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Genetic Algorithm Based Optimization of Fuzzy Controllers Tuning in Level Control

Snejana Yordanova, Aneliya Georgieva

The control of level of liquids in boilers, evaporators, reactors, etc., is especially important as related to energy balance. The plant is nonlinear, inertial, with model uncertainty and difficult to model and control employing classical methods. Fuzzy logic controllers (FLCs) offer an intelligent solution to the control of such plants achieving in a unified and simple way system stability, robustness and good performance. The aim of this research is to develop a procedure for optimization of the tuning of PI and PID FLCs as well as linear controllers using genetic algorithms (GAs) and to prove by comparison the improvement of the systems performance. The main results are: 1) a method for off-line multi-criteria optimization of the tuning parameters of FLCs and linear controllers with a proposed fitness function based on integral squared relative error and control action and an estimate of the maximal overshoot during the step responses in various operation points, evaluated via control system simulations; 2) application of the method for level control and 3) performance assessment of the designed systems via simulation.

Оптимизация на настройката на размити регулатори при управление на ниво чрез генетични алгоритми (Снежана Йорданова, Анелия Георгиева). *Регулирането на ниво на течности в котли, изпарители, реактори и др., е актуална задача, свързана с енергийния баланс. Обектът е нелинеен, инерционен, с моделна неопределеност и трудно се моделира и управлява с класически методи. Размитите регулатори (РРи) предлагат интелигентно решение за управление на такива обекти като осигуряват по унифициран и несложен начин устойчивост, робастност и добри показатели на системата. Цел на настоящото изследване е да се разработи процедура за оптимизация на настройката на ПИ и ПИД РРи, както и на линейни регулатори на основа на генетични алгоритми (ГА) и да се покаже подобряване на показателите на системата. Основните резултати са: 1) метод за оф-лайн многокритериална оптимизация на параметрите за настройка на РР и линейни регулатори с предложен функционал на основа на интеграли от квадрата на относителните грешка и управляващо въздействие и оценка на максималното пререгулиране в преходните процеси в различни работни точки, получени при симулация на системата; 2)приложение на метода за управление на ниво и 3) оценка на показателите на синтезираните системи чрез симулация.*

Introduction and State of the Art

Level control is important in many installations – boilers, evaporators, reactors, etc., as it is closely related to energy balance. The plant is nonlinear, inertial, with model uncertainty and difficult to model and control by employing classical control approaches. The linear controller design is based on a linear plant model and ensures a good system performance only in a close area around the operating point for which the plant model is derived. The existing enhancements to the linear controllers such as dead zone for damping oscillations due to discretisation and noise effects, anti-wind-up circuitry for integration, etc., introduce nonlinearity and complicate the controller tuning. The nonlinear controllers on the other side are richer in facilities but have complicated and unique for each nonlinear plant design, based also on a plant model, computationally heavy and cause system stability problems. Therefore, the popularity of fuzzy logic controllers (FLCs) as a specific class of nonlinear controllers grows now-a-days. The reason is the FLC simplicity in structure and design, the universal design approach, which is independent of plant type (presence of nonlinearity, or inertia, or time delay, etc.), demands no plant model and ensures system stability, robustness and good performance by simple means [1]. A FLC for level control by changing the pump flowrate on the basis of Takagi-Sugeno (T-S) plant model is designed in [2]. It is built on the principle of parallel distributed compensation (PDC) of the local linear plants. In [3-7] are suggested FLCs for level control using two (system error and rate of error) or three (level, flowrate and pressure) input variables and one (valve opening) or three (valve opening, fuel and steam flowrate) output variables.

The tuning of the FLC concludes in adjustment of the scaling factors (SFs), the membership functions (MFs) and the fuzzy rules. Most commonly the SCs are tuned as by this simple technique an adaptive FLC's resolution is achieved which is equivalent to changes of the MFs and the fired rules [8]. Next by GA tuning a reduction of the number of rules is often aimed at. There is a variety of approaches for designing of FLCs and tuning of their parameters. In [9] a frequency domain design method on the basis of the Popov stability criterion modified with Morari robustness condition is developed and illustrated on various suggested structures of PI/PID FLCs. In [9, 10] the tuning of the FLC parameters is based on a designed supervisory FLC for nonlinear multi-criteria on-line optimisation of selected performance measures. An effective and simple approach to reach desired system performance and robustness is by employing optimisation techniques. Among the diverse optimisation methods the genetic algorithms (GAs) seem most suitable for off-line FLC tuning. The GAs tackle multi-criteria optimisation with respect to a great amount of parameters when a global minimum is searched for multimodal and nonlinear functionals under different restrictions as GAs are non-gradient stochastic methods. The most frequently used criteria are minimisation of integral squared error (ISE) without and with restriction to the control action or relative ISE, or minimisation of other performance indices such as settling time t_s, overshoot σ, etc., and their combinations. The optimisation is carried out off-line on the basis of simulations using a plant model. If not available analytically, the nonlinear plant model can be derived by GA minimisation of a function of the error between collected experimental plant output data and the output of an accepted plant model with respect to model parameters. There are various applications of GAs for the design of linear controllers and FLCs. In [11] GA is applied for tuning of linear PID controllers. The tuning by GA of a linear PID for level control in connected tanks is described in [12/6]. The GA tuned PID system outperforms the ordinary tuned PID system. In [6] GA is used for reduction of the number of rules in the design of a FLC for the level control in a boiler. Simulations and a comparison with a linear PID controlled system prove a decrease of overshoot and settling time. Tuning of 39 parameters of the MFs and the fuzzy rules of a FLC for the control of the liquid level in a tank on the basis of GA and artificial neural networks is suggested and tested in real time control in [13]. The performance of the closed loop FLC system has been improved by a decrease of t_s and σ. A PID FLC has been designed in [14, 15]. Reduction of the number of rules and optimisation of the parameters of the MFs are reached by application of GA technique with several fitness functions and combinations of them. Simulations show decreased t_s and σ of the system response and also smooth control and reduction of energy consumption when compared to linear PID system or PID FLC system designed empirically. GAs find application in fuzzy model predictive control design in [16/10].

The aim of the present work is to optimise via GA the parameters of the pre- and post-processing units of PI/PID FLCs with widely distributed structure - with system error and derivative-of-error as inputs and integral and proportional-plus-integral (PI) post-processing respectively and the parameters of linear PI/PID controllers, designed for level control, and to compare the performances of the closed loop systems via simulation investigations in Simulink-MATLAB™ environment. The plant is based on a laboratory level control system.

Preliminary Investigation and Problem Formulation

The laboratory system for level control of the liquid in a tank is shown in Fig.1. The tank inflow is ensured by a DC pump. The inflow flowrate Q_1 is proportional to the voltage U=[0-10]V that feeds the pump. The outflow is free as result of the hydrostatic pressure. The generalised plant has input U and controlled output variable – the liquid level H at the output of the Simulink voltage-to-level converter of the output of the couple level sensor [0-0.5]m - transmitter [2-10]V. The simplified plant model differential equation is derived on the basis of the material balance in the following form [17]:

$$\frac{dH}{dt}=\frac{1}{A}(Q_1 - S\sqrt{2gH}), \qquad (1)$$

where A is the tank cross-sectional area, S – the valve opening diameter, g - the gravity acceleration. with nominal values A = 225.10 $^{-4}$m², S=0,1.10 $^{-4}$m², Q_1=1,56 l/h for U=1, V.

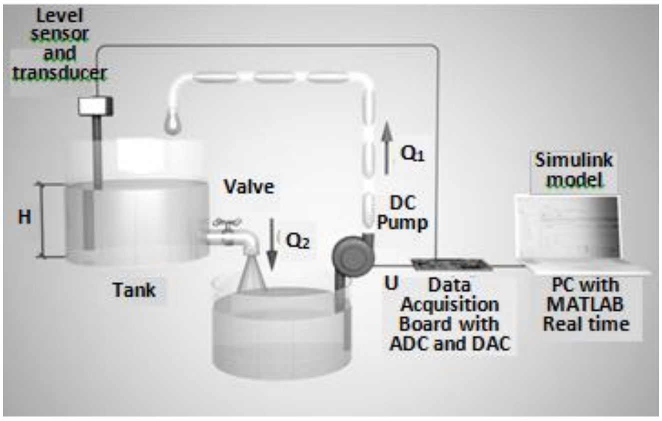


Fig.1. Laboratory level control system

The Simulink model for identification of the plant is shown in Fig.2.

The simulated step responses are depicted in Fig.3. The graphically obtained parameters of the Ziegler-Nichols model – $W(s)=\frac{K_e^{-\tau s}}{Ts+1}$ in the separate operating points are different and this confirms the nonlinearity of the plant and justifies the selection of nonlinear FLC. The mean and the worst with respect to the closed loop system stability parameters are denoted with subscript "mean" and "w" respectively and are used for the initial tuning of the linear PI/PID controllers.

The PI FLC and PID FLC are Mamdani controllers and are shown in Fig.4. They both use two-inputs to the Fuzzy Unit (FU) – the normalized system error $e(t)=y_r-y(t)$ – the difference between the reference y_r and the plant output $y(t)$, which in this case is the tank level $y(t)=H(t)$, and its normalized derivative $\dot{e}(t)$, computed by a first order differentiator with the transfer function $W_d(s)=K_d\frac{T_d s}{T_d s+1}$. The FU inputs and output are normalized in the range [-1, 1] by the scaling factors K_e, K_{de} (included in the differentiator's gain) and the output is denormalised by K_{du} (included in the post- processing gain). The post-processing for PI FLC is an integrator $W_{2PI}(s)=K_a/s$ and for PID FLC - a PI algorithm - $W_{2PI}D(s)=K_p(1+1/T_i s)$ in order that the FLC makes an incremental PI/PID nonlinear controller:

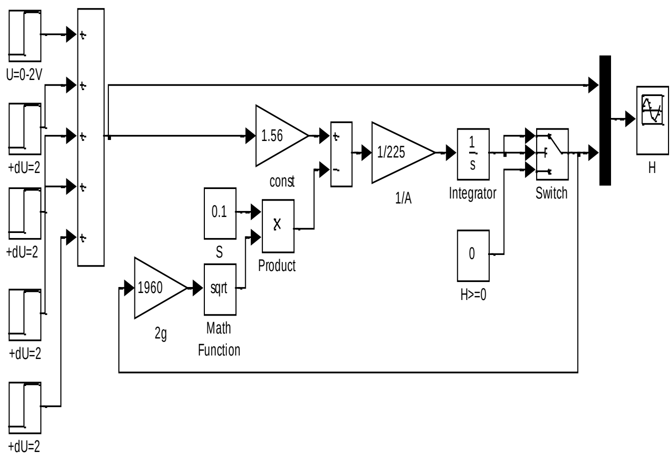


Fig.2. Simulink plant model

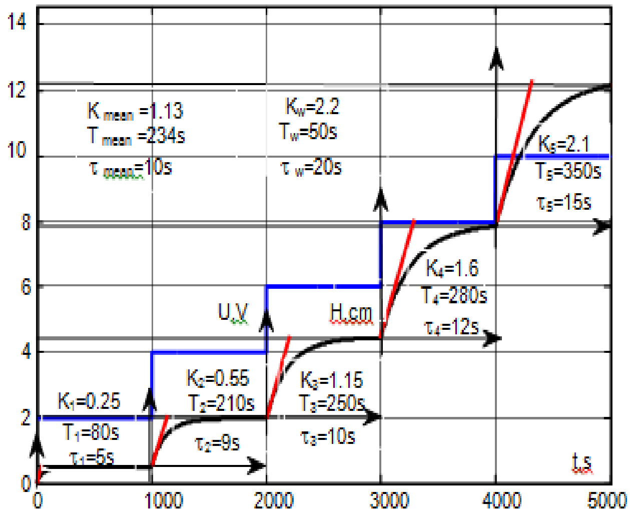


Fig.3. Simulated plant step responses in different operating points

$$u_{PI}(t)=K_eK_a\int K_{FU}(e,\dot{e})e(t)dt+$$

$$K_{de}K_a e(t)\int K_{FU}(e,\dot{e})dt$$

$$u_{PID}(t)=K_eK_p/T_i\int K_{FU}(e,\dot{e})e(t)dt+$$

$$K_{de}(K_p/T_i)K_{FU}(e,\dot{e})e(t)+K_eK_pK_{FU}(e,\dot{e})e(t)$$

$$u_{PID}(t)=(K_e+K_{de}/T_i)K_pK_{FU}(e,\dot{e})e(t)+$$

$$K_eK_p/T_i\int K_{FU}(e,\dot{e})e(t)dt+K_{de}K_pK_{FU}(e,\dot{e})e(t)$$

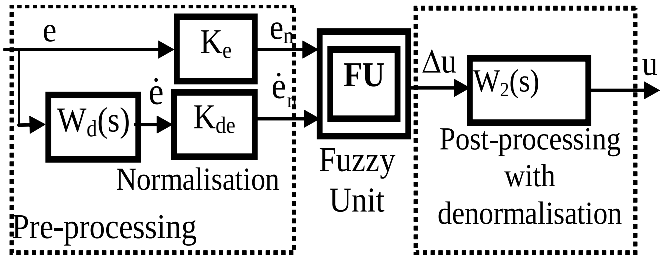
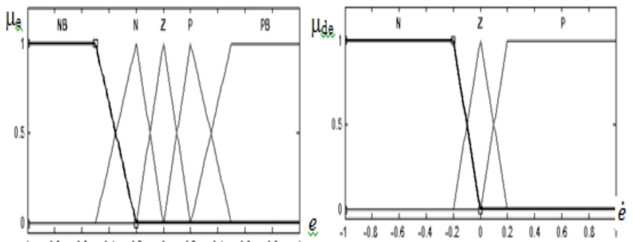
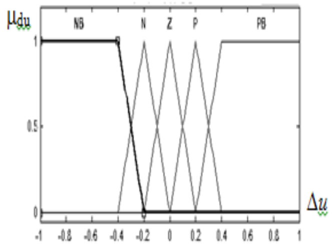


Fig.4. Incremental PI/PID FLC





Δu		e				
		NB	N	Z	P	PB
de	N	NB	NB	N	Z	P
	Z	NB	N	Z	P	PB
	P	N	Z	P	PB	PB

Fig.5. FU membership functions and fuzzy rules of PI/PID FLC, NB-negative big, N-negative, Z-zero, P-positive, PB-positive big

The design of the PI/PID FLC is based on the same FU with standard MFs and rules, shown in Fig.5, and needs no plant model. The defuzzification method is the centre-of-gravity COG. The tuning parameters are $q_{FPI}=[K_e\ (K_{de}.K_d)\ T_d\ K_a]$ for PI FLC and $q_{FPID}=[K_e\ (K_{de}.K_d)\ T_d\ K_p\ T_i]$ for PI FLC. They are tuned initially empirically, considering maximal error $|e_{max}|=5$ cm (5.10^{-2}m) - $K_e=0,2$, $K_{de}\ K_d=1$. Inputs to the FU beyond the range [-1, 1] are limited. The differentiator's time-constant is selected $T_d=2$s to ensure effective differentiation and noise filtering from the requirement $T_d=(2\div5)\Delta t$, where Δt is the sampling period and $\Delta t \le 0,1.\min(T_{mean},\tau_{mean})$, $\Delta t=0,5$ and $K_a=K_p=10$, $T_i=T_d=2$s.

Initially the tuning parameters of the linear PI and PID controllers $q_{PI/PID}=[\ K_p\ \ T_i\ \ T_d]$ is based on engineering empirical formulas for ensuring small overshoot [18] considering the mean plant model parameters:

gain $K_p=1,4.T_{mean}/(K_{mean}.\tau_{mean})=30$ cm/V
initial integral action time $T_i=0,22.T_{mean}=50$s
differentiation time-constant $T_d=\tau_{mean}=10$s (PID)

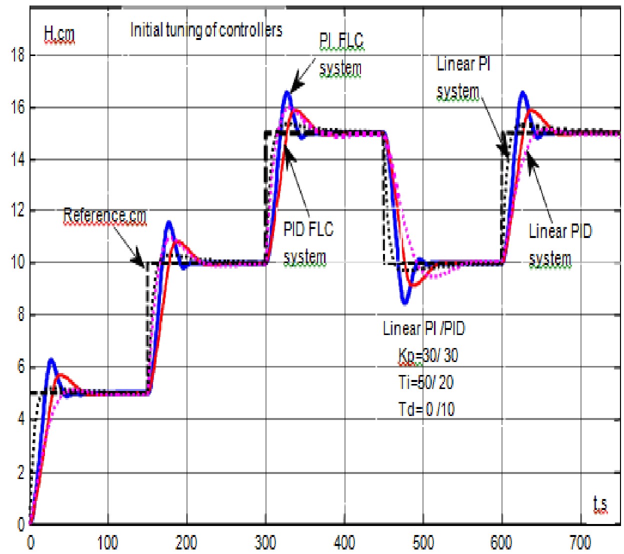


Fig.6. Step responses for different references in the four designed closed loop systems with PI/PID FLC and linear PI/PID controllers (dotted line)

The systems with initially tuned parameters have simulated step responses, shown in Fig.6.

The FLC systems preserve the performance t_s and σ of the step responses in different operation points, where the plant has different parameters due to nonlinearity, which is an evidence for good robustness unlike the systems with the linear PI/PID controllers. However, the FLC systems have worse performance as a whole but are easily designed with no use of plant model.

The problem is to optimize off-line the performances of the systems employing genetic algorithms (GAs) as off-line non-gradient stochastic method for the tuning of $q_{FPI}, q_{FPID}, q_{PI/PID}$. The accepted criterion is:

$$F=\int[e(t)^2/y_r^2+u(t)^2/u_{max}^2]dt+ \\ +\max|e_{min}(t)/y_r| \mapsto \min_{q_{FPI},q_{FPID},q_{PI/PID}} \qquad (2)$$

In (2) are combined three criteria – minimization of the relative error accounting for the minimum relative control action and estimate for the maximum overshoot $\max\left|\frac{e_{min}(t)}{y_r}\right|$.

Optimisation of FLC and Linear Controllers' Parameters via GA

The optimization of the FLC and linear controllers tuning is carried out using a MATLAB™ genetic algorithm embedded in a developed program with the following algorithm [19].

1. Input data – number of generations, size of population in a generation, fitness function, initial upper and lower bound for the tuning parameters, fitness function, end condition (reached number of generations), selection method (roulette), crossover points (in one point), mutation method (in one bit)

2. Initialise the population with randomly generated individuals (as chromosomes) and evaluate the fitness of each individual.

3. Select survivors - two parents from the population with probabilities proportional to their fitness values.

4. Randomly vary individuals.

a. Apply crossover with a probability equal to the crossover rate.

b. Apply mutation with a probability equal to the mutation rate.

5. Evaluate the fitness function and accept in the new generation if better than the parents, else repeat from 2. To 6.

7. Repeat 2. to 5. until enough members are generated to form the next generation.

8. Repeat from 3 till the number of generations or the desired accuracy (minimum) is reached.

Each parameter set is first encoded for instance into a concatenated bit string representation making a chromosome for specific parameters values. Each parameter in the chromosome is a gene. After a population is created the fitness (objective) function is computed for each member (chromosome). Then parents are selected with probability proportional to their fitness value for producing off-springs for the new generation. The idea is to let members with above-average fitness reproduce and replace members with below-average fitness. Crossover generates new chromosomes that are expected to retain the good features of the previous generation. In a single point crossover, the point is selected at random and the parent chromosomes swap their bit strings to the right of this point. Then mutation takes place by flipping a bit. The mutation prevents the population from converging towards a local minimum. The mutation rate is low in order to preserve good chromosomes.

Genetic algorithm mimics the evolution of populations. First, different possible solutions to a problem are generated. They are tested for their performance, that is, how good a solution they provide. A fraction of the good solutions is selected, and the others are eliminated (survival of the fittest). Then the selected solutions undergo the processes of reproduction, crossover and mutation to create a new generation of possible solutions, which is expected to perform better than the previous generation. Finally, production and evaluation of new generations is repeated until convergence. Such an algorithm searches for a solution from a broad spectrum of possible solutions, rather than where the results would normally be expected. The penalty is computational intensity.

This algorithm is repeated 10 times - each time expanding the upper and lower bounds for the parameters, till a desired minimum of the fitness function (2) is reached. In this way the subjective assignment of these bounds is avoided. The fitness function is evaluated after running a Simulink model of the closed loop system with the plant model from Fig.2 and the current values for the controller's parameters and collecting data for evaluation of *F* from (2). In case of available experimental data from the plant first a fuzzy, neural or neural-fuzzy plant model can be obtained by training or GA optimization of the parameters of a model of a given structure. The GA optimisation is carried out for each ot the four types of controllers PI FLC, PID FLC, linear PI and Linear PID with chromosome structure defined by $q_{FPI}, q_{FPID}, q_{PI/PID}$ respectively. The optimal parameters are:

q_{FPI}=[K_e=0.03 ($K_{de}.K_d$) =3.3 T_d=2 K_a=155] for PI FLC

q_{FPID}=[K_e=0.039 ($K_{de}.K_d$) =0.35 T_d=2 K_p=176 T_i=3.3] for PI FLC

q_{PI}=[K_p=17.5 T_i=63]

q_{PID}=[K_p=11 T_i=91 T_d=0.52].

Performance Assessment of Closed Loop Systems with Optimised Controllers

The performance of the systems with the designed PI/PID FLC and PI/PID linear controllers with optimal tuning parameters is assessed from simulation investigations. The step responses in different operation points is obtained for the systems and compared with the step responses with initially tuned controllers. This comparison is shown in Fig.7 for the systems with FLCs. The PID FLC system has no overshoot and five times reduced settling time. The PI FLC system has reduced the settling time three times but marks an increase in the maximal deviation.

In Fig. 8 is shown the comparison of the step responses of the PI/PID controlled systems with initial and optimized tuning parameters. The PI and the PID systems with optimised parameters lead to improved system performance with respect to the initial – negligible overshoot and slightly reduced settling time. Here the performance of the PI system is better. The comparison between the FLC and linear PI/PID

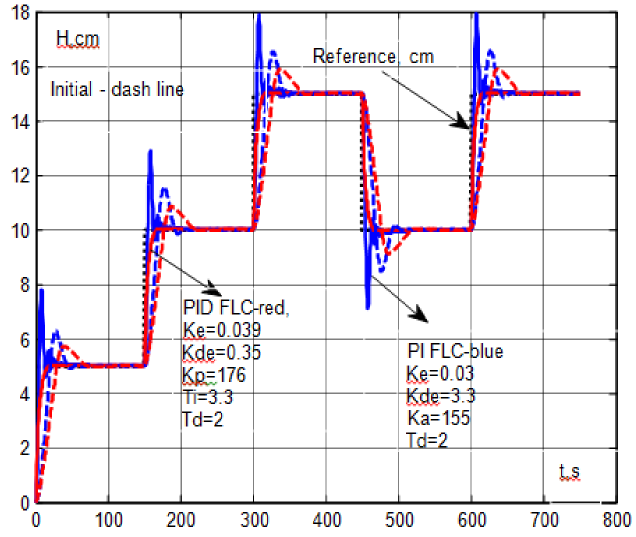


Fig.7. Step responses for different references in the FLC designed closed loop systems with initial (dash line) and optimized via GA parameters

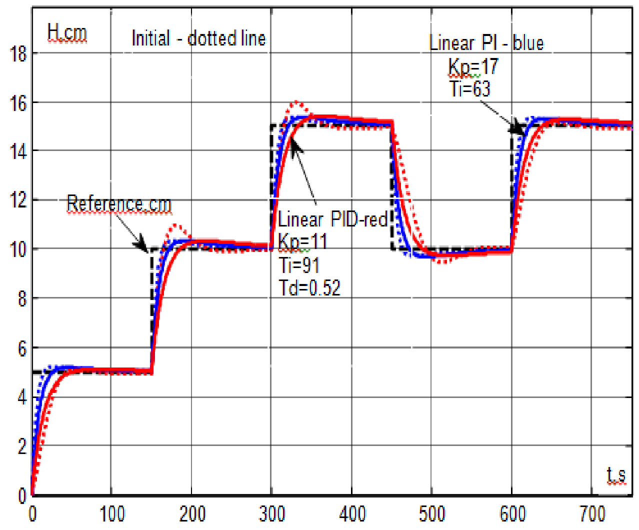


Fig.8. Step responses for different references in the PI/PID designed closed loop systems with initial (dotted line) and optimized via GA parameters

systems with optimized parameters rates the performance of the PID FLC system as the best. It is normal to expect a nonlinear plant to be better controlled by a nonlinear controller such as the FLC. The FLC systems outperform the systems with the linear controllers in reduced settling time, easy design without much knowledge and modeling the plant.

Conclusion and Future Work

The main contributions of the present investigation conclude in the following.

1. A method for off-line tuning of the parameters in the pre- and post-processing part of incremental PI and PID Mamdani FLCs and of linear controllers is suggested on the basis of genetic algorithms. A fitness function is proposed that binds three criteria related to integral squared relative system error, integral squared relative control action and an estimate of the maximal overshoot during the step responses in various operation points where the plant model has different parameters

2. The step responses in the designed four systems are simulated and their settling time and overshoot assessed. The FLC systems outperform the systems with the linear controller, which is expected since the plant is nonlinear.

3. The method can be successfully applied for simple off-line tuning of different FLCs and also extended to tuning of other parameters of the FLCs such as MFs, rules, etc.

4. The suggested tuning procedure is proper for fuzzy control of level.

Future investigation is foreseen in the real time control of the level in the laboratory system from Fig.1. The model of the plant in the FLC system for computing the fitness function can be extracted from experimental data, collected about the plant, via GA optimization of a suggested Sugeno plant model.

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REFERENCES

[1] Jantzen J., Foundations of Fuzzy Control, John Wiley & Sons Inc., 2007.

[2] Basil M. Al-Hadithi, Fernando M., A. Jiménez. Fuzzy Control for a Liquid Level System. In proceeding of: Proceedings of the 3rd Conference of the European Society for Fuzzy Logic and Technology, Zittau, Germany, September 10-12, 2003.

[3] Raduca M., E. Raduca, C. Hatiegan and D. Ungureanu. Fuzzy controller for adjustment of liquid level in the tank, Annals of the University of Craiova, Mathematics and Computer Science Series, Volume 38(4), 2011, Pages 33{43},ISSN: 1223-6934, Online 2246-9958.

[4] Disha, Mr. P. Pandey, R. Chugh. Simulation of Water Level Control in a Tank Using Fuzzy Logic. IOSR Journal of Electrical and Electronics Engineering (IOSRJEEE) ISSN: 2278-1676 Volume 2, Issue 3 (Sep-Oct. 2012), pp 09-12.

[5] Ahmad D., A. Ahmad, V. Redhu, U. Gupta. Liquid Level Control By Using Fuzzy Logic Controller.

International Journal of Advances in Engineering & Technology, July 2012, ISSN: 2231-1963.

[6] Malhotr R., R. Sodhi. Boiler Flow Control Using PID and Fuzzy Logic Controller. IJCSET, Vol 1, July 2011, Issue 6,315-319, ISSN:2231-0711.

[7] Kumar A., Rajbir, Kuldeepak. Performance Comparison of Level Control with the Three, Five & Nine Fuzzy Rules based method. International Journal of Advanced Research in Computer Science and Electronics engeneering, Vol.2, Issue 7, July 2013.

[8] Li H.-X., S.K. Tso. A Fuzzy PLC with Gain-Scheduling Control Resolution for a Thermal Process. A Case Study, J. Control Engineering Practice, No 7, 1999, pp. 523-529.

[9] Yordanova S. Methods for Design of Fuzzy Controllers for Robust Process Control, KING, Sofia, 2011, 344, ISBN 987-954-9518-68-9 (in Bulgarian).

[10] Yordanova S., V.Yankov. Design and Implementation of Fuzzy Two-Level Control. Proceedings of the Technical University of Sofia (Int.conf. Automatics'2013, FA, 14-16 June 2013, Sozopol), Vol. 63, Issue 1, 2013, ISSN 1311-0829, pp. 79-88.

[11] Иванова Д., М. Попова, Н. Вълов. Приложение на генетичен алгоритъм за настройка на ПИД регулатори. Научни Трудове На Русенския Университет - 2009, Том 48, серия 3.1.

[12] Kumar B., R. Dhiman. Optimization of PID Controller for liquid level tank system using Intelligent Techniques. Canadian Journal on Electrical and Electronics Engineering Vol. 2, No. 11, November 2011.

[13] Turker Tekin Erguzel. Fuzzy Controller Parameter Optimization Using Genetic Algorithm for a Real Time Controlled System. Proceedings of the World Congress on Engineering 2013 Vol 2, WCE 2013, July 3 - 5, 2013, London, U.K.

[14] Ali M., S. Koh, K. Chong, S. Tiong, Z. Obaid. Genetic Algorithm Tuning Based PID Controller for Liquid-Level Tank System. Proceedings of the International Conference on Man-Machine Systems (ICoMMS) 11 – 13 October 2009, Batu Ferringhi, Penang, Malaysi.

[15]] Cho H., K. Cho, B. Wang. Fuzzy-PID hybrid control:Automatic rule generation using genetic algorithms. Fuzzy Sets and Systems 92 (1997) 305-316.

[16] Sarimveis H., G. Bafas. Fuzzy model predictive control of non-linear processes using genetic algorithms. Fuzzy Sets and Systems 139 (2003) 59–80.

[17] Наплатаров К. Промишлени системи за нискостойностна автоматизация. ТУ София, 1998г.

[18] Neshkov T., S. Yordanova, I. Topalova. Process Control and Production Automation. Technical University of Sofia, S., 2007, 152, ISBN 978-954-438-597-2.

[19] Jang R., C. Sun, E. Mizutani. Neuro-Fuzzy and Soft Computing. A Computational Approach to Learning and Machine Intelligence. MATLAB Curriculum Series, Prentice-Hall, Inc., Upper Saddle River, NJ, USA, 1997. ISBN 0-13-261066-3

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