Open Access Journal

Journal of Power Technologies 92 (3) (2012) 192–200

journal homepage:papers.itc.pw.edu.pl

Optimal Intelligent Control for HVAC Systems

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Abstract

In this paper a novel Optimal Fuzzy Proportional-Integral-Derivative Controller (OFPIDC) is designed for controlling the air supply pressure of a Heating, Ventilation and Air-Conditioning (HVAC) system. The parameters of input membership functions and first order Sugeno output polynomial functions, along with PID controller coefficients are optimized simultaneously through random inertia weight Particle Swarm Optimization (RNW-PSO). Simulation results prove that the proposed controller performs better than a similar non-optimal fuzzy controller.

Keywords: HVAC Systems, Sugeno-Type Fuzzy Inference, Fuzzy Proportional-Integral-Derivative Controller (OFPIDC), random inertia weight Particle Swarm Optimization (RNW-PSO)

1. Introduction

Heating, Ventilating and Air-Conditioning (HVAC) mechanisms are used to control environmental variables including: temperature, moisture and pressure. As with other industrial uses, most of the processes associated with HVAC are controlled by PID controllers. The prevalent PID controllers are extensively applied because of their easy calculations, easy application, appropriate robustness, high dependability, stabilizing and zero persistent state error. However, the HVAC mechanism is a non-linear and time variant mechanism. It is hard to access favorable tracking control efficiency because automatic tuning and self-adapting adjustment of parameters are a perennial issue with PID controllers. During recent decades various methods for identifying PID controller parameters have been presented. In some techniques the open loop response information of system is used, for instance the Cohen-Coon reaction curve procedure [1].

In recent years, researchers have extensively used the fuzzy logic for modeling, identification, and control of highly nonlinear dynamic systems [2–5]. In [6–13], different combination of control methods are suggested to improve the efficiency of fuzzy PI or PID controllers. The adjustment process of PID controller coefficients can be difficult, time-consuming and costly [14, 15]. Usually a proficient gainer attempts to control the process by adjusting the coefficients of controller according to error and change rate of error in order to achieve the optimal response. In this paper the optimal adjustment is obtained by

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random inertia weight Particle Swarm Optimization (RNW-PSO).

In the HVAC mechanism the supply air pressure is tuned by changing the speed of a supply air fan. The relationship between fan speed and pressure of air source can be expressed by a delayed second order transfer function as described by Bi and Cai [16]. Since in various operating conditions both fans and dampers show non-linear behavior, even a well-regulated controller is unable to meet design requirements due to the existing uncertainties in parameters of the system.

Motivated by the aforementioned research, the goal of this paper is to present a novel optimal fuzzy Sugeno-type Proportional Integral Derivative (PID) controller for regulating the air supply pressure of a Heating, Ventilating and Air-Conditioning (HVAC) system. The parameters of input membership functions, first-order Sugeno output polynomial functions, and PID controller coefficients are optimized simultaneously through random inertia weight Particle Swarm Optimization (RNW-PSO).

Simulation results indicate that the new optimal fuzzy-PID controller enjoys faster response, smaller overshoot and higher accuracy than PID, ANF, and STFPIC under the normal condition and in the presence of uncertainties in parameters of the model.

2. Sugeno Type Fuzzy Inference

In this section the Sugeno method of deductive inference for fuzzy systems based on linguistic rules is introduced. The Sugeno procedure was proposed in an endeavor to expand a systematic method for producing fuzzy rules from a certain input-output data collection. A generic rule in a Sugeno model, which has two—inputs x and y, and output z, is as follows:

IF x is A and y is B, THEN z is $z = f(x, y)$

Where $z = f(x, y)$ is a crisp function. Usually $f(x, y)$ is a polynomial function of the inputs x and y. However, in general it can be any public function characterizing the output of the system inside the fuzzy area.

When $f(x, y)$ is a constant the inference system is known as a zero-order Sugeno model.

It is a particular case of the Mamdani system in which each rule's resultant is determined as a fuzzy singleton. When $f(x, y)$ is a linear function of x and y, the inference system is known as a first-order Sugeno model, which was used in article [17]. In [17] it was indicated that the output of a zero-order Sugeno model is a flat function of its input variables until the neighbor membership functions in the antecedent have adequate overlap.

By contrast, the overlap of the membership functions in the consequent of a Mamdani model does not have a decisive effect on the smoothness; it is the overlap of the antecedent membership functions that determines the smoothness of the resulting system behavior. In a Sugeno model each rule has a crisp output presented by a function; for this reason the total output is gained via a weighted average defuzzification (Eq. 1). This procedure eschews the time consuming methods of defuzzification needed in the Mamdani model. The weighted average method is one of the most popular methods used in fuzzy applications as it is a very effective method in terms of calculation. The algebraic expression is as follows:

$$Z^* = \frac{\mu c(z) \cdot z}{\mu c(z)} \tag{1}$$

Where Σ represents the algebraic sum while z is the centroid of each symmetric membership function. In the design procedure of such a controller two input linguistic variables are used, namely error (e) as X and its rate of change ($\dot{e}$) as Y. Increasing or decreasing the control signal is assumed as output linguistic variable (U). In order to form fuzzy $If - Then$ Rules 3 Gaussian membership functions are considered for input linguistic variables (X) and (Y), respectively. The general shape of input membership functions are as follows:

$$\mu(z) = \exp\left(\frac{(z \cdot c)^2}{2\sigma}\right) \tag{2}$$

Where c is the mean and σ is the variance of each membership function. The parameter z is the crisp input amount which has to be fuzzified and $\mu(z)$ is its membership function degree with a numerical value in the interval $[0, 1]$. Also nine output polynomial functions are defined for first-order Sugeno type fuzzy inference.

Applying inputs' membership functions and output polynomial functions will result in a rule-base which is composed of 9 rules:

R_1 : IF X is Negative and Y is Negative THEN, $U_1 = p_1 x + q_1 y + r_1$

R_2 : IF X is Negative and Y is Zero THEN, $U_2 = p_2 x + q_2 y + r_2$

R_3 : IF X is Negative and Y is Positive THEN, $U_3 = p_3 x + q_3 y + r_3$

R_4 : IF X is Zero and Y is Negative THEN, $U_4 = p_4 x + q_4 y + r_4$

R_5 : IF X is Zero and Y is Zero THEN, $U_5 = p_5 x + q_5 y + r_5$

R_6 : IF X is Zero and Y is Positive THEN, $U_6 = p_6 x + q_6 y + r_6$

R_7 : IF X is Positive and Y is Negative THEN, $U_7 = p_7 x + q_7 y + r_7$

R_8 : IF X is Positive and Y is Zero THEN, $U_8 = p_8 x + q_8 y + r_8$

R_9 : IF X is Positive and Y is Positive THEN, $U_9 = p_9 x + q_9 y + r_9$

As shown in Fig. 1, the above nine IF-THEN rules are combined together in the form of first-order Sugeno model.

3. Particle Swarm Optimization

The PSO algorithm is a partly new population-based heuristic optimization method which is based on a metaphor of social interaction, specifically bird flocking. The main benefits of PSO are: 1) The cost function's gradient is not needed, 2) PSO is more compatible and robust than other classical optimization techniques, 3) PSO guarantees convergence to the optimum solution, and 4) compared with GA, PSO takes less time for each function evaluation as it does not apply many GA operators such as mutation, crossover and selection operator.

In PSO, any nominee solution is named "Particle". Each particle in the swarm demonstrates a nominee solution to the optimization problem and if the solution is composed of a series of variables, the particle can be a vector of variables. In PSO, each particle is flown through the multidimensional search space regulating its position based on its momentum and both personal and global histories. Then the particle uses the best position faced by itself and that of its neighborhood to position itself toward an optimal solution. The appropriateness of each particle can be assessed based on the cost function of optimization problem. At each repetition, the speed of every particle will be computed as follows:

$$v_i(t+1) = \omega v_i(t) + c_1 r_i (P_{id} - x_i(t)) + c_2 r_2 \left(P_{gd} - x_i(t)\right) \tag{3}$$

Where $x_i(t)$ is the present position of the particle, p_{id} is one of the finest solutions this particle has achieved and p_{gd} is one of the finest solutions all the particles have achieved. Finally, r_1 and r_2 are two random numbers in the range $[0, 1]$. Having computed the speed, the new position of each particle will be computed as follows

$$x_i(t+1) = x_i(t) + v_i(t+1) \tag{4}$$

The PSO algorithm is replicated using Eqs. 3 and 4, which will be updated at each repetition until the pre-defined number of generations is achieved.

Although Standard PSO (SPSO) includes some significant improvements by providing a high rate of convergence in particular problems, it does demonstrate some deficiencies. It is shown that SPSO has a weak capability to look for a fine particle due to the lack of a speed control mechanism. Most of the procedures were tried in an attempt to ameliorate the efficiency of SPSO through applying changeable inertia weight. The inertia weight is essential for the efficiency of PSO, which equilibrates global exploration and local exploitation capabilities of the swarm. A large inertia weight simplifies exploration, but it prolongs the convergence of the particle. However, a small inertia weight leads to rapid convergence, but it sometimes results in a local optimum.

Therefore, different inertia weight conformity algorithms have been recommended in the literature [18]. In 2003 Zhang [19] studied the effect of random inertia weight on PSO (RNW-PSO), presenting empirical results which proved its superior efficiency compared to LDW-PSO [20]. Eberhart and Shi [21] recommended a random inertia weight factor for tracking dynamic systems. In this improvement, the inertia weight factor was set to change randomly based on the following equation:

$$\omega = 0.5 + \frac{Rand}{2} \tag{5}$$

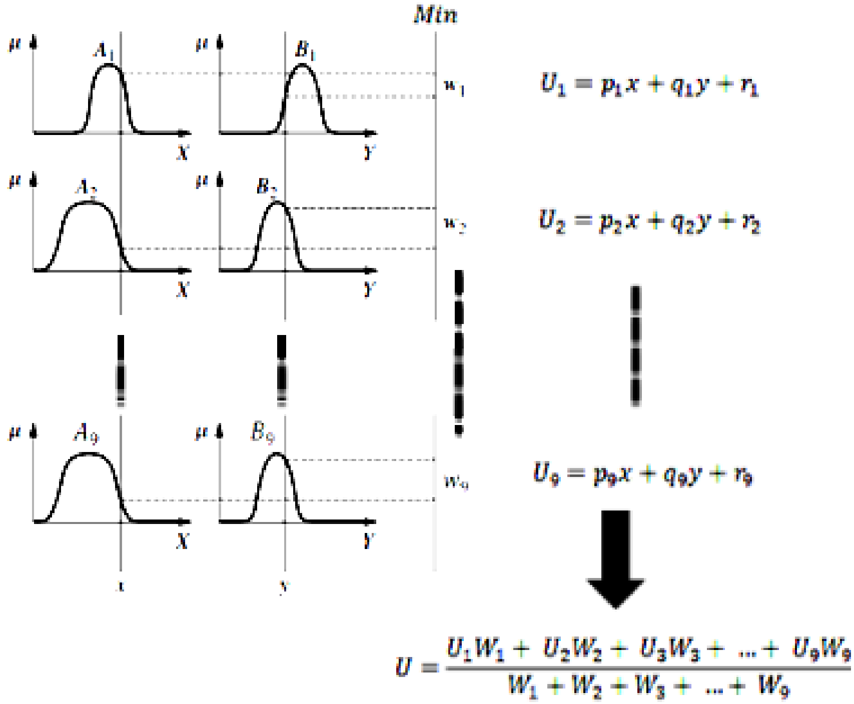

Figure 1: The Sugeno fuzzy model

Table 1: The used parameters of RNW-PSO

Parameter	Value
Size of the Swarm	50
Dimension of Problem	38
Maximum Number of iterations	100
Cognitive Parameter C_1	1
Social Parameter C_2	1
Constriction Factor C	1

where *rand* was a uniformly distributed random number inside the interval $[0, 1]$. Before proceeding with the optimization operations, a performance criterion should be first defined.

Generally, a heuristic algorithm like PSO only requires the cost function to be checked for guidance of its search. It no longer requires information about the system. So, in this paper, the Least Mean Square (LMS) of error is applied. The parameters of RNW-PSO are also listed in Table 1.

4. The Proposed Control Method

The general scheme of the proposed controller is shown in Fig. 2. The two inputs of the controller are the error e and the change rate of error $\dot{e}$, respectively and the output of the controller is U. The main shortage of the optimal fuzzy-PID controller is the lack of systematic approaches to define fuzzy rules and fuzzy membership functions. Most fuzzy rules are based on human knowledge and differ from one person to another despite the same system performance. Hence, it is naive to assume that the given expert's knowledge captured in the form of the fuzzy controller leads to optimal control. Therefore, an efficient approach for tuning membership functions and control rules without trial and error is evidently required.

Accordingly, the idea of employing RNW-PSO algorithm to achieve best rising time (t_r), settling time (t_s), % peak overshoot (M_p), steady-state error (E_{ss}) is represented [22]. In applying Gaussian membership functions three different cases arise: 1) Gaussian membership functions with the same means and variances, 2) Gaussian membership functions with the same means and variable variances, and 3) Gaus-

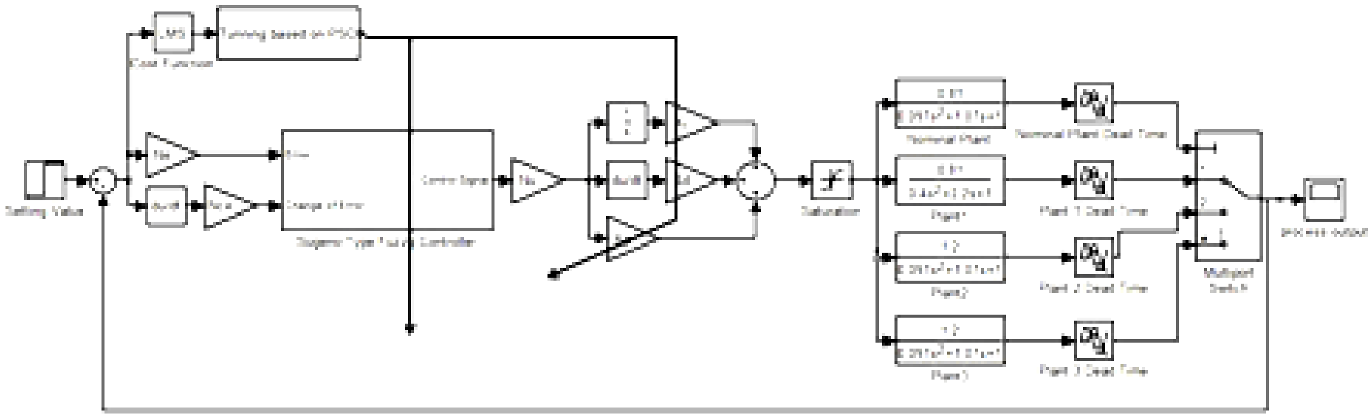

Figure 2: Optimal Fuzzy-PID controller

Table 2: Optimal parameters of Gaussian membership functions

Input variables	Membership functions	[Variance, Mean]
Error (E)	Negative	[0.6021, -1.4923]
	Zero	[0.6021, 0.0689]
	Positive	[0.6021, 0.5149]
Change of Error (CE)	Negative	[0.2936, -0.7016]
	Zero	[0.2936, 0.2458]
	Positive	[0.2936, 0.0550]

Table 3: Optimal parameters of output polynomial functions

Output polynomial functions	[q_i, p_i, r_i]
$U_1 = p_1x + q_1y + r_1$	[0.6173, 0.0588, 0.3469]
$U_2 = p_2x + q_2y + r_2$	[-0.0056, 0.0102, -0.8901]
$U_3 = p_3x + q_3y + r_3$	[-0.8860, -0.1164, 0.4295]
$U_4 = p_4x + q_4y + r_4$	[-0.4039, -0.7338, -1.1432]
$U_5 = p_5x + q_5y + r_5$	[0.5043, -0.2675, -0.1391]
$U_6 = p_6x + q_6y + r_6$	[0.2194, 0.4623, -0.9929]
$U_7 = p_7x + q_7y + r_7$	[-0.6865, 0.0261, -0.4878]
$U_8 = p_8x + q_8y + r_8$	[-0.1315, -0.4345, -0.2374]
$U_9 = p_9x + q_9y + r_9$	[0.3640, 0.2626, -1.5937]

sian membership functions with variable means and the same variances. In [23] an optimal fuzzy-PI controller is designed for a nonlinear delay differential model of glucose-insulin regulation system, and it is shown that Gaussian membership functions with variable means and the same variances have better performance in controlling this system. Therefore, the same idea is applied here.

The specifications of input and output variables are given in Tables 2 and 3, respectively. Furthermore, the optimal parameters of the PID controller are given in Table 4.

5. Simulation and Results

In the HVAC system, outside air is mixed with return air from the building. Then the mixed air (supply air) flows through the cooling coil via a filter by means of a supply air fan. In the HVAC system, the supply air pressure is tuned through the speed of a supply air fan. Increasing the fan speed will increase the supply air pressure, and vice versa. Variations of supply air pressure directly affect the temperature.

Table 4: Optimal parameters of PID controller

Parameter	Value
Proportional Gain (K_p)	1.1814
Derivative Gain (K_d)	0.0473
Integral Gain (K_i)	1.5056

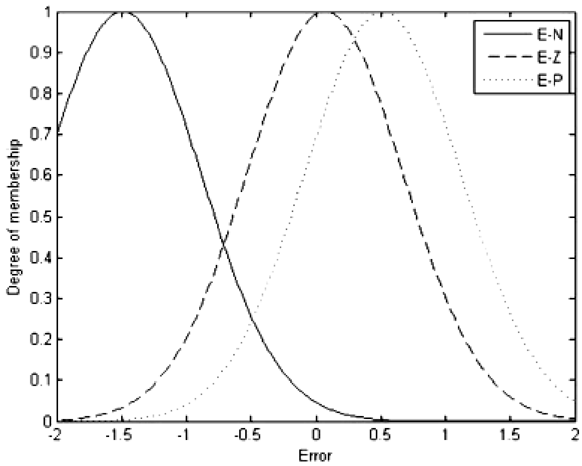

Figure 3: Obtained membership functions of input 1

MATLAB software is used to simulate the proposed controller. The transfer function of the supply air pressure loop under normal circumstances is as follows:

$$G(s) = \frac{0.81e^{-2s}}{(0.97s + 1)(0.1s + 1)} \tag{6}$$

where gain $(K) = 0.81$, $\tau_1 = 0.97$, $\tau_2 = 0.1$ and dead time $(\delta) = 2\,sec$. For this process weighting parameters are defined as $N_e = 0.9$, $N_{\dot{e}} = 5$ and $N_u = 2.5$. It should be mentioned that τ_1 and τ_2 are the time parameters of the transfer function of the supply air pressure loop. Input membership functions of the optimal fuzzy-PID controller, namely error (Input 1) and change of error (Input 2), are shown in Fig. 3 and 4, respectively. These Figs. show that RNW-PSO improved the logical sequence of membership functions. For instance, about input 2 the membership function CE-P comes before CE-Z.

This issue leads to a nonlinear control operation surface as demonstrated in Fig. 5.

In order to evaluate the controller performance against the existing uncertainties in parameters of the nominal model three different transfer functions

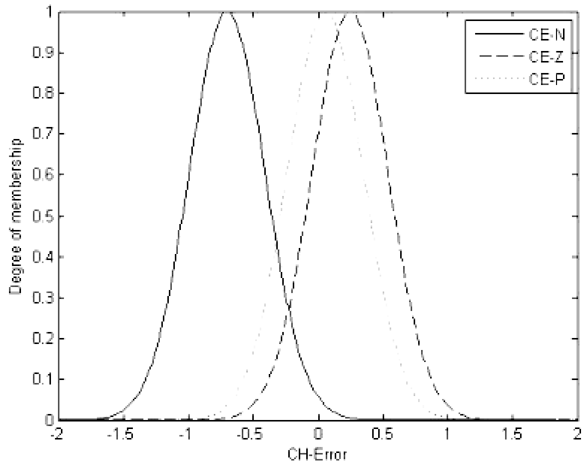

Figure 4: Obtained membership functions of input 2

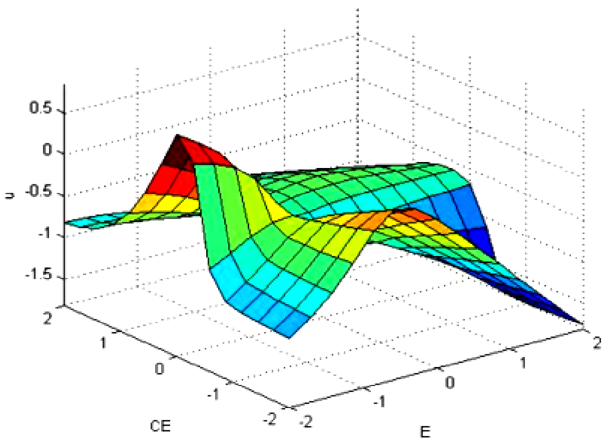

Figure 5: Control Surface

were introduced. To investigate this issue the applied transfer functions in [24] are used.

1. when gain $(K) = 0.81$, $\tau_1 = 0.2$, $\tau_2 = 2$ and dead time $(\delta) = 2\,sec.$, then the transfer function of the supply air pressure loop is as follows:

$$G(s) = \frac{0.81e^{-2s}}{(0.2s + 1)(2s + 1)} \tag{7}$$

For this process weighting parameters are defined as $N_e = 0.9$, $N_{\dot{e}} = 15$ and $N_u = 0.3$.

2. when gain $(K) = 1.2$, $\tau_1 = 0.97$, $\tau_2 = 0.1$ and dead time $(\delta) = 3\,sec.$, then the transfer function of the supply air pressure loop is as follows:

$$G(s) = \frac{1.2e^{-3s}}{(0.97s + 1)(0.1s + 1)} \tag{8}$$

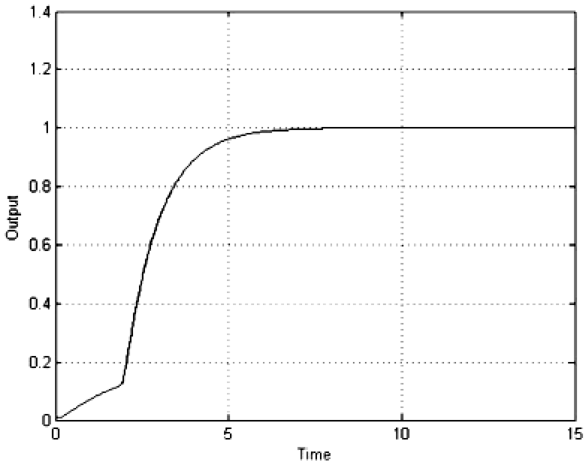

Figure 6: Performance of the transfer function: $G(s) = \frac{0.81e^{-2s}}{(0.97s+1)(0.1s+1)}$

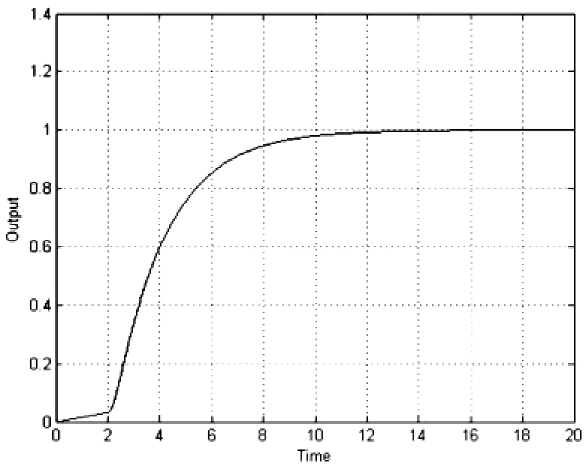

Figure 7: Performance of the transfer function: $G(s) = \frac{0.81e^{-2s}}{(0.2s+1)(2s+1)}$

For this process weighting parameters are defined $N_e = 0.9$, $N_{\dot{e}} = 3$ and $N_u = 1$.

3. when gain $(K) = 1.2$, $\tau_1 = 0.97$, $\tau_2 = 0.1$ and dead time $(\delta) = 4$ *sec*., then the transfer function of the supply air pressure loop is as follows:

$$G(s) = \frac{1.2e^{-4s}}{(0.97s+1)(0.1s+1)} \tag{9}$$

For this process weighting parameters are defined as $N_e = 0.9$, $N_{\dot{e}} = 3$ and $N_u = 1$.

In Figs. 6–9 and Table 5 we can see that the supply air pressure loop of HVAC acts satisfactorily under nominal transfer function and existing uncertainties

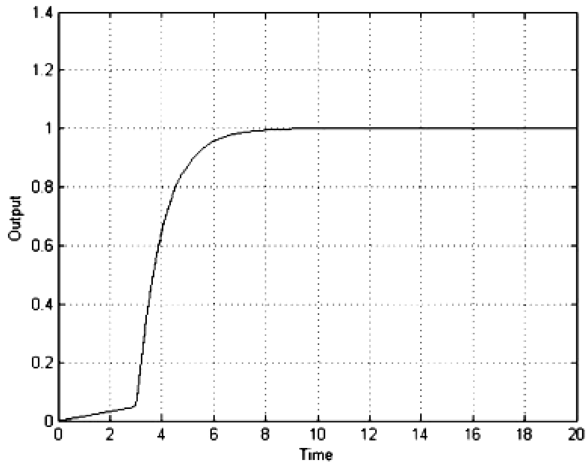

Figure 8: Performance of the transfer function: $G(s) = \frac{1.2e^{-3s}}{(0.97s+1)(0.1s+1)}$

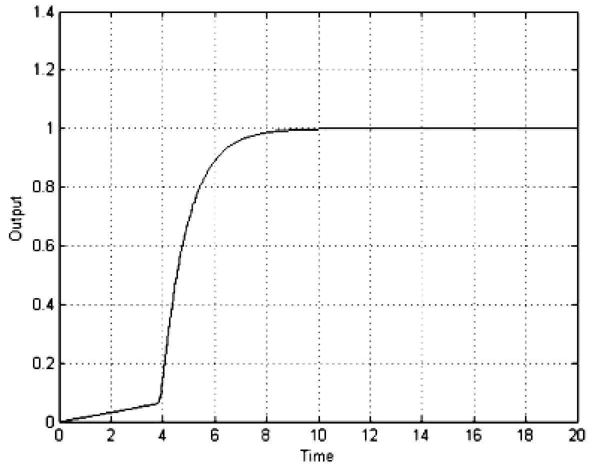

Figure 9: Performance of the transfer function: $G(s) = \frac{1.2e^{-4s}}{(0.97s+1)(0.1s+1)}$

in parameters of the model. Table 6 implies that both the rise time and settling time are highly appropriate. Peak overshoots are also insignificant when the Optimal Fuzzy-PID Controller (OFPIDC) is applied.

Furthermore, the proposed controller in this paper is much less complicated than the existing non-optimal fuzzy controller in [18]. The proposed controller in this paper has only 9 rules, whereas with these limited rules the design requirements are satisfied. But in [18] in order to achieve satisfactory results 49 rules are defined. This fact proves the superiority of the proposed controller in this paper over the controller proposed in [18].

Table 5: Performance analysis of OFPIDC for different HVAC-Supply Air Pressure Loop

Transfer Function of the Supply Air Pressure Loop	Rise Time t_r, sec.	Settling Time t_s, sec.	Peak Overshoot M_p, %	Steady State Error E_{ss}, %
$G(s) = \frac{0.81e^{-2s}}{(0.97s+1)(0.1s+1)}$	2.58	4.74	0.00	0.12
$G(s) = \frac{0.81e^{-2s}}{(0.2s+1)(2s+1)}$	4.44	8.17	0.00	0.01
$G(s) = \frac{1.2e^{-3s}}{(0.97s+1)(0.1s+1)}$	2.16	5.88	0.00	0.08
$G(s) = \frac{1.2e^{-4s}}{(0.97s+1)(0.1s+1)}$	2.26	6.75	0.00	0.06

Table 6: Comparison between performance of PID, ANF, STFPIC and OFPIDC under the normal condition and under existing uncertainties in parameters of model

Transfer Function of the Supply Air Pressure Loop	Controller Type	Peak Overshoot M_p, %	Settling Time t_s, sec.
$G(s) = \frac{0.81e^{-2s}}{(0.97s+1)(0.1s+1)}$	PID	3.9	6.7
	ANF	3.5	7.5
	STFPIC	0.00	3.6
	OFPIDC	0.00	4.74
$G(s) = \frac{0.81e^{-2s}}{(0.2s+1)(2s+1)}$	PID	17.9	16.2
	ANF	0.9	10.6
	STFPIC	0.088	8.9
	OFPIDC	0.00	8.17
$G(s) = \frac{1.2e^{-3s}}{(0.97s+1)(0.1s+1)}$	PID	63	37
	ANF	56	19
	STFPIC	17.6	6
	OFPIDC	0.00	5.88
$G(s) = \frac{1.2e^{-4s}}{(0.97s+1)(0.1s+1)}$	PID	100	120
	ANF	59	32
	STFPIC	25	6.9
	OFPIDC	0.00	6.75

6. Summary/Conclusions

In this paper an optimal fuzzy-PID controller was suggested for the supply air pressure control loop of a Heating, Ventilation and Air-Conditioning (HVAC) system. Simulation results indicated that the optimal fuzzy-PID controller enjoyed faster response, smaller overshoot and higher accuracy compared with PID, Adaptive Neuro Fuzzy (ANF) method and Self-Tuning Fuzzy PI Controller (STFPIC) under the normal condition and in the presence of uncertainties in parameters of the model. The new optimal fuzzy-PID controller can be extensively applied in the HVAC industry.

References

[1] Z. Radakovic, V. Milosevic, S. Radakovic, Application of temperature fuzzy controller in an indirect resistance furnace, Applied Energy 73 (2002) 167–182.

[2] H. Nguyen, N. Prasad, C. Walker, E. Walker, A First Course in Fuzzy and Neural Control, Chapman & Hall/ CRC, USA, 2003.

[3] M. Komareji, J. Stoustrup, H. Rasmussen, N. Bidstrup, P. Svendsen, F. Nielsen, Optimal set-point synthesis in hvac systems, in: American Control Conference, New York, NY, 2007, pp. 5076–5081.

[4] N. Bidstrup, P. Svendsen, F. Nielsen, Optimal model-based control in hvac systems, in: American Control Conference, Seattle, WA, 2008.

[5] M. M. Haghighi, Modeling and optimal control algorithm design for hvac systems in energy efficient buildings, Master's thesis, EECS Department, University of California, Berkeley (February 2011).

[6] W. Z. Qiao, M. Mizumoto, Pid type fuzzy controller and parameters adaptive method, Fuzzy sets and systems 78 (1996) 23–35.

[7] W. Pedrycz, J. de Oliveira, Optimization of fuzzy models, IEEE Trans. Syst., Man, Cyber. 26 (4) (1996) 627–636.

[8] C. Hyun-Joon, C. Kwang-Bo, W. Bo-Hyeun, Fuzzy-pid hybrid control: automatic rule generation using genetic algorithm, Fuzzy sets and systems 92 (3) (1997) 305–316.

[9] R. Alcala, J. Casillas, O. Cordon, A. Gonzalez, F. Herrera, A genetic rule weighting and selection process for fuzzy control of heating, ventilation and air conditioning systems, Engineering application of Artificial Intelligence 28 (2005) 279–296.

[10] X. Qiang, C. Wen-Jian, H. Ming, A practical decentralized pid auto-tuning method for tito systems under closed–loop control, International Journal of Innovative Computing, Information and Control 2 (2) (2006) 305–322.

[11] Rishel, B. James, Control of variable speed pumps for hvac water systems, in: ASHRAE Winter meeting, 2003.

[12] B. Arguello-Serrano, M. Velez-Reyes, Nonlinear control of a heating, ventilating, and air conditioning system with thermal load estimation, Control Systems Technology, IEEE Transactions on 7 (1) (1999) 56–63.

[13] S. Larsen, C. Filippin, G. Lesino, Thermal behavior of building walls in summer: Comparison of available analytical methods and experimental results for a case study, In Building Simulation 2 (2009) 3–18.

[14] W. Qing-Gao, H. Chang-Chieh, Z. Yong, B. Qiang, Multivariable controller auto-tuning with its application in hvac systems, in: Proc. of the American Control Conf., Vol. 6, 1999, pp. 4353–4357.

[15] R. Mudi, N. Pal, A robust self-tuning scheme for pi and pd type fuzzy controllers, IEEE trans. on fuzzy sys. 7 (1) (1997) 2–16.

[16] Q. Bi, W. Cai, Q. Wang, C. Hang, E. Lee, Y. Sun, K. Liu, Y. Zhang, B. Zou, Advanced controller auto-tuning and its application in hvac systems, Control Engineering Practice 8 (6) (2000) 633–644.

[17] J. Jang, C. Sun, E. Mizutani, Neuro-Fuzzy and Soft Computing: A Computational Approach to Learning and Machine Intelligence, 1st Edition, Prentice Hall, 1997.

[18] H. Modares, A. Alfi, M. N. Sistani, Parameter estimation of bilinear systems based on an adaptive particle swarm optimization, Eng. Appl. Artifi. Intell. 23 (2010) 1105–1111.

[19] L. Zhang, H. Yu, S. Hu, A new approach to improve particle swarm optimization, in: Proc. of the international conf. on Genetic and evolutionary computation, 2003, pp. 134–139.

[20] Y. Shi, R. Eberhart, A modified particle swarm optimizer, in: Proc. of the IEEE Conf. On Evolutionary Computation, Singapore, 1998, pp. 69–73.

[21] R. Eberhart, Y. Shi, Tracking and optimizing dynamic systems with particle swarms, in: Proc. IEEE Congr. Evolutionary Computation, Seoul, Korea, 2001, pp. 94–97.

[22] W. Jian, C. Wenjian, Development of an adaptive neuro-fuzzy method for supply air pressure control in HVAC system, Syst., Man, Cybern., IEEE, 2000.

[23] M. Al-Fandi, M. Jaradat, Y. Sardahi, Optimal pi-fuzzy logic controller of glucose concentration using genetic algorithm, International Journal of Knowledge-based and Intelligent Engineering Systems 15 (2011) 99–117.

[24] A. Pal, R. Mudi, Self-tuning fuzzy pi controller and its application to hvac systems, IJCC 6 (1) (2008) 25–30.