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Fuzzy Logic Control Optimal Realization Using GA for Multi-Area AGC Systems

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Abstract

An on line Fuzzy Logic Controller (FLC) realization with Genetic Algorithm (GA) optimization for Automatic Generation Control (AGC) system is developed. By rearranging the multi area AGC system into integration of the SISO cascade loops, the simple FLC Decision Table algorithm could be used in the complex AGC system. This Decision Table looking up algorithm for FLC with GA optimization is suitable for the nonlinear element in AGC, such as generator rate constraint (GRC) and saturation. A Four area AGC system simulation has shown that the approach is available for the AGC system performance optimization.

Keyword: Automatic generating control, Fuzzy logic control, Genetic algorithm, Optimization.

I. Introduction

Large scale power systems are normally composed of control areas or regions representing coherent groups of generators. Area load changes and abnormal conditions lead to mismatches in frequency and scheduled power interchanges between areas. These mismatches have to be corrected by Automatic Generation Control (AGC), which is defined as the regulation of the power output of generators within a prescribed area [1]. The paper [2] presents a critical review of the recent philosophies in the area of AGC. The modeling and control of AGC power plants and power systems involve a considerable part because of their highly nonlinear and complex structures [3] [4]. The fast change in frequency requires the intelligent control methods. Recently, many studies exploiting the fuzzy logic concept in AGC regulator design dealing with various system aspects have appeared in the literature [3-5]. More contributions considering the problem of decomposition of multivariable systems for the purpose of distributed fuzzy control was reported by Gegov [6]. The proposed decomposition method has reduced the number of interactive fuzzy relations among subsystems. The concept and development of AGC using ANN and fuzzy set theory to utilize the novel aspects of both in single hybrid AGC system design for power systems has also been mooted [7]. Since GA is the most popular and widely used algorithm of all the intelligent algorithms, GAs have been widely applied to solve complex nonlinear optimization problems in a number of engineering disciplines in general and particularly in the area of AGC of power systems ([7,8]). An optimum adjustment of the classical AGC parameters using GAs is investigated in [9]. A reinforced GA has been proposed as an appropriate optimization method to tune the membership functions and rule sets for fuzzy gain scheduling of load frequency controllers of multiarea power systems to improve the dynamic performance in [8]. Shoureshi [10] described a neural based fuzzy control algorithm to avoid the state space model design problems. In recent paper [11] a self tuning mechanism that changes the input and output scaling factors (I/O SF) of the main fuzzy PID (Proportional Integration and Derivative) type controller is provided for the AGC problem. Ghoshal [4] provides an optimization approach for dealing with AGC controller parameters, where all o-line, nominal gains and corresponding nominal system parameters are stored as tables for the use of on-line Sugeno fuzzy logic control for varying system parameters, for fixed integral gain controllers for nominal operating conditions fail to provide best control performance over a wide range of o-nominal operating conditions.

The performance of the initial design attempt of a FLC for multi-area AGC system will, in general, not be satisfactory in terms of certain design criteria such as steady-state error of the controller, the oscillatory behavior of the system, etc. This is due to the fact that a FLC is designed based on the expert’s knowledge of the process. Unfortunately, no standard method exists for transforming human knowledge or experience into the rule base of the FLC. The initial designed FLC is still need to be improved. Paper [12] analyzes the limitations of loop controllers for implementing fuzzy logic control in terms of the computation time and memory required. It was shown that general fuzzy logic control algorithms are not suitable for loop controllers. It was shown in the paper that the decision table is suitable for loop control with regard to both computation time and the memory requirement. One of the rule based FLC with decision table is also given in [13].

This paper will develop an on line algorithm for Fuzzy Logic Controller (FLC) with Genetic Algorithm (GA) optimization strategy to improve the multi-area AGC control performance. By de-coupling the multi-area AGC system into integration of the cascade control system loops, the complex AGC control systems are separated into individual single-input single-output (SISO) system. This SISO cascade loop models consider the fast load changes and slow plant utility response as different disturbances. With the cascade structure, a Decision Table looking up algorithm for FLC, which is suitable for on line parameter optimization, is developed and the approach is easy to be realized on AGC loops. The nonlinear elements such as generator rate constraint (GRC) and saturation could be compensated, Simulation have proved the proposed strategy.

II. Multi-area Agc System Model Analysis

The mathematical model for Multi-Area AGC system used in this paper is a four-area interconnected power system model with reheat nonlinearity effect of the steam turbine and upper and lower constraints for generation rate nonlinearity of hydro turbine [14]. Figure 1 shows an illustration of the model, where area No.1, No.2 and No.3 are all equipped with reheat thermal turbine, while only area No.4 is a hydro turbine. The Boiler-Turbine-Generator (BTG) unit with its Coordinate Control System (generally controlled with Distributed Control System) and the interconnected linear tie-line model for Matlab/Simulink simulation structure is sketched in Figure 2,where the controller is in PID form.

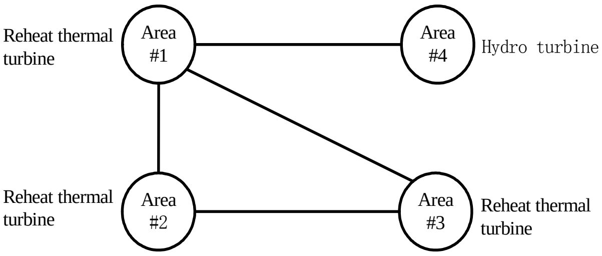

Fig. 1. A Four Area Tie-Line Model Of AGC System

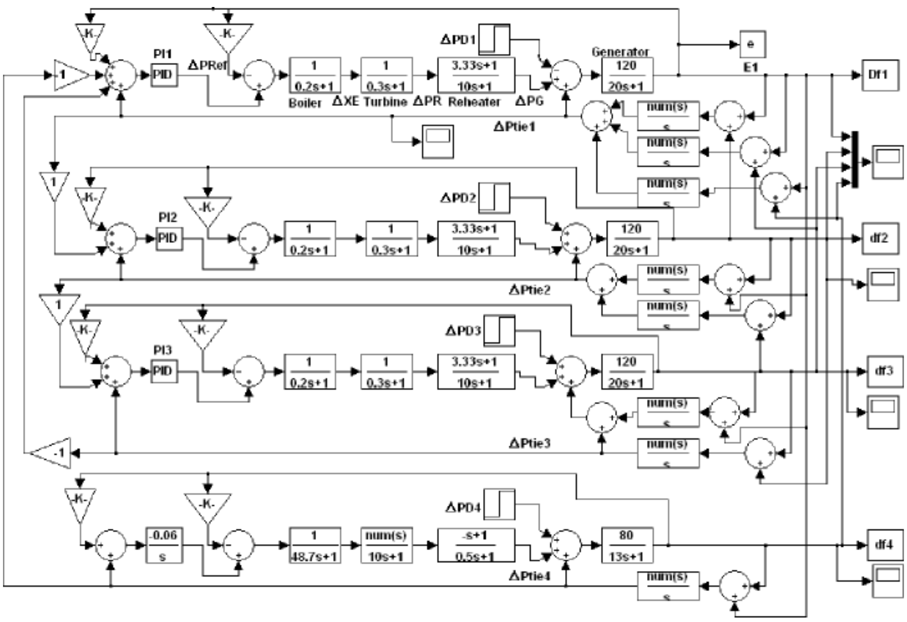

Fig. 2. Four Area AGC Simulation Model In Simulink

When taking the nonlinear elements, such as GRC and dead band or saturation, into account, one single area model for multi-area AGC system can be expressed in Figure 3. By considering the Area Control Error (ACE) expression for this area m as [8]:

$$ACE_m = \Delta P_{tiem} + B_m \Delta F_m + a_m \varepsilon_m + \alpha_m I_m \tag{1}$$

where ΔP_{tiem} is the incremental change in tie-line power, B_m the frequency bias constant, ΔF_m the incremental frequency change, a_m the time error bias setting, ε_m the time error, a_m the inadvertent interchange bias setting, and I_m the inadvertent interchange accumulation, and m is the area number. The equivalence of PID control action for Equation (1) then can be analyzed. Define

$$ACE = \Delta P_{tiem} + B_m \Delta F \,,\ \ a_m / \alpha_m = 50 B_m \tag{2}$$

with

$$\begin{cases} \varepsilon_m = \dfrac{1}{50}\int \Delta F_m \mathrm{dt} \\ I_m = \int \Delta P_{tiem} \mathrm{dt} \end{cases}$$

then Equation (1) can be rewritten in a unified form:

$$ACE_m = \Delta P_{tiem} + B_m \Delta F_m + \alpha_m \int (\Delta P_{tiem} + B_m \Delta F_m)\mathrm{dt} \tag{3}$$

That is

$$ACE_m = ACE + \alpha_m \int ACEdt \tag{4}$$

This ACE_m in area *m* is named ACEN for short. It is a summation of the conventional ACE and its integration (with coefficients α_m). Note that this summation is similar to PI control law. If the inadvertent interchange bias setting α_m is tuned properly, the control action of ACE_m will guarantee zero steady state time error and inadvertent interchange. Further more, the AGC loop controller can also be designed in PI form [10] instead of integration function (*K/s* block) as:

$$U_m(t) = -K_{mp} ACE_m(t) - K_{mi} \int ACE_m(t)dt \tag{5}$$

There are many approaches to tune the parameters of K_{mp}, K_{mi} and α_m, depending on the ACE_m and the model structure of the interconnected power systems. It is naturally to take the Derivative action (D) to Equation (5). The use of PID instead of PI (or traditional only I) could improve the control performance [4]. Because that *ACEN* is a PI of *ACE*, the increment form of PI control of *ACEN* in Equation (5), that is, $\Delta U_m(t) = U_m(t) - U_m(t-1)$ is equivalent to the increment of ($ACE + \int ACE + \iint ACE$) with suitable coefficients. Note that the derivative action in PID will improve the control performance by this $\iint ACE$ item.

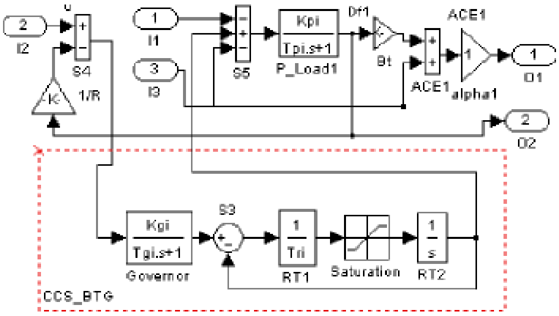

Fig. 3. Subsystem Model For One Area AGC System

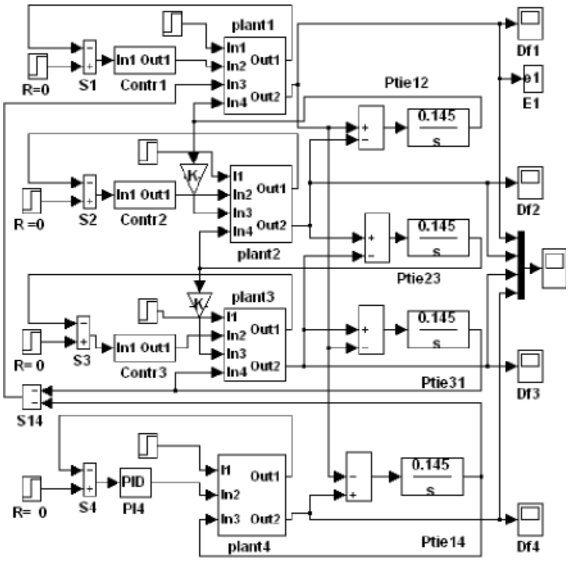

Fig. 4. Cascade System Model For Multi Area AGC System

For further analysis the system easily, an alternative structure for control area 1 in figure 2 is redrawn in Figure 3, where the outputs are defined as: *O*2 represents for *Df* 1, which is the frequency deviation; and *O*1 stands for *ACEN*. The interaction between control areas then can be shown in figure 4, where plant1 is a subsystem, sketched in Figure 5, for boiler-turbine-generator unit with power system load. Note there *R* = 0 means that the determination of the controller parameters is based on tuning the controller parameter under the restriction of disturbance rejection for this AGC outer loop. The AGC loops of cascade system in figure 6 have a very typical property, that is, the frequency band width for outer loop is much big than that of inner loop, or the response of the outer loop is much fast than that of the inner loop. By considering that
R = 0 for this cascade system, the stability and other control performance could be interpreted accordingly.
Under the figure interpretation, we have following:

Remark 1 *Consider the A GC system defined in Figure (2 to Figure 6). The control action for multi-area A GC system could be optimized on: (1) disturbance rejection for outer loop controller, which could be in PID (as shown in Figure 4) or FLC form; and (2) fast tracking the instruction coming from the cascade outer loop controller for inner BTG loop.*

Remark 2 *Zero reference input to the A GC system in Figure 4 does not change the characteristic Equation of the system. The stability of the cascade AGC system is kept by the multiply inner BTG loops.*

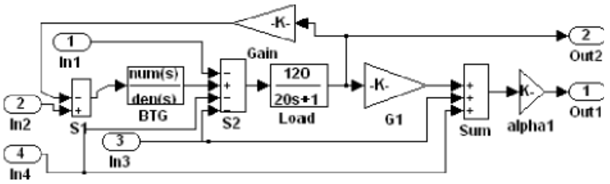

Fig. 5. Plant model for An AGC Control System

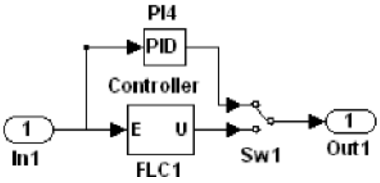

Fig. 6. PID and FLC controller For An AGC Control System

The optimal performance design for controller can be obtained by many intelligent algorithms [7]. Among them Fuzzy Logic Control algorithm with Genetic Algorithm (GA) are more feasible. In order to overcoming the limitations of loop controllers for implementing fuzzy logic control in terms of the computation time and memory required [12], the Decision Table looking up algorithm for discrete sample system will be developed below.

III. Fuzzy Logic Controller Optimization of Agc Systems

The fuzzy logic control concept departs significantly from traditional control theory, which is essentially based on mathematical models of the controlled process. Instead of deriving a controller via modeling the controlled process quantitatively and mathematically, the fuzzy control methodology tries to establish the controller directly from domain experts or operators who are controlling the process manually and successfully. For a typical fuzzy logic controller with decision table structure sketched in Figure 7. Suppose the fuzzy control rules are expressed in the following form

If *e* is *Ei* and $\dot{e}$ is *CEj* Then *u* is U_{Rij}

where *e* is the error and *ce* the change of error (*de/dt*), $U_{Rij} \in U(i \in I, j \in J)$ are the fuzzy rules and (*i,j*) are membership function discrete indices for $I = [-n_i \ldots,-2,-1,0,1,2\ldots n_i]$, $J = \lfloor -m_j \ldots -2,-1,0,1,2,\ldots,m_j \rfloor$. The fuzzy relation matrix is

$$R_{ij} = E_i \times CE_j \times U_{Rij} \tag{6}$$

Thus,

$$R = \cup R_{ij} = \max_{i \cdot j}(R_{ij}^{kp}) \tag{7}$$

where, $k = 1,2,\ldots,r,; p = 1,2,\ldots,s$ for the number of linguistic values and $i = 1,2,\ldots,n,; j = 1,2,\ldots,m$ for the number of membership functions discrete valued indices of *E* and *CE* respectively. That is, (*i,j*) is the element index in the rule base for the E^k and CE^p linguistic values. The symbol *X* stands for Cartesian product. Suppose that $n = 2n_i + 1$ and $m = 2m_j + 1$, then the dimension of U_{Rij} is $n \times m$, and the correspondent $\dim(E_j^k) = n \times r, \dim(CE_j^p) = m \times s$.

Applying the Center Of Gravity (COG) method to defuzzify the fuzzy subset, the linguistic output of the controller U_{kp} will be

$$U_{kp} = (E^k \times EC^p) \circ R \tag{8}$$

where $k = 1,2,\ldots,r,; p = 1,2,\ldots,s$.

For optimizing the control system performance, three scaling factors K_e, K_d and $K_u = \alpha + \beta \int$ are generally introduced to produce normalized input and output signals for the fuzzy controller as:

$$E^k = e / K_e, CE^p = \dot{e} / K_{ce}, U_{kp} = u / K_u \tag{9}$$

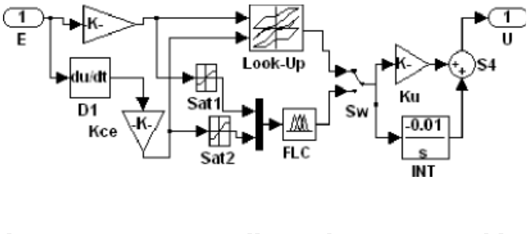

Fig. 7. Typical Fuzzy Logic Controller with Decision Table Simulation Structure

In an on line control or loop controller situation [12], the control output U_{kp} is generally indexed from a stored table called the Decision Table (DT) [13], which is generated based on Equation (8), while the control rules U_{Rij} are stored as a Control State (CS) table for modification.

Generally the Decision Table is difficult to update on line. In order to get the recursive algorithm, consider the component in the relation matrix *R* defined in Equation (8). This *R* can be computed on the Cartesian product space according to the control state U_{Rij} and the input variables E_i, CE_j by

$$R = R^{vq} = \bigcup_{i=1,\, j=1}^{n,m} R_{ij}^{vq} \underset{=}{\Delta} \max_{i\in[1,n],\, j\in[1,m]} \left\{R_{ij}^{vq}\right\} \tag{10}$$

and

$$R_{ij}^{vq} = \left(E_i^k \times CE_j^p\right)\times U_{Rij} \underset{=}{\Delta} \min\left\{\left[\min\left(E_i^k, CE_j^p\right)\right]_v, U_{Rij}^q\right\} \tag{11}$$

where $v \underset{=}{\Delta} (k-1)s+p, q\in[1,t],$ and the other sub-indexes are:
$i\in[1,n], j\in[1,m], k\in[1,r], p\in[1,s]$ The notation $[.]_v$ stands for column index such that $\dim[.]_v = x\times 1$.

The elements in the decision table for fuzzy inference decision making then can be expressed as:

$$DT_{ij} = \sum_{q=1}^{t}\left(\mu\left(u_{ij}^q\right)\cdot u_{ij}^q\right) \Big/ \sum_{q=1}^{t}\mu\left(u_{ij}^q\right) \tag{12}$$

where

$$u_{ij}^q = \min\left(E_{ik}, CE_{jp}\right)_v \circ R^{vq} \tag{13}$$

For on line control output calculation, an algorithm from Equation (10)-(12) is used by taking $E\times CE$ as index to look up the Decision Table, and then to output the required crisp value u for control. More details about the Decision Table Looking Up algorithm could be found in paper [15].

For improving the performance of the algorithm, Genetic Algorithms (GAs) can be easily integrated into the FLC approach developed above. GAs are stochastic optimization algorithms that were originally motivated by the mechanisms of natural selection and evolutionary genetics. A simple GA is an iterative procedure that maintains a constant size population N of candidate solutions. During each iteration step, or generation, three genetic operators (reproduction, crossover, and mutation) are performing to generate new populations (o-springs), and the chromosomes of these new populations are evaluated via the value of fitness which is related to some cost functions. On the basis of these genetic operators and the evaluations, the better new populations of candidate solution are formed. Paper [16] has shown that MATLAB/Simulink model with GA is a feasible solution for nonlinear system optimization in power system AGC engineering.

Ⅳ. Simulations

A four-area interconnected power system model with reheat nonlinearity effect of the steam turbine and upper and lower constraints for generation rate nonlinearity of hydro turbine was considered for the investigation, the plant parameters are same as in [8]. Figure 8 is the simulation results for step input to DeltaPD1 in area 1. Note that the variations of the four-area frequency deviation are mainly on area No.1 and area No.4.

Using the algorithm given in last section the Decision Table is designed as in Table 1, where E and CE are fuzzy variables for error of the ACE and the change of the error. Matlab/Simulink GA toolbox could be used to tuning of the FLC scaling factors for better results. The area No.1 and area No.4 of the AGC system using FLC with GA is simulated in Figure 9, where GA toolbox is used for the optimization of the FLC scaling factors. The objective function for GA is to minimize the error e1 in Figure 2 for area No.1.

Table 1. Decision Table for FLC

CE/E	-2	-1	0	1	2
-2	-0.6000	-0.6000	-0.3333	-0.3333	-0.0000
-1	-0.6000	-0.3939	-0.0789	0.0000	0.3333
0	-0.3333	-0.0789	0.0000	0.0789	0.3333
1	-0.3333	0.0000	0.0789	0.3939	0.6000
2	-0.0000	0.3333	0.3333	0.6000	0.6000

From the comparing curves it has shown that the performance of the FLC algorithm is better than that of PI controller. The results have also suggested that the simplification of cascade optimization suits for the AGC nonlinear system.

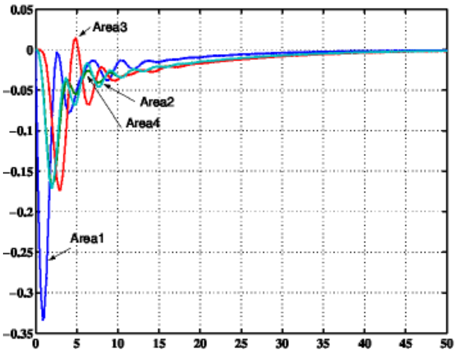

Fig. 8. Four Area AGC System Simulation

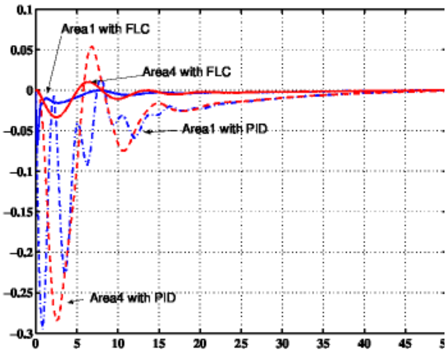

Fig. 9. Comparing For FLC And PID Controller Of the AGC System simulation

Ⅴ. Conclusion

A Decision Table looking up algorithm for Fuzzy Logic Controller with GA optimization for AGC system is developed. A single-input single-output Decision Table FLC approach is introduced to deal with the interconnection of the SISO loops. The generation rate constraint (GRC) and turbine dead band are easily to be considered in the system. A method to rearranging the multi area AGC system into integration of the SISO cascade loops is developed. The proposed method is easy to make the system have good performance in engineering application. The simulation of a four area power system is reported.

References

[1] Jaleeli, N., VanSlyck, L., Ewart, D., et al.: Understanding automatic generation control. IEEE Trans Power Systems 7 (1992) 1106

[2] 2Ibraheem, Kumar, P., Kothari, D.: Recent philosophies of automatic generation control strategies in power systems. IEEE Transactions On Power Systems 20 (2005) 346357-135.

[3] Indulkar, C., Raj, B.: Application of fuzzy controller in automatic generation control. Electric Machines Power Syst. 23 (1995) 209220

[4] Ghoshal, S.: Application of ga based optimal integral gains in fuzzy based active power-frequency control of non-reheat and reheat thermal generating systems. J. Electric Power Syst.Res. 67 (2003) 7988

[5] Talaq, J., Al-Basari, F.: Adaptive fuzzy gain scheduling for load frequency control. IEEE Trans. Power Syst. 14 (1999) 145150

[6] Gegov, A.E., Frank, P.M.: Decomposition of multivariable systems for distributed fuzzy control (power system load frequency control). Fuzzy Sets Syst 73 (1995) 329340

[7] Karnavas, Y., Papadopoulos, D.: Agc for autonomous power system using combined intelligent techniques. Electric Power Systems Research 62 (2002) 225239

[8] Chang, C., Wu, W., Wen, F.: Load frequency control using genetic algorithm based fuzzy gain scheduling of pi controllers. Electric-machines and Power Systems 26 (1998) 3652

[9] Abdel-Magid, Y.L., Dawoud, M.M.: Optimal agc tuning with genetic algorithms. Elect. Power Syst. Res. 38 (1996) 231238

[10] Shoureshi, R., et.al., B.H.: Neural-based generation control for highly varying and uncertain loads. In: IEEE 2001 PPT conference, Porto,Portugal (2001)

[11] Yesil, E., Guzelkaya, M., Eksin, I.: Self tuning fuzzy pid type load and frequency controller. Energy Conversion and Management 45 (2004) 377390

[12] Kim, Y.H., Ahn, S.C., Kwon, W.H.: Computational complexity of general fuzzy logic control and its simplification for a loop controller. Fuzzy Sets and Systems 111 (2000) 215224

[13] Gao, X., Feng, Z.: Design study of an adaptive fuzzy-pd controller for pneumatic servo system. Control Engineering Practice (2004)

[14] Zeynelgil, H.L., Demiroren, A., Sengor, N.S.: The application of ann technique to automatic generation control for multi-area power system. Elect. Power Energy Syst. 24 (2002) 345354

[15] Li, P., Du, X., Liu, Y.: A recursive rule base looking up algorithm for fuzzy logic controller realization. In: 11th International Fuzzy Systems Association World Congress (IFSA 2005), Beijing,China (2005) 840845

[16] Li, P., Du, X., Liu, Y.: Agc parameters optimization using real coded genetic algorithm. In: IEEE PowerCON02. Volume 1. Yunnan Science and Technology Press, Kunming, China (2002) 646650

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