DECISION TABLE LOOKING UP APPROACH FOR FUZZY LOGIC CONTROL OF MULTI-AREA AGC SYSTEMS

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Abstract: A Decision Table looking up algorithm for Fuzzy Logic Controller (FLC) with Genetic Algorithm (GA) optimization for Automatic Generation Control (AGC) system is developed. The single-input single-output (SISO) cascade loop structure of the AGC system is analyzed first. Then the interaction between the fast Area Control Error (ACE) loop and slow inner Boiler-Turbine-Generator (BTG) loop is decoupled by the FLC Decision Table algorithm based on the Relation Matrix recursive algorithm. The outer AGC frequency loop is optimized for disturbance rejection, and inner BTG loop is tuned for tracking the AGC instruction with the FLC. The Decision Table algorithm for FLC with GA optimization is suitable for the nonlinear element in AGC, such as generator rate constraint (GRC) and saturation. Simulations have shown that the approach is available for the AGC system performance optimization.

Keywords: Automatic Generating Control, Fuzzy Logic Control, Genetic Algorithm, Optimization.

1. INTRODUCTION

Modern power generation control areas consist of large power plants and many industrial customers. Various areas are interconnected through tie lines. The tie lines are utilized for contractual energy exchange between areas and provide inter-area support in case of abnormal conditions. 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 (Jaleeli *et al.*, 1992). The modelling and control of power plants and power systems involve a considerable part because of their highly nonlinear and complex structures (Indulkar and Raj, 1995)(Ghoshal, 2003). The fast changes in frequency requires the intelligent control methods including the fuzzy logic control (FLC)((Indulkar and Raj, 1995),(Talaq and Al-Basari, 1999)), and many other control strategies such Artificial Neural Network ((Shoureshi and et.al., 2001),(Ahamed *et al.*, 2002)) and various optimization algorithms (Karnavas and Papadopoulos, 2002).

There have been many research papers on using FLC approach for AGC. When considering the generator rate constraint (GRC) and saturation, the calculation and optimization of the AGC controller parameter are complex and onerous. Chang (Chang *et al.*, 1998) uses Genetic Algorithm based fuzzy gain scheduling of PI (Proportional Integral) controllers to deal the load frequency control. Shoureshi (Shoureshi and et.al., 2001) described a neural base fuzzy control algorithm to avoid the state space model design problems. In recent paper (Yesil *et al.*, 2004) a self tuning mechanism that changes the input and output scaling factors (I/O SF) of the main fuzzy PID type controller is provided for the AGC problem. Ghoshal (Ghoshal, 2003) provides an optimization approach for dealing with AGC controller parameters, where all off-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 off-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 (Hong and Chen, 2000). 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 (Kim *et al.*, 2000) 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 (Gao and Feng, 2004).

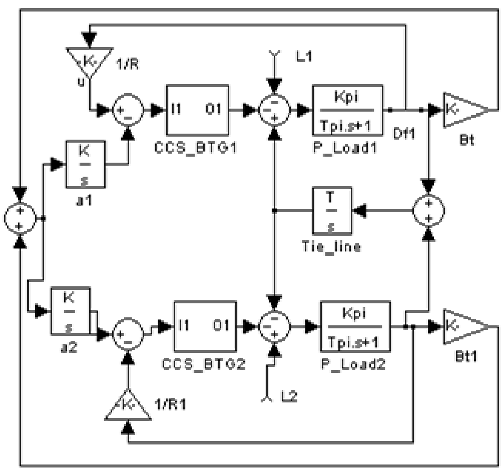

Fig. 1. A Two Area Tie-Line Model Of AGC System

This paper will develop a Decision Table looking up 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 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 and field test have proved the proposed strategy.

2. MULTI-AREA AGC SYSTEM MODEL ANALYSIS

The most widely used mathematical model for AGC is a two-area interconnected linear tie-line model. Figure 1 shows an illustration of the model, where CCS_BTG represents the Boiler-Turbine-Generator unit with its Coordinate Control System (generally controlled with Distributed Control System). The state space model for this AGC system is (Shoureshi and et.al., 2001):

$$\begin{aligned} \dot{X} &= AX + Bu + E\Delta P_d \\ Y &= CX \end{aligned} \quad (1)$$

where $X = [X_1, X_2, \cdots, X_n]^T$, $u = [u_1, u_2, \cdots, u_n]^T$, $\Delta P_d = [\Delta P_{d1}, \Delta P_{d2}, \cdots, \Delta P_{dn}]^T$ are state and input and disturbance vectors respectively, as defined in (Shoureshi and et.al., 2001).

The model is suit to research but is not good for engineering application because it is difficult to consider the nonlinear elements, such as GRC and dead band or saturation. Another model for multi-area AGC system comes from (Chang *et al.*, 1998) by considering the Area Control Error (ACE) expression for area m as:

$$ACE_m = \Delta P_{tiem} + B_m \Delta F_m + a_m \varepsilon_m + \alpha_m I_m \quad (2)$$

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, α_m the inadvertent interchange bias setting, and I_m the inadvertent interchange accumulation, and m is the area number. To show the equivalence of PI control action for Equation (1) and (2), define

$$ACE = \Delta P_{tiem} + B_m \Delta F_m, \quad a_m/\alpha_m = 50B_m \quad (3)$$

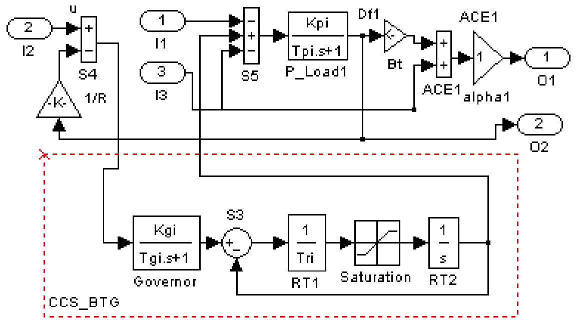

Fig. 2. Subsystem Model For AGC System

$$\begin{cases} \varepsilon_m = \frac{1}{50} \int \Delta F_m \mathrm{d}t \\ I_m = \int \Delta P_{tiem} \mathrm{d}t \end{cases}$$ then Equation (2) can be rewritten in a unified form:

$$\begin{aligned} ACE_m = & \ \Delta P_{tiem} + B_m \Delta F_m + \\ & \alpha_m \int (\Delta P_{tiem} + B_m \Delta F_m) \mathrm{d}t \end{aligned} \tag{4}$$

That is,

$$ACE_m = ACE + \alpha_m \int ACE \mathrm{d}t \tag{5}$$

This ACE_m is called New ACE in area m and 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 (Proportional Integration) 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 (Shoureshi and et.al., 2001) instead of integration function (K/s block in Figure 1) as:

$$U_m(t) = -K_{mp} ACE_m(t) - K_{mi} \int ACE_m(t) \mathrm{d}t \tag{6}$$

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 add the derivative action (D) to Equation (6). The use of PID instead of PI could improve the control performance (Ghoshal, 2003). Because that $ACEN$ is a PI of ACE, the PI control of $ACEN$ in Equation (6) is equivalent to $ACE + \int ACE + \iint ACE$ with suitable coefficients. Derivative action in PID will improve the control performance by adding $\iint ACE$ item to the system.

For further analysis the system easily, an alternative structure for control area 1 in figure 1 is redrawn in Figure 2, where the outputs are defined as: $O2$ represents for $Df1$, which is the frequency deviation; and $O1$ is for $ACEN$. The interaction between the control area 1 and 2 is shown in figure 3, where $plant1$ is a representation for figure 2. 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. In order to see the cascade structure more clearly, one AGC control area in figure 1 is further redrawn as figure 4, where block $C2$ for a1 and $C1$ for CCS controller in CCS_BTG block. Disturbance $w2$ is for power demand disturbance $L1$ in figure 1 (or $Pdem$ in figure 3); $w1$ is added for tie-line disturbance. $P1$ and $p2$ stands for the Boiler-Turbine Generator (BTG) with the power system load as the control objects, block F stands for feed forward control from the neighborhood area.

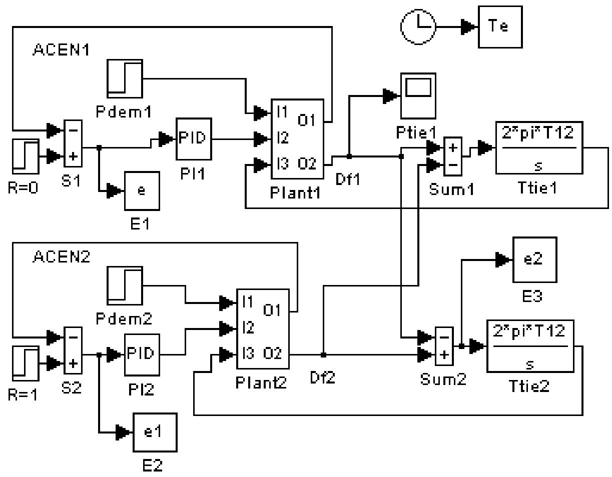

Fig. 3. Cascade System Model For Multi Area AGC System

The AGC loops of cascade system in figure 4 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 conclusions:

Remark 1. Consider the AGC system defined in Figure (1-4). The control action for multi-area AGC system could be optimized on: (1) disturbance rejection for outer loop controller,which could be in PID (as shown in Figure 3)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 AGC system in Figure 3 does not change the characteristic Equation of the system. The stability of the cascade AGC system is kept by the multiply inner BTG loops.

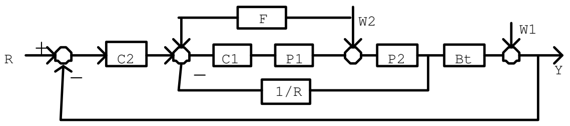

Fig. 4. SISO System Model For An AGC Control Area

The optimal performance design for controller $C1$ and $C2$ can be obtained by many intelligent algorithms (Karnavas and Papadopoulos, 2002). 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 (Kim *et al.*, 2000), the Decision Table looking up algorithm for discrete sample system will be developed below.

3. FUZZY LOGIC CONTROLLER OPTIMIZATION OF AGC SYSTEMS

Fuzzy controllers are usually constructed as a set of heuristic control rules, and the control signals are directly induced from the knowledge base and the fuzzy inference. For a general Fuzzy Logic Controller sketched in Figure 5, suppose the fuzzy control rules are expressed in the following form

If e is E_i and $\dot{e}$ is CE_j Then u is U_{Rij}

where $U_{Rij} \in U(i \in I, j \in J)$ are the fuzzy rules and (i,j) are membership function discrete indices for $I = [-n_i....,-2,-1,0,1,2.....n_i]$, $J = [-m_j.....-2,-1,0,1,2....,m_j]$.

The fuzzy relation matrix is

$$R_{ij} = E_i \times CE_j \times U_{Rij} \qquad (7)$$

Thus,

$$R = \cup R_{ij} = \max_{i \cdot j} \left(R_{ij}^{kp} \right) \qquad (8)$$

where, $k = 1,2,\cdots,r$; $p = 1,2,\cdots,s$ for the number of linguistic values (or universal) and $i = 1,2,\cdots,n$, $j = 1,2,\cdots,m$ 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. Suppose that $n = 2n_i + 1$ and $m = 2m_j + 1$, then the dimension of U_{Rij} is $n \times m$, and the correspondent $dim(E_i^k) = n \times r$, $dim(CE_j^p) = m \times s$.

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

$$U_{kp} = \left(E^k \times EC^p \right) \circ R \qquad (9)$$

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

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:

$$E^k = e/K_e, CE^p = \dot{e}/K_{ce}, U_{kp} = u/K_u \qquad (10)$$

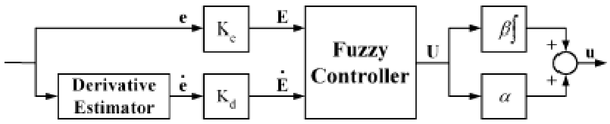

Fig. 5. Fuzzy Logic Controller Structure

In an online control or loop controller situation (Kim *et al.*, 2000), the control output U_{kp} is generally indexed from a stored table called the Decision Table (DT) ((Gao and Feng, 2004)(Wu and Mizumoto, 1996)), which is generated based on Equation (9), 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 (9). 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

$$R = R^{vq} = \bigcup_{i=1,j=1}^{n,m} R_{ij}^{vq} \triangleq \max_{i\in[1,n],j\in[1,m]} \left\{ R_{ij}^{vq} \right\} \qquad (11)$$

and

$$\begin{aligned} R_{ij}^{vq} &= (E_i^k \times CE_j^p) \times U_{Rij} \\ &\triangleq \min \left\{ [\min \left(E_i^k, CE_j^p \right)]_v, U_{Rij}^q \right\} \end{aligned} \qquad (12)$$

where $v \triangleq (k-1)s + p$, $q \in [1,t]$, and the other subindexes 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 $dim[.]_v = v \times 1$.

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

$$DT_{ij} = \sum_{q=1}^{t} \left(\mu \left(u_{ij}^q \right) \cdot u_{ij}^q \right) \bigg/ \sum_{q=1}^{t} \mu \left(u_{ij}^q \right) \qquad (13)$$

where

$$u_{ij}^q = \min \left(E_{ik}, CE_{jp} \right)_v \circ R^{vq} \qquad (14)$$

The algorithm for creating the rule based decision table can be now summarized as follows:

Algorithm 1:

(1) Obtain the E and CE values: E^k and CE^p from $k = p = 1$;

(2) Compute the values of all membership functions E_i and CE_j for all $i \in [1, n], j \in [1, m]$;

(3) Compute the premise $RF_{ij} = E_i^k \times CE_j^p = min(E_i^k, CE_j^p)$ for all i, j;

(4) Compute $R_{ij}^{vq} = U_{Rij} \times RF_{ij}$ for all i, j, and then form R using Equation (11);

(5) Cycle through all areas until $k = r$ and $p = s$ to determine the COG and store the result in the Decision Table using Equation (13).

For online control output calculation, the algorithm 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 will be found in paper (Li *et al.*, 2004).

Remark 3. The algorithm above provides the simple method for FLC design and application. It differs from rule deletion and addition algorithms such as proposed in (Hong and Chen, 2000). Here the elements in the relation matrix R are accurately located. After the input variables are defined and the rule base relation matrix R (and hence the decision table) are formed, the fuzzy control output can be obtained by look up within the DT table. GA optimization is needed to the three scaling factors K_e,K_{ce} and K_u to achieve the good performance of the control system.

Remark 4. If the input universe of discourse in a controller is discrete, it is always possible to calculate all possible combinations of the inputs before putting the controller into operation. In a table-based controller the relation between all input combinations and their corresponding outputs are arranged in a look-up table. This table implementation improves execution speed, as the run-time inference is reduced to a table looking up which is faster, at least when the correct entry can be found without too much searching.

The sensitivity of the FLC with respect to variations in the rule decision tables has been tested by changing the original decision table values in a limited range. It is pointed out in (Hong and Chen, 2000) that these variations in the rule decision tables do not cause any instability in the proposed fuzzy logic controller.

4. SIMULATIONS

Based on the figure 1 which has shown a two-area interconnected AGC system, the parameters in (Ahamed *et al.*, 2002) are used to demonstrate the cascade loop simulation, that is, $T_{pi} = 20s; T_{gi} = 0.08s; T_{ri} = 10s; T_{ti} = 0.3s; K_{ri} = 0.5; R = 2.4; K_{pi} = 120Hz/pu; T_{ij} = 0.545; B_i = 0.425$.

Using the Algorithm 1 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. Note that a properly automatic tuning of the FLC scaling factors could produce better results. The two area AGC system is shown in Figure 2 and Figure 3, where PID is replaced by FLC as in Figure 5. The simulation results are sketched in Figure 6. The results have shown the availability of cascade decoupled optimization suit for the AGC nonlinear system.

Table 1. Decision Table for FLC

$CE\backslash E$	-2	-1	0	1	2
-2	-0.7586	-0.7586	-0.2571	-0.0769	0.0000
-1	-0.7586	-0.4412	-0.0789	-0.0000	0.0769
0	-0.2571	-0.0789	0.0000	0.0789	0.2571
1	-0.0769	-0.0000	0.0789	0.4412	0.7586
2	0.0000	0.0769	0.2571	0.6897	0.7586

Based on the AGC simulation, the other example from paper (Karnavas and Papadopoulos, 2002) for a power plant AGC control system is simulated in Figure 7, where MATLAB GA toolbox is used for the optimization of the FLC scaling factors. The curves are compared for different scaling factor for FLC and PI controller. The performance of the FLC algorithm is much better than that of PI controller.

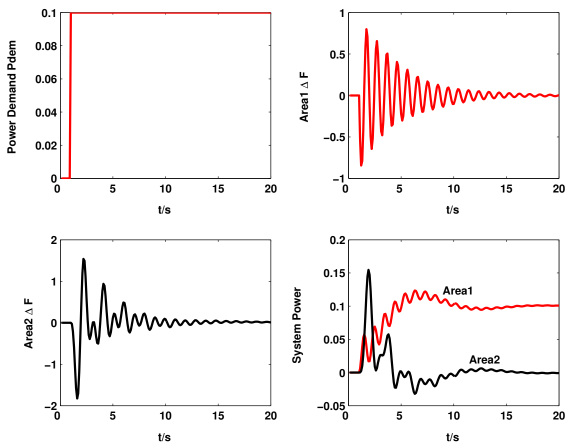

Fig. 6. Two Area AGC System Simulation

The field data experiment has also been carried and GA optimization algorithm is applied for AGC power unit. The data curve is shown in Figure 8, where generator output follows the AGC output quickly. Based on the research the optimization of the power plant AGC system is successful and the plant load tracking rate has promoted from 1% to 3% (9000KW/Min).

5. CONCLUSION

The main contributions of the paper are:

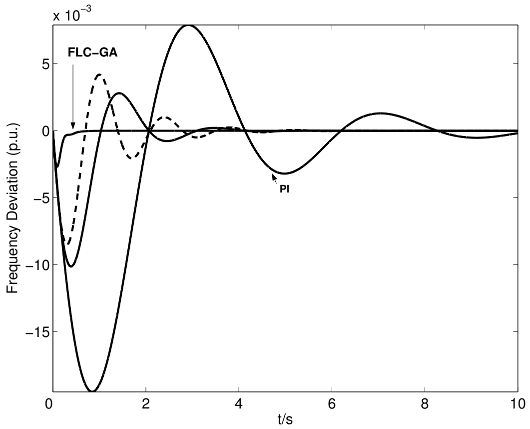

Fig. 7. Comparing For FLC And PID Controller Of An AGC System simulation

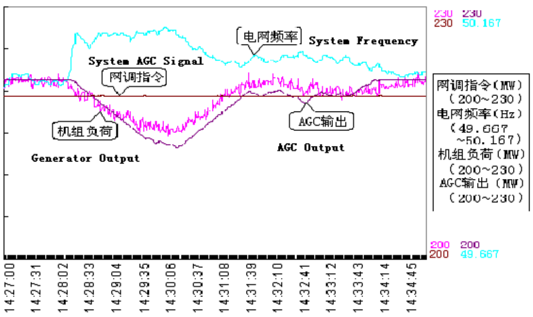

Fig. 8. FLC Field Data For AGC Parameter Optimization Experiment

1. The single-input single-output (SISO) cascade loop structure of the multi-area AGC system is analyzed. zero reference values for setting points of the cascade loops establish the stability between fast outer loop and slow inner loops. The proposed method has de-coupled the multi area AGC system to integration of the SISO cascade loops. This makes the simple FLC algorithm could be used in the AGC system.

2. A Decision Table looking up algorithm for Fuzzy Logic Controller with GA optimization for AGC system is developed. Instead of using traditional state space model to optimize the controller parameters, a model free single-input single-output robust FLC 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.

3. The optimizing method is easy to make the system have good performance in engineering application. The simulation of a two area power system is reported and a power plant AGC-CCS field optimization results are given.

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