An Adaptive PID Tuning For LFC System Using Neuro-Fuzzy Inference System

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Abstract— A new control scheme, based on Artificial Neuro-Fuzzy Inference System (ANFIS) is used to design a robust Proportional Integral Derivative (PID) controller for Load Frequency Control (LFC). The controller algorithm is trained by the results of off-line studies obtained by using particle swarm optimization. The controller gains are optimized and updated in real-time according to load and parameters variations. Simulation results of this method on a multi-machine system in comparison with conventional fuzzy controller show the satisfactory results, especially where the parameters of the system change.

Index Terms— Load Frequency Control, Fuzzy Control, PID Controller, Particle Swarm Optimization

I. INTRODUCTION

Recently due to dependence of load efficiency to network frequency and being as one of the power quality indices, frequency control is one of the main issues in power systems. However, area load changes and abnormal conditions, such as outages of generation lead to have changes in frequency and scheduled power interchanges between areas [1]. Automatic Generation Control (AGC) (also named, load frequency control) is then widely used to balance between generated power and load demands in each control area in order to maintain the system frequency at nominal value and the power exchange between areas at its scheduled value. The concept of AGC in vertically integrated power systems is well discussed in reference [2]. In this paper different control techniques are presented. Among them PI (Proportional Integra) and PID controllers are widely used. Different techniques such as pole placement and bode diagrams are utilized to set their parameters [3].

Because of the inherent characteristics of the changing loads, the operating point of a power system changes continuously during a daily cycle. Thus, a fixed controller may no longer be suitable in all operating conditions. Therefore, a lot of approaches have been reported to solve this problem such as adaptive control [4], robust control [5], evolutionary algorithms based control [6], fuzzy logic control [7], neural network based control [8].

Intelligent algorithms have, in general, advantageous and disadvantageous when applied to power systems [7, 9, and 10]. Therefore, it is common to combine these techniques to overcome the main problems. In reference [7] membership function of a fuzzy PID controller is optimized by Particle Swarm Optimization (PSO) algorithm. However, this controller is designed at nominal operating condition and fails to provide best control performance over a wide range of operating conditions. In reference [9] genetic algorithm is used to optimize the PI gains for a number of operation conditions of power system. The obtained gains are used to train the ANFIS to provide optimal control gains. In reference [9] the frequency bias factor and synchronizing torque coefficients are used to train the ANFIS algorithm but load variation which is a main parameter has not been considered. In reference [10] PSO algorithm is used to generate the training sets by considering only load variation but ignoring others to train the ANFIS network.

In this paper PSO algorithm is used to optimize the gains of a PID controller for a number of operation conditions of power system. These optimal gains which are obtained offline will train the ANFIS by using Hybrid Learning Algorithm. Then, ANFIS provides a general mapping between the operation conditions and the optimal gains. In fact, ANFIS will tune the PID controller parameters online to cope with the changing power system conditions. The comparative results of the proposed PID-ANFIS with PI-ANFIS and conventional fuzzy controllers show that a much better dynamic performance is achieved.

II. SYSTEM MODEL

Frequency changes occur because system load varies randomly throughout the day so that an exact forecast of real power demand cannot be assured. The imbalance between real power generation and load demand (plus losses) throughout the daily load cycle causes kinetic energy of rotation to be either added to or taken from the on-line generating units, and frequency throughout the interconnected system varies as a result. Each control area has a central facility called the energy control center, which monitors the system frequency and the actual power flows on its tie lines to neighboring areas.
The deviation between desired and actual system frequency is then combined with the deviation from the scheduled net interchange to form a composite measure called the area control error, or simply.

\[ AGCi = \beta AFi + \Delta P_{tie} \]  

(1)

In general, for satisfactory operation of power units running in parallel it is most desirable to have the frequency and tie-line power fixed on their nominal and scheduled values even when the load alters and, therefore, to remove area control error \((AGCi=0)\). To help understand the control actions at the power plants for LFC, let us consider the boiler–turbine–generator combination of a thermal generating unit.

Since all the movements are small the frequency–power relation for turbine–governor control can be studied by a linearized block diagram [1]. However, the computer simulation will be carried out using the actual nonlinear system. The linear model is shown in Fig. 1 for a two-machine power system where the blocks are [1]:

\[
\begin{align*}
\text{Governor} &= \frac{1}{T_s s + 1} \\
\text{Turbine} &= \frac{1}{T_s s + 1} \\
\text{Generator} &= \frac{1}{Ms + D}
\end{align*}
\]

(2)

The uncontrolled system is shown with the continuous lines and the control loops are indicated by the bold lines. The parameters of the test system are given in Appendix A.

III. FUZZY BASED CONTROLLER DESIGN

Fuzzy set theory and fuzzy logic establish the rules of a nonlinear mapping. Fuzzy control is based on a logical system called fuzzy logic which is much closer in spirit to human thinking and natural language than classical controllers. Because of the complexity and multi-variable conditions of the power system, conventional control methods may not give satisfactory solutions. The application of fuzzy logic to PID control design can be a simple solution and is classified in two major categories according to the way of their construction [7]:

1. A typical LFC is constructed as a set of heuristic control rules, and the control signal is directly deduced from the knowledge base.
2. The gains of the conventional PID controller are tuned on-line in terms of the knowledge based and fuzzy inference, and then, the conventional PID controller generates the control signal.

Fig. 2 shows the block diagram of fuzzy type controller to solve the LFC problem for each control area. The membership function sets for \(ACE_i\), \(\Delta ACE_i\), \(K_i\), \(K_d\), \(K_p\), and \(K_f\) are given in Appendix B.

IV. SUGENO FUZZY MODEL

Unlike Mamdani model, Sugeno output membership functions are either linear or constant [11]. If a fuzzy system has two inputs \(x\) and \(y\) and one output \(f\), then for a first order Sugeno fuzzy model, a common rule set with two fuzzy if then rules is as follows:

\[ \text{Rule 1: If } x \text{ is } A1 \text{ and } y \text{ is } B1, \text{ then } f1 = p1x + q1y + r1 \]

\[ \text{Rule 2: If } x \text{ is } A2 \text{ and } y \text{ is } B2, \text{ then } f2 = p2x + q2y + r2 \]

For a zero-order Sugeno model, the output level is a constant \((p_i=q_i=0)\). The output level \(fi\) of each rule is weighted by the firing strength \(wi\) of the rule. For example, for
an AND rule with \( \text{Input 1} = x \) and \( \text{Input 2} = y \), the firing strength is:
\[
w_i = \text{AND method } (A_1(x), B_1(y)).
\]

Where, \( A_1 \) and \( B_1 \) are the membership functions form Input 1 and Input 2, respectively. The final output of the system is the weighted average of all rule outputs, computed as:
\[
\text{Final Output} = \frac{\sum_{i=1}^{n} w_i f_i}{\sum_{i=1}^{n} w_i}
\]

**Layer 3:** Here, the \( i \)th node calculates the ratio of the \( i \)th rule’s firing strength to the sum of all rule’s firing strengths.
\[
O_i^3 = \frac{W_i}{w_i + w_2} \quad i = 1, 2
\]

**Layer 4:** Every node \( i \) in this layer is an adaptive node with a node function:
\[
O_i^4 = \overline{w_i} f_i = \overline{w_i} (x p_i + y q_i + r_i)
\]

Where, \( w_i \) is a normalized firing strength from layer 3 and \( \{p_i, q_i, r_i\} \) is the parameter set of the node. These parameters are referred to as consequent parameters.

**Layer 5:** The single node in this layer is a fixed node labeled \( \Sigma \), which computes the overall output as the summation of all incoming signals:
\[
O_i^5 = \text{Overall Output} = \sum_i \overline{w_i} f_i = \sum_i \frac{w_i f_i}{\sum w_i}
\]

In this paper, the hybrid learning algorithm is used for training of ANSIF networks. This algorithm is a combination of least square and back propagation method. Details of this algorithm have been published in reference [11].

## VI. TRAINING PATTERNS

As mentioned earlier, fixed gain controllers are designed at nominal operating conditions and fail to provide best control performance over a wide range of operating conditions. It is desirable to keep system performance near its optimum. Therefore, the presented method tracks different system operating conditions and updates the gains of PID controllers according to loads and parameters variation. In this paper, the PSO is used for preparing the training patterns. Details of this algorithm have published in reference [12]. Thus, the objective function of the optimization of the performance of the system is defined as:

\[
\text{Fitness Function} = \int_0^\infty \left( \alpha P_{ne} + \beta (\Delta f_1 + \Delta f_2) \right) dt
\]

The coefficients \( \alpha \), \( \beta \) and \( \gamma \) are assumed to be 1. Now, the optimal values of PID controller gains should be calculated for area load variation and synchronizing torque coefficients in order to minimize Equation (10) by using PSO technique.

The fitness function is evaluated and the population is updated iteratively until the stopping criterion is obtained. The first step in using ANFIS is preparing training patterns to train it. In this paper, the training data set consists of several disturbances. These disturbances are combinations of the load variations in the range of \(-0.1 \) to \(0.1 \) pu and synchronizing torque coefficient variation in the range \(0\) of \(1.5 \) to 3. Therefore, for each load disturbance \((\Delta P_{1l}, \Delta P_{2l})\), eleven values in range of \(-0.1 \) to \(0.1 \) with \(0.02 \) step are considered. Four values of \(1.5, 2, 2.5, \) and \(3 \) are also considered for Torque Coefficient variation. Finally, the training set consists of 484 elements.
Then, the optimal gains of PID controllers are computed for each of these disturbances using PSO method and the objective function given in Equation (10). After gathering these data, it is possible to train ANFIS. For each gain, one neuro-fuzzy network is trained. After computing the optimal gains, two matrices with 484 rows and 6 columns (three columns for input variation and the three columns representing the optimal gains), and one matrix for each controller, is fed to ANFIS for training.

VII. PROPOSED CONTROL APPROACH

When the training is done, the two trained neuro-fuzzy networks can estimate the optimal gains for any disturbances taken place in the power system and online control can be implemented. It should be noted that the efficiency of ANFIS can be enhanced by choosing a bigger training set. The proposed method can be applied to small and intermediate power systems easily. However, although all of the time-consuming computations are carried out offline, for large and very large power systems, computation time will be somehow exorbitant and more powerful computers or advanced computing techniques will be necessary to be used.

The test system shown in Fig. 4 is used to illustrate the behavior of the proposed method. For ANFIS, the settings to be used were Gaussian membership function, four membership functions for load variation, three membership functions for parameter variation, hybrid optimization method and epoch = 15. PSO settings were as follows: population size = 50, \(c_1 = c_2 = 2\), \(\omega_{\text{max}} = 0.9\), \(\omega_{\text{min}} = 0.4\), maximum speed = 2. The proposed controller is a two-level controller. The first level is ANFIS network and the second one is PID controller.

In this strategy, the gains \(K_p\), \(K_i\), and \(K_d\) in Equation (11) are tuned on-line based on load variation and Synchronizing Torque Coefficient variation. The PIANFIS is similar to PIDANFIS but \(K_d = 0\).

VIII. SIMULATION RESULTS

In order to validate the proposed controller for load frequency control three different cases are considered and are given as follows;

A. Case 1:

In this case, the following load variations are considered: \(\Delta P_{L1} = 0.02\), \(\Delta T_{L2} = 0.02\) and no disturbances occur in area II. From Fig. 5 (a) and Fig. 5 (b) can be seen that PIDANFIS according to nominal operation point, improves the dynamic performance.

The proposed ANFISPID controller for each area.

\[ u_i = K_p, \Delta P_{L1} + K_i, \int_0^t \Delta P_{L1}(t)dt + K_d, \Delta P_{L1}(t) \quad (11) \]

The structure of the ANFISPID controller is shown in Fig. 4, where the PID controller gains are tuned online for each of the control areas. Therefore, \(u_i\) is a control signal that applies to governor set point in each area. By taking \(ACE_i\) as the system output, the control vector for a conventional PID controller is given by:

\[ u_i = K_p, ACE_i(t) + K_i, \int_0^t ACE_i(t)dt + K_d, ACE_i(t) \quad (11) \]

Fig. 5. System response for case 1. (a) \(\Delta\omega_1\), (b) \(\Delta\omega_2\), (c) \(\Delta P_{\text{tie}}\). (Solid: PIDANFIS, Dashed: PIANFIS, Doted: Conventional fuzzy)
B. Case 2:

In this case, the synchronizing torque coefficient changes to 2.5, but the demand load is similar to the case 1. The simulation results depicted in Fig. 6 show that system with conventional fuzzy controller fails to provide a desirable performance when parameters vary, because the conventional fuzzy controller was designed based on $T_{12}=2$.

![Fig. 6. System response for case 2. (a) $\Delta \omega_1$, (b) $\Delta \omega_2$. (Solid: PIDANFIS, Dashed: PIANFIS, Dotting: Conventional fuzzy)](image)

C. Case 3:

In this case, a bounded random step load change shown in Fig. 7 appears in each control area. The purpose of this case is to test the robustness of the proposed controller against random load disturbances. The frequency deviations of both systems for nominal operating condition (case 1) are shown in Fig. 8 (a) and (b).

![Fig. 7. Load disturbances in two areas.](image)

From Fig. 8 (a) and Fig. 8 (b), it can be seen that the ANFISPID controller tracks the load fluctuations and for a wide range of operating conditions.

IX. CONCLUSION

Optimization of the PID gains for a two-area load frequency controller using PSO algorithms has been proposed. Such optimization technique has the advantage of being systematic and weakly dependent on the model. But, the time consumed for computing optimal gains using PSO directly is too much for real-time control and is not practical. However, the trained ANFIS response time is reasonable and practical.

The gains for 484 operating conditions were used to train an adaptive neuro-fuzzy inference system in order to obtain a general mapping between the operating condition and optimal PID gains. A comparison between the proposed schemes, PI controller based on ANFIS and conventional fuzzy controller revealed that the system performance can be improved.

APPENDICES

- Appendices A:

  The system parameters are as follows (frequency = 60Hz, base = 1000 MVA):

  System #1:
  $H = 5$; $D = 0.8$; $T_g = 0.2$; $T_h = 0.5$; $R = 0.05$; $\beta = 20.8$

  System #2:
  $H = 4$; $D = 0.9$; $T_g = 0.3$; $T_h = 0.6$; $R = 0.0625$; $\beta = 16.9$
- Appendices B:

The membership function sets for $ACE_i$, $\Delta ACE_i$, $K_i$, $K_d$ and $K_P$ are shown in Fig. 9. The appropriate rules for the proposed control strategy are given in TABLES I and II.

Table 9. a) Membership for $ACE_i$, b) Membership for $\Delta ACE_i$, c) Membership for $K_d$, $K_P$ and $K_i$.

Table I

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Table II

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References


BIOGRAPHIES

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