

ARTIFICIAL INTELLIGENCE OPTIMIZED CONTROLLER DESIGN FOR AUTOMATIC GENERATION CONTROL IN RESTRUCTURED POWER SYSTEMS

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Received: March 19, 2024; Revised: May 07, 2024; Accepted: May 27, 2024

Abstract

This paper presents an investigation on automatic generation control (AGC) in restructured power systems with multiple interconnected areas and multiple machines. A particle swarm optimized combined optimal fuzzy controller has been proposed. The results obtained with the proposed controller have been compared with the conventional PI controller and optimal controller to exhibit its robust performance. Furthermore, the proposed controller aims to rapidly achieve zero deviations in frequency and tie line power, thereby maintaining system synchronism. The PSO-optimized combined optimal fuzzy controller demonstrates superior performance in terms of peak transient deviation, settling periods, and dynamic oscillations compared to other controllers.

Keywords: Automatic Generation Control (AGC); Fuzzy controller; Optimal controller; Particle Swarm Optimization (PSO); Restructured power system; Combined optimal fuzzy controller

Nomenclature

a_{ij} = Area capacity ratio
 b_i = Frequency droop constants
 f = Rated frequency
 Δf_i = Frequency Deviation
 K_{ps} = Power system gains
 K_i = Optimal controller gains

K_{li} = Integral controller gains
 R_i = Governor speed regulation parameters
 T_{ti} = Turbine time constants
 T_{ps} = Power system time constants
 T_{sgi} = Governor time constants

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Introduction

The functioning of a connected power system depends on maintaining frequency in each location. In addition, tie-line power variations owing to load fluctuations should be regulated to bring them to zero.

Due to the dynamic nature of active power demand, continuous control of the mechanical input to the turbo generator is essential to meet it. Failure to do so would lead to fluctuations in the tie-line power and frequency of the interconnected power system, potentially causing a loss of synchronism. Consequently, the controller for automatic generation control adjusts the output power in response to the load demand.

Various strategies for Automatic Generation Control (AGC) have been explored in several studies (Elgerd and Fosha, 1970; Shayeghi *et al.*, 2009; Alhelou *et al.*, 2018; Hameed and Ramasubramanian, 2022). The authors (Ullah *et al.*, 2021) conducted a comprehensive review of different AGC models applicable to a variety of power system scenarios. In another investigation, a multi-area system was examined concerning AGC (Amil *et al.*, 2020). The impact of electric vehicles on AGC in a multi-area system was studied using a combined fuzzy controller (Arya, 2022).

A Novel methodology, encompassed a hybrid optimization technique that combined Particle Swarm Optimization (PSO) and Gravitational Search Algorithm (GSA) with the goal of attaining an optimal AGC scheme. This novel approach was designed to significantly improve the performance of AGC systems (Hasni, 2019).

Furthermore, (Panigrahi *et al.*, 2011) presented theoretical and algorithmic insights into Particle Swarm Intelligence techniques, demonstrating their real-world applicability. They showcased how swarm intelligence approaches can be effectively employed in practical scenarios.

Feedback from all states generates control inputs in optimal control, with feedback constants determined according to an optimal criterion. The control vector for full state feedback is made up of a linear combination of all states (Liaw, 1991; Subbaraj and Manickavasagam, 2008; Dahiya *et al.*, 2016). Due to the inherent nature of varying loads, the operational state of a power system might oscillate throughout a daily cycle. In such cases, a fixed gain controller set at the nominal operating point may prove inadequate in delivering the most optimal dynamic response. Fuzzy logic controllers are recognized to be more robust than traditional controllers (Grefenstette, 1986; Kumar, 1998;

Magzoub and Alquthami, 2022; Muhammad, 2023), Applications of FACTS to improve AGC performance has been discussed (Sinha *et al.*, 2011). PI controllers are mostly used by researchers for AGC and other control applications (Acharya, 2023; Singh *et al.*, 2023).

A novel controller that combines optimal and fuzzy control techniques has been developed to investigate automatic generation control in a complex restructured power system with two areas and a three-area restructured power system. The controller parameters are optimized by application of the Particle Swarm Optimization (PSO) artificial intelligence technique. Subsequently, the performance of the proposed controller was compared to that of a conventional integral controller and an optimal controller in these systems. PSO is computationally more efficient than conventional tuning methods such as trial and error or gradient-based optimization techniques. It searches the solution space by adjusting particles' positions and velocities, which can converge to optimal solutions faster, especially in high-dimensional spaces (Sinha *et al.*, 2011). It is capable of finding global optima rather than getting stuck in local optima and easy to implement, requiring minimal parameter tuning in comparison to conventional optimization techniques.

The simulation results demonstrated that the proposed controller exhibited notable enhancements in overshoot and settling time outcomes in both the two-area restructured thermal-thermal system and the three-area thermal-thermal-hydro system. These findings highlight the effectiveness and superiority of the combined controller over the conventional ones in regulating power generation and maintaining stability in the power system.

Optimal Controller Design For Restructured System

For the design of optimal controller, all system states are linearly integrated to yield two control inputs (Sinha *et al.*, 2012). For the system under consideration, there are a total of 13 state variables. Figure 1 displays the various blocks in terms of state variables. The following variables have been defined in the block diagram of Figure 1:

$$\begin{aligned} x_1 = \Delta f_1; x_2 = \Delta P_{g1}; x_4 = \Delta f_2; x_5 = \Delta P_{g3}; x_{10} = \Delta P_{g2}; x_{12} = \Delta P_{g4}; w_1 = \Delta P_{L1} + \Delta P_{L2} + \Delta P_{UCL1} + \Delta P_{UCL2}; w_2 = \Delta P_{L3} + \Delta P_{L4} + \Delta P_{UCL3} + \Delta P_{UCL4}; \end{aligned}$$

The differential equations for each block can be written as follows:

$$\dot{x}_1 = -\frac{1}{T_{ps1}}x_1 + \frac{K_{ps1}}{T_{ps1}}x_2 - \frac{K_{ps1}}{T_{ps1}}x_7 + \frac{K_{ps1}}{T_{ps1}}x_{10} - \frac{K_{ps1}}{T_{ps1}}w_1 \quad (1)$$

Similarly,

$$\dot{x}_2 = -\frac{1}{T_{t1}}x_2 + \frac{1}{T_{t1}}x_3 \quad (2)$$

$$\dot{x}_3 = -\frac{1}{R_1T_{sg1}}x_1 - \frac{1}{T_{sg1}}x_3 + \frac{1}{T_{sg1}}u_{11} \quad (3)$$

where, $u_{11} = apf_1u_1 + cpf_{11}\Delta P_{L1} + cpf_{12}\Delta P_{L2} + cpf_{13}\Delta P_{L3} + cpf_{14}\Delta P_{L4}$

$$\dot{x}_4 = -\frac{1}{T_{ps2}}x_4 + \frac{K_{ps2}}{T_{ps2}}x_5 + \frac{a_{12}K_{ps2}}{T_{ps2}}x_7 + \frac{K_{ps2}}{T_{ps2}}x_{12} - \frac{K_{ps2}}{T_{ps2}}w_2 \quad (4)$$

$$\dot{x}_5 = -\frac{1}{T_{t3}}x_5 + \frac{1}{T_{t3}}x_6 \quad (5)$$

$$\dot{x}_6 = -\frac{1}{R_3T_{sg3}}x_4 - \frac{1}{T_{sg3}}x_6 + \frac{1}{T_{sg3}}u_{21} \quad (6)$$

where, $u_{21} = apf_3u_2 + cpf_{31}\Delta P_{L1} + cpf_{32}\Delta P_{L2} + cpf_{33}\Delta P_{L3} + cpf_{44}\Delta P_{L4}$

$$\dot{x}_7 = 2\pi T_{12}x_1 - 2\pi T_{12}x_4 \quad (7)$$

$$\dot{x}_8 = b_1x_1 + x_7 \quad (8)$$

$$\dot{x}_9 = b_2x_4 - a_{12}x_7 \quad (9)$$

$$\dot{x}_{10} = -\frac{1}{T_{t2}}x_{10} + \frac{1}{T_{t2}}x_{11} \quad (10)$$

$$\dot{x}_{11} = -\frac{1}{R_2T_{sg2}}x_1 - \frac{1}{T_{sg2}}x_{11} + \frac{1}{T_{sg2}}u_{12} \quad (11)$$

where, $u_{12} = apf_2u_1 + cpf_{21}\Delta P_{L1} + cpf_{22}\Delta P_{L2} + cpf_{23}\Delta P_{L3} + cpf_{24}\Delta P_{L4}$

$$\dot{x}_{12} = -\frac{1}{T_{t4}}x_{12} + \frac{1}{T_{t4}}x_{13} \quad (12)$$

and,

$$\dot{x}_{13} = -\frac{1}{R_4T_{sg4}}x_4 - \frac{1}{T_{sg4}}x_{13} + \frac{1}{T_{sg4}}u_{22} \quad (13)$$

where, $u_{22} = apf_4u_2 + cpf_{41}\Delta P_{L1} + cpf_{42}\Delta P_{L2} + cpf_{43}\Delta P_{L3} + cpf_{44}\Delta P_{L4}$

The vector matrix representations of equations (1) to (13) are as follows:

$$\dot{x} = Ax + BU + \tau P + Fp \quad (14)$$

The matrices A, B, F and τ are obtained as below:

$$A = \begin{bmatrix} -\frac{1}{T_{ps1}} & \frac{K_{ps1}}{T_{ps1}} & 0 & 0 & 0 & 0 & -\frac{K_{ps1}}{T_{ps1}} & 0 & 0 & \frac{K_{ps1}}{T_{ps1}} & 0 & 0 & 0 \\ 0 & -\frac{1}{T_{t1}} & \frac{1}{T_{t1}} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ -\frac{1}{R_1T_{sg1}} & 0 & -\frac{1}{T_{sg1}} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & -\frac{1}{T_{ps2}} & \frac{K_{ps2}}{T_{ps2}} & 0 & \frac{a_{12}K_{ps2}}{T_{ps2}} & 0 & 0 & 0 & 0 & \frac{K_{ps2}}{T_{ps2}} & 0 \\ 0 & 0 & 0 & 0 & -\frac{1}{T_{t3}} & \frac{1}{T_{t3}} & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & -\frac{1}{R_3T_{sg3}} & 0 & -\frac{1}{T_{sg3}} & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 2\pi T_{12} & 0 & 0 & -2\pi T_{12} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ b_1 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & b_2 & 0 & 0 & -a_{12} & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & -\frac{1}{T_{t2}} & \frac{1}{T_{t2}} & 0 & 0 \\ -\frac{1}{R_2T_{sg2}} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & -\frac{1}{T_{sg2}} & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & -\frac{1}{T_{t4}} & \frac{1}{T_{t4}} \\ 0 & 0 & 0 & -\frac{1}{R_4T_{sg4}} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & -\frac{1}{T_{sg4}} \end{bmatrix}$$

$$B^T = \begin{bmatrix} 0 & 0 & \frac{apf_1}{T_{sg1}} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \frac{apf_2}{T_{sg2}} & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & \frac{apf_3}{T_{sg3}} & 0 & 0 & 0 & 0 & 0 & 0 & \frac{apf_4}{T_{sg4}} \end{bmatrix}$$

$$F^T = \begin{bmatrix} -\frac{K_{ps1}}{T_{ps1}} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & -\frac{K_{ps2}}{T_{ps2}} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

$$U = \begin{bmatrix} u_1 \\ u_2 \end{bmatrix}, P = \begin{bmatrix} \Delta P_{L1} \\ \Delta P_{L2} \\ \Delta P_{L3} \\ \Delta P_{L4} \end{bmatrix}, p = \begin{bmatrix} \Delta P_{UCL1} \\ \Delta P_{UCL2} \\ \Delta P_{UCL3} \\ \Delta P_{UCL4} \end{bmatrix}$$

$$\tau = \begin{bmatrix} -\frac{K_{ps1}}{T_{ps1}} & -\frac{K_{ps1}}{T_{ps1}} & 0 & 0 \\ 0 & 0 & 0 & 0 \\ \frac{cpf_{11}}{T_{sg1}} & \frac{cpf_{12}}{T_{sg1}} & \frac{cpf_{13}}{T_{sg1}} & \frac{cpf_{14}}{T_{sg1}} \\ 0 & 0 & 0 & 0 \\ 0 & 0 & -\frac{K_{ps2}}{T_{ps2}} & -\frac{K_{ps2}}{T_{ps2}} \\ \frac{cpf_{31}}{T_{sg3}} & \frac{cpf_{32}}{T_{sg3}} & \frac{cpf_{33}}{T_{sg3}} & \frac{cpf_{34}}{T_{sg3}} \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ \frac{cpf_{21}}{T_{sg2}} & \frac{cpf_{22}}{T_{sg2}} & \frac{cpf_{23}}{T_{sg2}} & \frac{cpf_{24}}{T_{sg2}} \\ 0 & 0 & 0 & 0 \\ \frac{cpf_{41}}{T_{sg4}} & \frac{cpf_{42}}{T_{sg4}} & \frac{cpf_{43}}{T_{sg4}} & \frac{cpf_{44}}{T_{sg4}} \end{bmatrix}$$

Within this context, the control vector 'U' functions as governor feedback, while the disturbance vectors P and p indicate changes in load/un-contracted load demand by DISCOs.

Feedback from all thirteen states generates the u_1 and u_2 control inputs in the optimum control scheme, with feedback constants determined according to an optimal criterion.

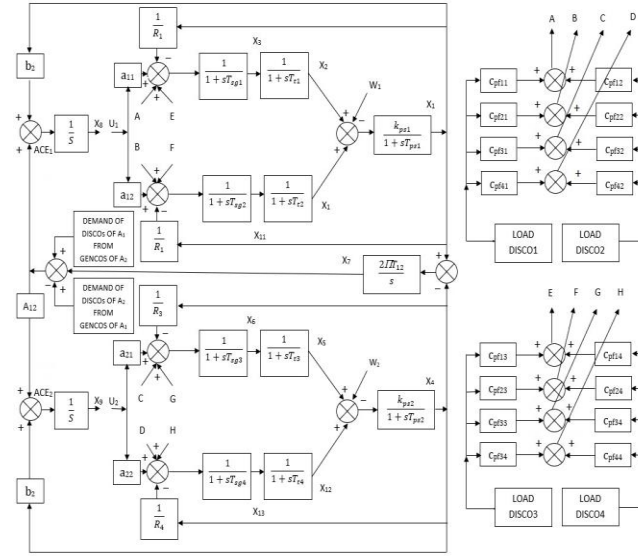


Figure 1. Shows Block Diagram: Re-structured Power System having Optimal Controller

The control vector U is created by linearly combining all states to facilitate state feedback, whereas Q is defined as follows.

$$Q = \begin{bmatrix} b_1^2 & 0 & 0 & 0 & 0 & 0 & b_1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & b_2^2 & 0 & 0 & -a_{12}b_2 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ b_1 & 0 & 0 & -a_{12}b_2 & 0 & 0 & 1 + a_{12}^2 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

The sparsity of the matrices in fact helps in faster operations. If only the non-zero elements are considered, operations on sparse matrices may be much faster. The zero values aren't explicitly stored. The total storage is still significantly decreased because large matrices are extremely sparse.

Particle Swarm Optimization Technique

Particle swarm optimization represents a population-based stochastic optimization method. It commences with a random population of solutions and iterates through generations to identify the most optimal one. Within PSO, particles traverse the problem space by following the current optimal particles, which are potential solutions. Participants adjust their flight path based on their individual and companions' experiences in PSO. Each particle keeps track of the problem space coordinates

corresponding to the best solution (fitness) it has encountered so far, denoted as 'pbest.' Moreover, the particle swarm optimizer maintains a record of the overall best value achieved by any particle in the population, referred to as the 'global best value' or 'gbest.' The equations presented below govern the computation of current position and velocity vectors.

$$V_{ik+1} = wV_{ik} + c_1 \text{rand}_1() * (p_{\text{best}i} - S_{ik}) + c_2 \text{rand}_2() * (g_{\text{best}} - S_{ik}) \quad (15)$$

$$w = w_{\text{Max}} - [(w_{\text{Max}} - w_{\text{Min}}) * \text{iter}] / \text{max}_{\text{iter}} \quad (16)$$

$$S_{ik+1} = S_{ik} + V_{ik+1} \quad (17)$$

where,

v_{ik} = velocity of particle i at iteration k , w = weighting function,

c_j = learning factor, usually $c_1 = c_2 = 2$

rand = random number between 0 and 1,

S_{ik} = current position of particle i at iteration k , $p_{\text{best}i}$ = p_{best} of particle i ,

Optimal Fuzzy Controller

A combined optimal fuzzy controller is developed to study the restructured power system as shown in Figure 2. In order to optimize the X and Y scaling factors, PSO has been utilized as an optimization technique. In Figure 3, sets of fuzzy terms are explained. Tuning of fuzzy scaling factors of is shown in Figure 4. The scaling factors have been optimized by GA also. The comparison of convergence plots is shown in Figure 4a. The PSO technique results in much faster convergence.

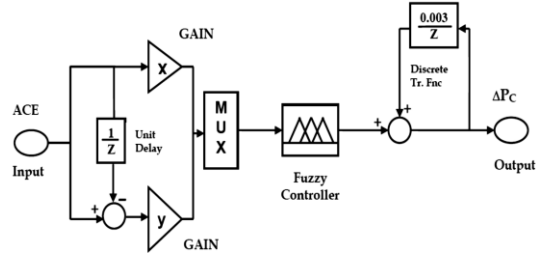


Figure 2. Shows Controller subsystem

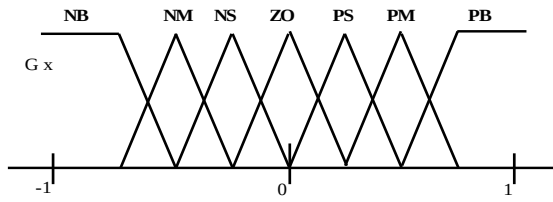


Figure 3. Shows Membership functions

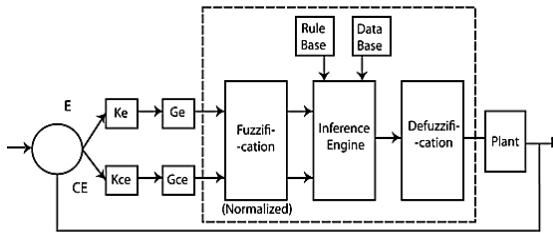


Figure 4. Shows Input scaling factors tuning parameters

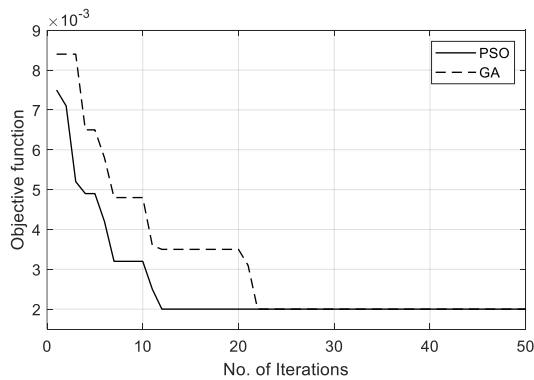


Figure 4a. Shows Convergence plots of PSO and GA for scaling factors optimization

The applied PSO technique has been depicted by flow chart shown in Figure 5.

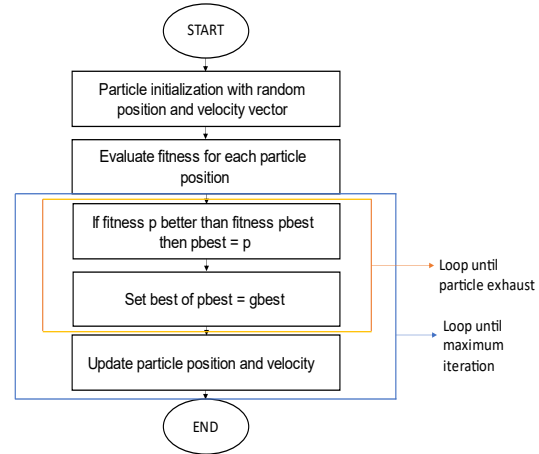


Figure 5. Shows PSO implementation flow chart

First System Example

The following data used (Dahiya *et al.*, 2016):

$$f=60\text{Hz}, T_{sg1} = T_{sg2} = 0.08 \text{ sec}$$

$$T_{t1} = T_{t2} = 0.3 \text{ sec}, H_1 = H_2 = 5 \text{ sec}$$

$$D_1 = D_2 = 8.33 \times 10^{-3} \text{ puMW / Hz}$$

$$R_1 = R_2 = 2.4 \text{ Hz / puMW}$$

$$P_{r1} = P_{r2} = 2000 \text{ MW}, P_{tie, \max} = 200 \text{ MW}$$

$$b_1 = b_2 = D + \frac{1}{R} = 0.425$$

From the above, K_{ps} and T_{ps} are calculated by the following relations

$$K_{ps} = \frac{1}{D}; \text{ hence, } K_{ps1} = K_{ps2} = 120 \quad T_{ps} = \frac{2H}{Df};$$

hence, $T_{ps1} = T_{ps2} = 20 \text{ sec}$

Table 1 shows the optimum scaling factor values.

Table 1. Shows PSO and GA Optimized Scaling Factor Values

	X	Y
Values of X and Y without optimization	1	1
X and Y Values Optimized Using PSO	3.431	3.072
X and Y Values Optimized using GA	0.462	8.484

Three alternative controllers were used to simulate the system: an integral controller, an optimal controller, and a combined optimal controller. When modelling the AGC in a deregulated environment, the following factors

were taken into account. DISCOs and GENCOs enter into contracts based on the DPM matrix below:

$$M = \begin{bmatrix} 0.5 & 0.25 & 0.0 & 0.30 \\ 0.20 & 0.25 & 0.0 & 0.0 \\ 0.0 & 0.25 & 1.0 & 0.7 \\ 0.30 & 0.25 & 0.0 & 0.0 \end{bmatrix}$$

As per the DPM matrix, every DISCO necessitates 0.02 pu MW of power sourced from GENCOs. The following ACE participation factors determine how GENCOs participate in AGC:

$$apf1=0.75, apf2=0.25, apf3=0.50 \text{ and } apf4=0.50$$

As per the DPM matrix, every DISCO necessitates 0.02 pu MW of power sourced from GENCOs. The following ACE participation factors determine how GENCOs participate in AGC:

Loads that have not been contracted are presumed to be zero. A, B, Q, and R, matrices have been computed and are shown below:

$$A = \begin{bmatrix} -0.05 & 6 & 0 & 0 & 0 & 0 & -6 & 0 & 0 & 6 & 0 & 0 & 0 \\ 0 & -3.33 & 3.33 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ -5.2083 & 0 & -12.5 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & -0.05 & 6 & 0 & 6 & 0 & 0 & 0 & 6 & 0 & 0 \\ 0 & 0 & 0 & 0 & -3.33 & 3.33 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0.525 & 0 & 0 & -5.2083 & 0 & -12.5 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0.425 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0.425 & 0 & 0 & -1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & -3.33 & 3.33 & 0 & 0 \\ -5.2083 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & -12.5 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & -3.33 & 3.33 \\ 0 & 0 & 0 & -5.2083 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & -12.5 \end{bmatrix}$$

$$B^T = \begin{bmatrix} 0 & 0 & 9.375 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 3.125 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 6.25 & 0 & 0 & 0 & 0 & 0 & 6.25 & 0 \end{bmatrix}$$

$$R = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

$$Q = \begin{bmatrix} 0.1806 & 0 & 0 & 0 & 0 & 0 & 0.425 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0.1806 & 0 & 0 & -0.425 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0.425 & 0 & 0 & -0.425 & 0 & 0 & 2 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

Results And Discussions

The results obtained for feedback matrix K are:

$$K = \begin{bmatrix} -0.0758 & -0.1179 & -0.0280 & 0.2792 & 0.4936 & 0.1236 \\ 0.2792 & 0.4936 & 0.1236 & -0.0758 & -0.1179 & -0.0280 \\ -0.1356 & 0 & 1 & -0.1179 & -0.0280 & 0.4936 & 0.1236 \\ 0.1356 & 1 & 0 & 0.4936 & 0.1236 & -0.1179 & -0.0280 \end{bmatrix}$$

The comparison of performances of the three controllers has been shown in the plots of Figures 6 to 12 for a 2% step load by each DISCO.

Figure 6 and Figure 7 illustrate the frequency responses in regions 1 and 2, respectively. When compared to the optimal controller, the integral controller has a longer settling time. In the latter instance, the peak deviation is also substantially lower. There are further improvements with respect to these three parameters for combined optimal controlled system.

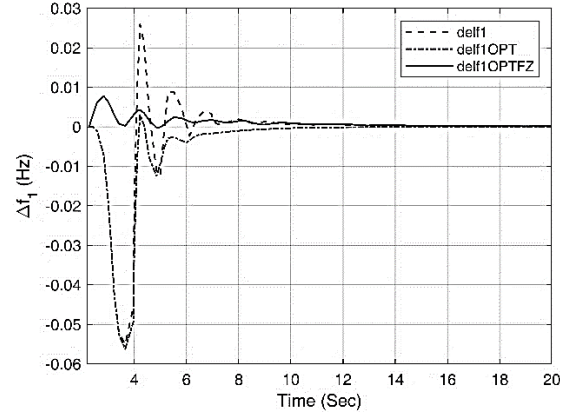


Figure 6. Shows Frequency change in area 1 (restructured system)

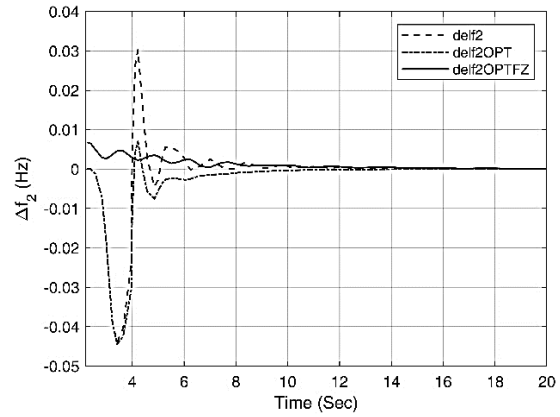


Figure 7. Shows Frequency change in area 2 (restructured system)

The tie line deviation owing to a step load disturbance is seen in Figure 8. The tie line deviation and settling time both drop when the optimal controller is used, and they decrease much more when the combined optimal controller is used. The power generated by the four GENCOs is compared in Figures 9 to 12. When the frequency deviation, time to dampen down oscillations, tie-line power deviation, and power generated by GENCOs

are all taken into consideration, the optimal controller clearly surpasses the typical PI controller, and that the results improve significantly when the proposed controller is used. The overshoots and settling times of the system responses are much lower with optimal and combined optimal controllers as compared to those of the integral controller. The results achieved with a combined optimal fuzzy controller, on the other hand, are the best. The un-contracted load of DISCO1 is represented the GENCOs of area 1. As a result, the GENCOs in the same region as the DISCO that is producing the un-contracted demand take on this extra load. GENCOs of area 2 generate power to meet their own needs.

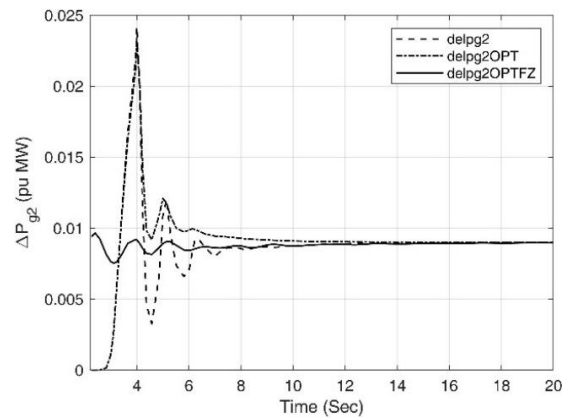


Figure 10. Change in generated power by GENCO 2

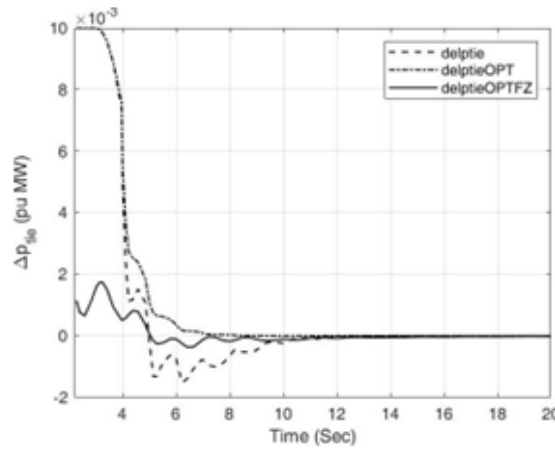


Figure 8. Shows Tie line power deviation

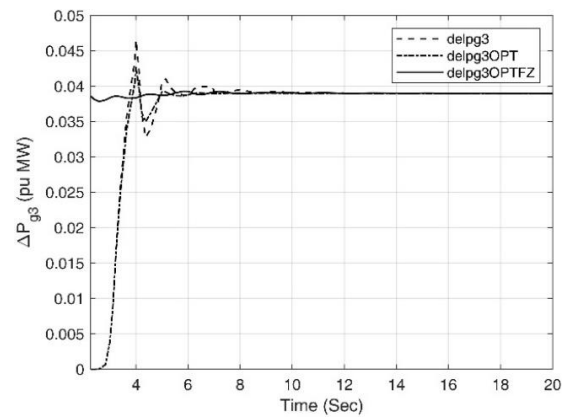


Figure 11. Shows Change in generated power by GENCO 3

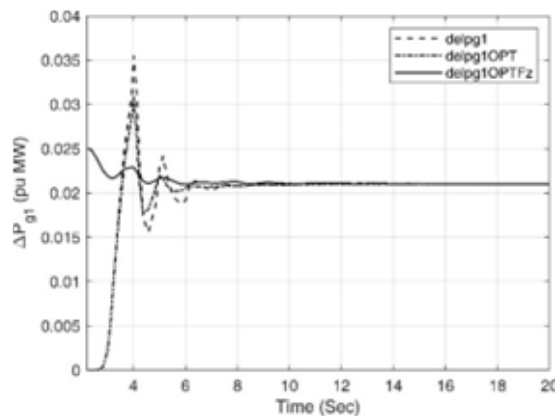


Figure 9. Shows Change in generated power by GENCO 1

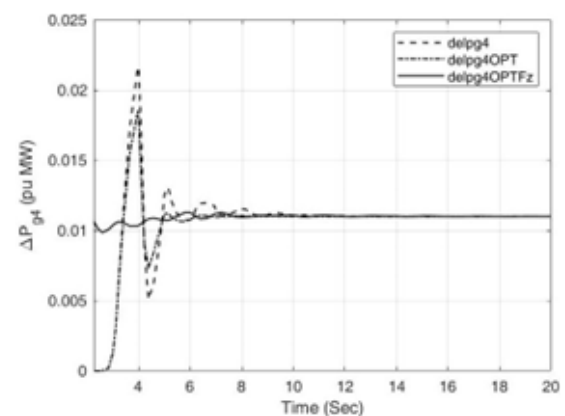


Figure 12. Shows Change in generated power by GENCO 4

Figure 14. Shows Frequency change in area 3 (1% SLP in first thermal area)

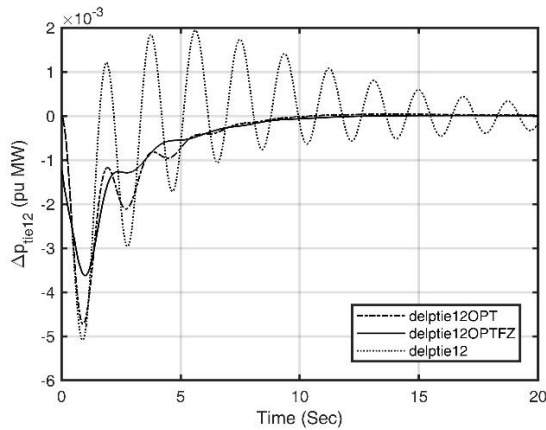


Figure 15. Shows tie line (1-2) power deviation (1% SLP in first thermal area)

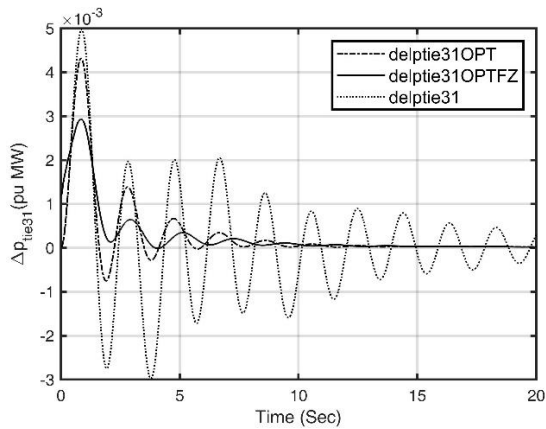


Figure 16. Shows tie line (3-1) deviation (1% SLP in first thermal area)

In the hydro area, simulations were also performed with 1% SLP. Figure 17 and Figure 18 give comparison of responses for the three controllers. In these plots the responses using optimal and combined optimal fuzzy controllers stabilize much faster, whereas that with conventional controller does not settle down over a simulation period of 30 seconds. The oscillations and peak deviations are prominent with the last controller. With optimal and combined optimal fuzzy controller oscillations of the responses damp out quickly and peak deviations are also reduced.

The combined optimal fuzzy controller consistently outperforms the other two controllers across all scenarios. The results and plots indicate that the proposed controller exhibits excellent performance, particularly in handling load disturbances. It effectively eliminates frequency and tie line power deviations, surpassing the performance of the alternative controllers.

A comparison is made between the suggested approach and the method available in literature (Donde *et al.*, 2011). Table 2 provides a comparative analysis of the findings.

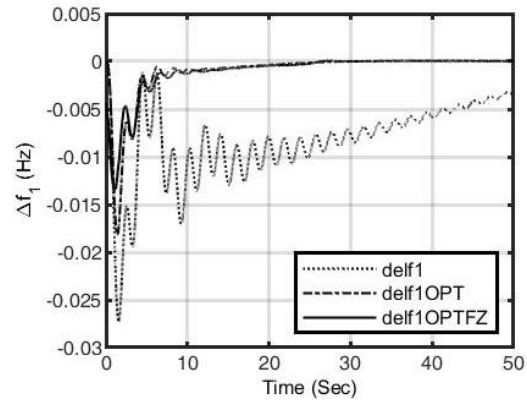


Figure 17. Shows Frequency change in area 1 (1% SLP in hydro area)

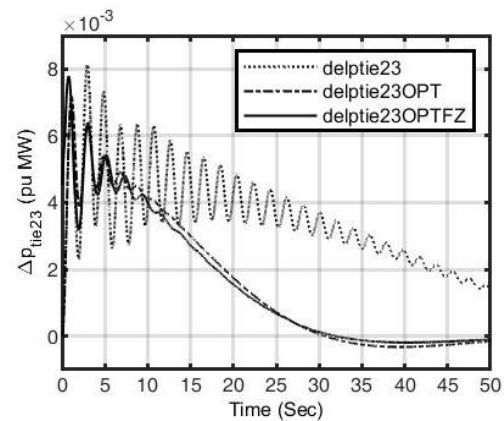


Figure 18. Shows tie line (2-3) deviation (1% SLP in hydro area)

Table 2 Shows Comparative assessment with available method

Parameters (Example 1)	Existing Technique (Donde et al., 2011).	Proposed Technique
Δf_1	10 sec. settling time.	9 sec. settling time.
Overshoot Area 1	Overshoot 0.159 HZ	Overshoot 0.005 Hz
ΔP_{tie}	Overshoot 0.01 pu MW	Overshoot 0.18x10 ⁻³ pu MW
ΔP_{g1}	Overshoot 0.145 pu MW	Overshoot .025 pu MW

Conclusions

The AGC technique presented in this work offers a direct and highly effective approach to minimize frequency and tie-line deviations. The simulation results showcase the superior dynamic performance of the proposed controller as compared to PI and optimal controllers. The proposed controller achieves substantial reductions in frequency deviations, settling time, and tie-line power exchange deviations remarkably. The comprehensive comparative analysis of controllers employed in multi-area multi-machine systems reveals the robustness of the proposed controller under changes in parameters, making it an ideal choice for optimal system control performance. Thus, by employing the combined optimal Fuzzy controller in place of conventional PI and optimal controllers, the AGC response of the system has been enhanced significantly. These findings emphasize the efficacy of the proposed AGC technique in improving system stability and control efficiency.

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