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Intelligent Control of Heat Exchangers

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This work deals with the design and application of a neuro-fuzzy controller for a heat exchanger. To deal with the problem of parameter adjustment, efficient neuro-fuzzy scheme known as the ANFIS (Adaptive Network-based Fuzzy Inference System) can be used. The ANFIS is a cross between an artificial neural network and a fuzzy inference system (FIS) and represents Takagi-Sugeno fuzzy model as generalized feedforward neural network, and trains it with plant I/O data, thereby adjusting the parameters of the antecedent membership functions as well as those of the functional consequents. The neuro-fuzzy control of the heat exchanger is compared with classical PID control. The simulation results confirm that fuzzy is one of the possibilities for successful control of heat exchangers. The advantage of this approach is that it is not a linear-model-based strategy. Comparison of the simulation results obtained using fuzzy and those obtained using classical PID control demonstrates the effectiveness and superiority of the proposed approach because of the smaller consumption of the heating medium.

1. Introduction

Fuzzy system has been known to provide a framework for handling uncertainties and imprecision by taking linguistic information from human experts. The universal approximation property of fuzzy systems is being widely used in many areas, in particular nonlinear modelling and complex control systems. The Takagi-Sugeno model is often used for modelling and identification of complex nonlinear systems from measured data. Sugeno and his co-workers demonstrated their identification methods on prediction of river water flow (Sugeno and Tanaka, 1991). Linguistic fuzzy modelling was used to construct a model of a human operator of a chemical plant from numerical data (Sugeno and Yasukawa, 1993). Clustering algorithms are used extensively not only to organize and categorize data, but are also useful for data compression and model construction. Data clustering is a process of putting similar data into groups. A clustering algorithm partitions a data set into several groups such that the similarity within a group is larger than among groups (Jang et al., 1997). The idea of data grouping, or clustering, is simple in its nature and is close to the human way of thinking (Duda and Hart, 1973). A more recent overview can be found in a collection of (Bezdek and Pal, 1992; Premalatha and Natarajan, 2010).
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

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complexity caused by many phenomena such as leakage, friction, temperature-dependent flow properties, contact resistance, unknown fluid properties, etc. (Chidambaram et al., 1992; Dugdale et al., 2002; Kakac 2002; Janna, 2009). Therefore, fuzzy and neuro-fuzzy controllers can be a better alternative to the PID control, although many industrial applications use PID control to maintain constant process variables.

2. Process Description

Consider a co-current tubular heat exchanger (Vasičkaninová et al., 2010), where petroleum (subscript 1) is heated by hot water (subscript 3) through a copper tube (subscript 2). The controlled variable is the outlet petroleum temperature T_{1out}. Among the input variables, the water flow rate $q_3(t)$, is selected as the control variable, whereas the other inlet variables are constant. 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 *in* denotes the inlet.

Table 1: Heat exchanger parameters and inputs

Variable	Unit	Value	Variable	Unit	Value
n		5	ρ_3	kgm^{-3}	1000
l	m	10	C_{P1}	$Jkg^{-1}K^{-1}$	2100
D_3	m	0.05	C_{P2}	$Jkg^{-1}K^{-1}$	418
D_{12}	m	0.025	C_{P3}	$Jkg^{-1}K^{-1}$	4186
D_{23}	m	0.028	q_1	m^3s^{-1}	3.7723×10^{-4}
α_{12}	$Js^{-1}m^{-2}K^{-1}$	750	q_{3in}^{s}	m^3s^{-1}	1.1111×10^{-4}
α_{23}	$Js^{-1}m^{-2}K^{-1}$	1480	T_{1in}^{s}	K	308.52
ρ_1	kgm^{-3}	810	T_{2in}^{s}	K	317.76
ρ_2	kgm^{-3}	8960	T_{3in}^{s}	K	324.82

Here, D is the tube diameter, ρ is the density, C_P is the specific heat capacity, α *is* the heat transfer coefficient, q is the volumetric flow rate.
The mathematical model of the heat exchanger is derived under several simplifying assumptions and described by three partial differential equations

$$\tau_1 \frac{\partial T_1(z,t)}{\partial t} + \tau_1 w_1 \frac{\partial T_1(z,t)}{\partial z} = -T_1(z,t) + T_2(z,t) \tag{1}$$

$$\tau_2 \frac{\partial T_2(z,t)}{\partial t} = Z_1 T_1(z,t) - T_2(z,t) + Z_2 T_3(z,t) \tag{2}$$

$$\tau_3 \frac{\partial T_3(z,t)}{\partial t} + \tau_3 w_3(t) \frac{\partial \mathrm{T}_3(z,t)}{\partial z} = \mathrm{T}_2(z,t) - \mathrm{T}_3(z,t) \tag{3}$$

where time constants τ_i, i = 1, 2, 3, liquid velocities w_1, w_3 and gains Z_1, Z_2 are calculated as follows

$$\tau_1 = \frac{D_1\rho_1C_{P1}}{4\alpha_1} \qquad \tau_2 = \frac{(D_2^2 - D_1^2)\rho_2C_{P2}}{4(D_1\alpha_1 + D_2\alpha_2)} \qquad \tau_3 = \frac{(D_3^2 - D_2^2)\rho_3C_{P3}}{4D_2\alpha_2}$$

$$Z_1 = \frac{D_1\alpha_1}{D_1\alpha_1 + D_2\alpha_2} \qquad Z_2 = \frac{D_2\alpha_2}{D_1\alpha_1 + D_2\alpha_2} \qquad w_1 = \frac{q_1}{\pi D_1^2} \qquad w_3(t) = \frac{q_3(t)}{\pi(D_3^2 - D_2^2)} \; .$$

3. Control of the Heat Exchanger

3.1 Fuzzy PID controller

The fuzzy controllers are usually based on the structure of the standard PID controller. Fuzzy PID-control has following (absolute) form:

$$u = F\left(e(t), \frac{d}{dt}e(t), \int e(\tau) \right) \tag{3}$$

Sugeno-type fuzzy inference system was generated using subtractive clustering in the form:

If e is A_i and de is B_i and $\int e$ is C_i Then $f_i = p_i\, e + q_i\, de + r_i \int e + s_i,\ i=1, \dots 3$ (4)

where e is the control error, $q_3(t)$ is the calculated control input and p_i, q_i, r_i are consequent parameters. The symmetric Gaussian function (*gaussmf* in MATLAB) is used for the fuzzification of inputs and it depends on two parameters σ and c as it is seen in (5)

$$f(x;\sigma,c) = e^{\frac{-(x-c)^2}{2\sigma^2}} \tag{5}$$

The parameters σ and c for *gaussmf* are listed in the Table 2. The consequent parameters in the control input rule (4) are listed in Table 3.

Table 2: Parameters of the Gaussian membership functions

e		de		$\int e$	
σ_i	c_i	σ_i	c_i	σ_i	c_i
0.43	-0.019	0.26	-0.0057	6.61	46.76
0.43	0.126	0.26	-0.0015	6.61	54.72
0.43	-0.078	0.26	0.0041	6.61	34.35

Table 3: Consequent parameters

p_i	q_i	r_i	s_i
3.9×10^{-4}	1.9×10^{-3}	1.2×10^{-5}	7.6×10^{-4}
4.4×10^{-6}	1.2×10^{-4}	4.2×10^{-7}	3.9×10^{-4}
5.5×10^{-4}	2.3×10^{-5}	1.8×10^{-6}	1.8×10^{-4}

3.2 PID Control of the heat exchanger

PID controllers described by the transfer function

$$C = k_p\left(1+\frac{1}{t_i s}+t_d s\right) \tag{6}$$

with k_p the proportional gain, t_i the integral time and t_d the derivative time, were tuned using Cohen-Coon and Ziegler-Nichols methods (Ogunnaike and Ray, 1994). 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

$$S = \frac{K}{(\tau s+1)^n}e^{-Ds} \tag{7}$$

The transfer function parameters are: the gain $K = 3.7\times10^4$, 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. The PID controller parameters obtained using the Cohen-Coon formulas are $k_p = 1.7\times10^{-4}$, $t_i = 32.7$ s, $t_d = 5$ s and those obtained using the Ziegler-Nichols formulas are $k_p = 1.4\times10^{-4}$, $t_i = 28.9$ s, $t_d = 7.2$ s

Simulation results obtained using designed fuzzy controller and two PID controllers are shown in Figs. 1, 2. Fig. 1 compares controlled outputs in the task of set point tracking. The set point changes from 313.15 K to 312.15 K at time 200 s and then to 313.65 K at time 400 s. The comparison of the controller outputs is shown in Fig. 2. Fig. 3 presents the simulation results of the fuzzy and PID control of the heat exchanger in the task of disturbace rejection. Disturbances were represented by inlet water temperature changes from 348.15 K to 344.15 K at time 200 s, from 344.15 K to 351.15 K at time 600 s and to 346.15 K at time 1000 s. The comparison of the controller outputs is shown in Fig. 4. The energy consumption is measured by the total amount of hot water consumed during the control process. The situation for fuzzy and PID control is presented in Figs. 5, 6 and it can be stated that the smallest energy consumption is assured using fuzzy controller. The results obtained by PID controllers are practically identical.

The control response obtained by fuzzy controller is the best one; it has the smallest overshoots and the shortest settling times. The simulation results were compared also using integral quality criteria *ise* (integrated squared error) and *iae* (integrated absolute error) (Ogunnaike and Ray, 1994). The results are compared in Table 4.

Table 4: Values of iae and ise

controller	set-point tracking		disturbance rejection	
	iae	*ise*	*iae*	*ise*
fuzzy	147	181	188	215
PID Cohen-Coon	164	214	225	232
PID Ziegler-Nichols	159	217	232	279

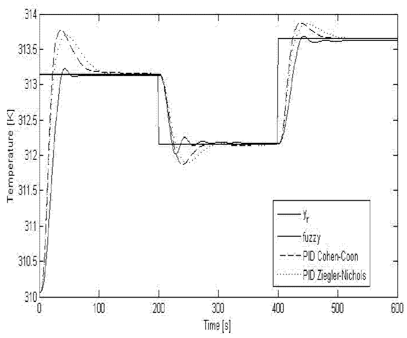

Figure 1: Comparison of the outlet petroleum temperature in the task of set point tracking: _ reference yr, - fuzzy control, -- Cohen-Coon PID controller, . . . Ziegler-Nichols PID controller.

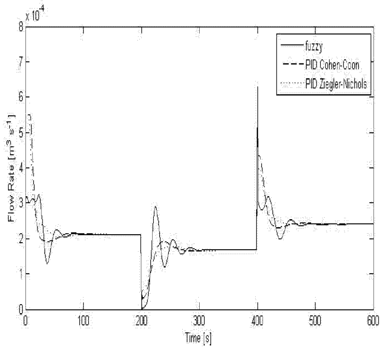

Figure 2: Comparison of the water flow rate in the task of set point tracking: - fuzzy control, -- Cohen-Coon PID controller, . . . Ziegler-Nichols PID controller.

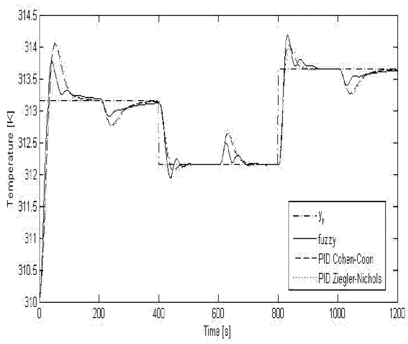

Figure 3: Comparison of the outlet petroleum temperature in the task of disturbance rejection.

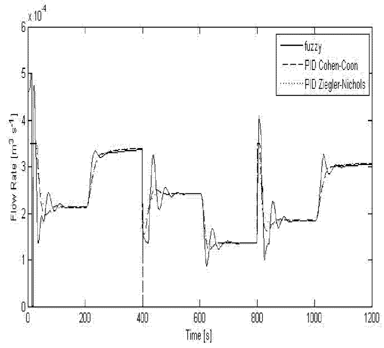

Figure 4: Comparison of the water flow rate in the task of disturbance rejection.

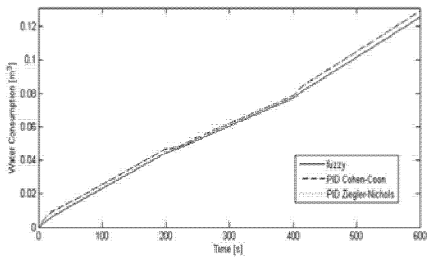

Figure 5: Hot water consumption in the task of set point tracking.

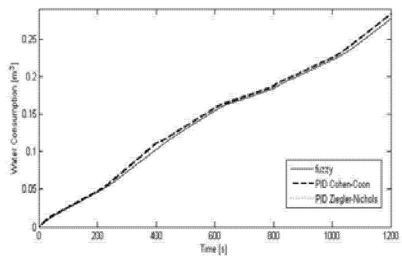

Figure 6: Hot water consumption in the task of disturbance rejection.

4. Conclusion

In this paper, an application of a fuzzy control to a heat exchanger is presented. The simulation results confirm that fuzzy control is one of the possibilities for successful control of heat exchangers. The advantage of this approach is that it is not a linear-model-based strategy. Comparison to classical PID control demonstrates the superiority of the proposed fuzzy control especially in the case, when the controlled process is affected by disturbances.

Acknowledgments

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