alpha \left\| x_k - x_j \right\|^2\right) \tag{1}$$

with $\alpha = \frac{\gamma}{(r_a)^2}$. P_k is the new potential-value of each examined point, α is the weight between i-data to j-data, x is the data point, γ is a variable (commonly set 4) and r_a is a cluster radius that is a positive constant representing the radius of data neighbourhood.
A data point will have a high density value if it has many neighbouring data points. The first cluster center x_{c1} is chosen as the point having the largest density value P_{c1}. Then the density measure of each data point x_i is revised as follows:

$$P_k' = P_k - P_{c1} \exp\left(-\beta \left\| x_k - x_{c1} \right\|^2\right) \tag{2}$$

where $\beta = \frac{\gamma}{(r_b)^2}$, $r_b = r_a\eta$ and r_b is a positive constant which defines a neighbourhood that has measurable reductions in density measure. Therefore, the data points near the first cluster center x_{c1} will have significantly reduced density measure. P_{c1} is the new potential-value data as cluster centre, β is the weight of i-data to cluster centre, η is the quash factor, usually set 1.5, r_i is the distance between cluster centre.

When the potential of all data points have been revised according to Eq.(2), the data point with highest remaining potential is selected as the second cluster center. We reduce further the potential of each data point according to their distance to the second cluster center. The process is repeated until the potential of the points reaches the stopping criterion $P_k' < \varepsilon P_{c1}$, where ε is the reject ratio, usually set 0.15.

The Takagi-Sugeno fuzzy system is an efficient method to produce a model from a given input-output data set (Tagaki and Sugeno, 1985). This model contains if-then rules and in our described approach the following fuzzy rules were used

$$R^i\text{: if } y(t\text{-}1) \text{ is } M_1^i \text{ and } u(t\text{-}1) \text{ is } M_2^i \text{ then } y(t) = p_i\, y(t-1) + q_i u(t-1) + r_i \tag{3}$$

where R^i (i = 1, ...,7) denotes the ith rule, M_j^i are fuzzy sets, y is the output, u is the input, t is the discrete time, p_i, q_i, r_i, are consequent parameters.

The symmetric Gaussian function is used for fuzzification of inputs and it depends on two parameters σ and c as it is seen in Eq.(4)

$$M_j^i(x_j | \sigma_j^i, c_j^i) = \exp\left(-\frac{(x_j - c_j^i)^2}{2(\sigma_j^i)^2} \right) \tag{4}$$

The parameters σ and c for Gaussian membership functions are listed in the Table 1 and Table 2. Rule viewer that simulates the entire fuzzy inference process is shown in Figure 2.

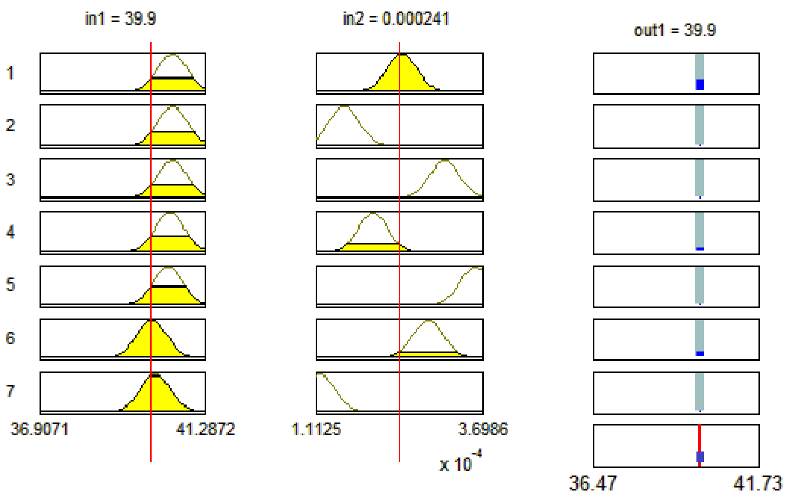

Figure 2: Fuzzy inference system

Table 1: Parameters of the Gaussian membership functions for the first input

σ_i	c_i
0.387	40.43
0.387	40.43
0.387	40.43
0.387	40.36
0.387	40.31
0.387	39.88
0.387	39.88

Table 2: Parameters of the Gaussian membership functions for the second input

σ_i	c_i
2.28×10^{-5}	2.45×10^{-4}
2.28×10^{-5}	1.55×10^{-4}
2.28×10^{-5}	3.11×10^{-4}
2.28×10^{-5}	2.00×10^{-4}
2.28×10^{-5}	3.58×10^{-4}
2.28×10^{-5}	2.86×10^{-4}
2.28×10^{-5}	1.18×10^{-4}

4. Neural network predictive control of the heat exchanger

Generally, the model predictive control problem is presented as on-line solving a finite horizon optimal control problem subject to system dynamics and constraints (Figure 3).

The nonlinear model predictive controller determines the control actions by solving an on-line optimisation problem which is minimising the following cost function

$$J(k)=\sum_{j=N_{\min}}^{N_{\max}}\left[y_p(k+j)-y_r(k+j)\right]^2+\lambda\sum_{j=1}^{N_u}\left[\Delta u(k+j-1)\right]^2 \tag{5}$$

where N_u is the control horizon, N_{min} and N_{max} are the minimum and maximum prediction horizons, y_r is the reference trajectory, y_p is the predicted controlled output, λ determines the contribution that the sum of the squares of the control increments has on the performance index, Δu is the sequence of the future control increments that have to be calculated. The cost function is minimised in order to obtain the optimum control input that is applied to the non-linear plant. The control input u may be constrained: $u_{min} \leq (k+j) \leq u_{max}$; j = 1, 2, …, N_u. The length of the control horizon N_u must satisfy following constraints: $0 < N_u \leq N_{umax}$. The value of N_{umax} should cover the important part of the step response curve. The output sequence of the optimal controller is obtained over the prediction horizon by minimising 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. 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.

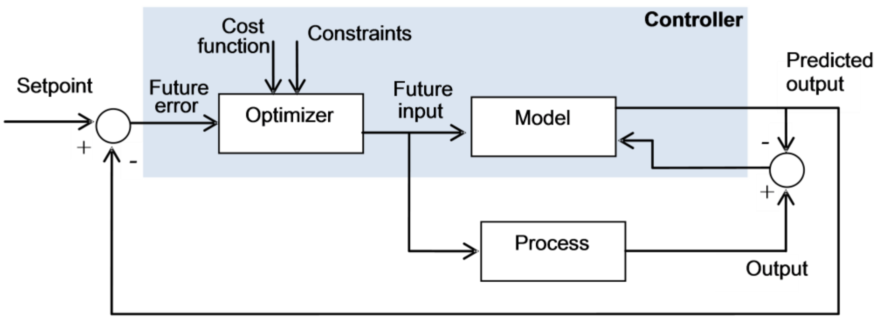

Figure 3: Model-based predictive control scheme.

The training data were obtained from the controlled process with the sampling interval 1 s. 1,200 training samples were used for the neural network training. The NN model was trained off line. The results of training are shown in Figure 4 for the training data and in Figure 5 for the validation data. The prediction error was sufficiently small and the process output and the NN model output fitted well. It is possible to state that the NN training was successful. The information and parameters for NNPC of the described heat exchanger were: the minimisation routine: *csrchbac*; the number of neurons in the hidden layer of the plant model network: 6; prediction and control horizons: N_{min} = 1, N_{max} = 13, N_u = 3; the weight coefficients in the cost function (5), $\lambda = 0.05$; the parameter for the reference trajectory calculation: $\alpha = 0.00012$; the control input constraints: $0 \leq q_{3in} \leq 3.5 \times 10^{-4}$ m^3 s^{-1}; the control output constraints: $36.6 \leq T_{1out} \leq 41$ °C.
Simulation results obtained using designed fuzzy neural network predictive control (FNNPC) in the task of set point tracking and in the task of disturbance rejection are shown in Figure 6. Disturbances were represented by petroleum flow rates changes +30 % at 150 s, -20 % at 450 s, +10 % at 750 s. The results are compared with two PID controllers (Vasičkaninová and Bakošová, 2014). The PID controller parameters obtained using the Cohen-Coon formulas are $k_p = 1.19 \times 10^{-4}$, t_i = 35.44 s, t_d = 4.55 s and those obtained using the Strejc formulas are $k_p = 4.32 \times 10^{-5}$, t_i = 48.1 s, t_d = 12.64 s (Vasičkaninová and Bakošová, 2014). The simulation results were compared also using integral criteria IAE (integrated absolute error). The results for different performance measures are compared in Table 3. The control response obtained by the FNNPC has the smallest values of IAE.

Table 3: Values of IAE

controller	IAE
FNNPC	128
Cohen-Coon PID controller	134
Strejc PID controller	248

5. Conclusions

In this paper, a fuzzy model neural network predictive control approach of a tubular heat exchanger was presented. The Takagi-Sugeno modelling methodology was used to generate a fuzzy convolution model of the heat exchanger. The neural network was used to predict the system outputs and trained on the fuzzy model by the Levenberg-Marquardt algorithm. The simulation results showed that the proposed control strategy has good set-point tracking and adequate disturbance rejection ability.

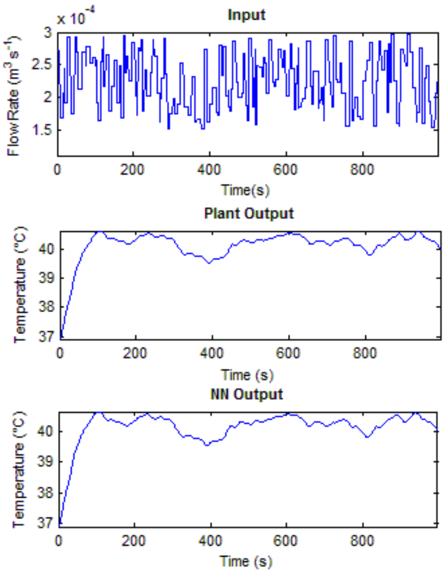

Figure 4: Training data for NN model.

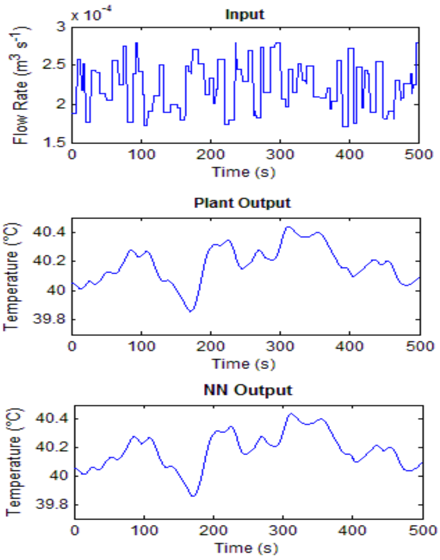

Figure 5: Validation data for NN model.

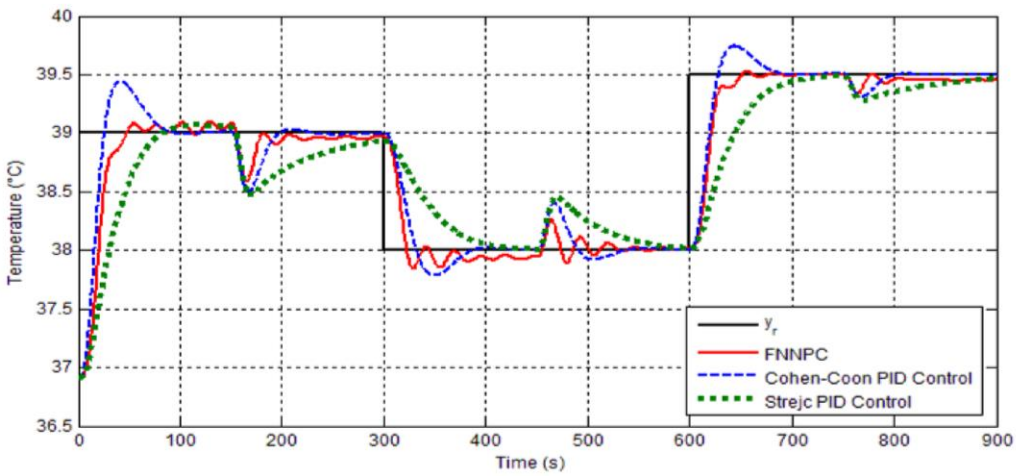

Figure 6: The outlet petroleum temperature control.

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