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A Novel Control Method for Enhancing Stability of Interconnected Three Areas System

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Abstract: In modern power systems, maintaining stability across interconnected areas is critical, especially with the growing complexity of the grid. This paper presents a Genetic Algorithm (GA)-based Proportional-Integral-Derivative (PID) controller design for enhancing the dynamic stability of a three-area power system. Traditional PID controllers often struggle with optimal tuning due to the non-linear and dynamic nature of power systems. In this study, a Genetic Algorithm is employed to optimize the PID parameters by minimizing a performance index, such as the Integral of Time-weighted Absolute Error (ITAE), thereby ensuring faster and more robust frequency and tie-line power oscillation damping. Simulation results demonstrate that the GA-tuned PID controller significantly improves the dynamic response compared to conventional tuning methods, providing better system resilience to disturbances and load variations. The proposed approach offers a promising solution for achieving reliable and efficient automatic generation control (AGC) in multi-area power systems.

Keywords: PID controller, Genetic Algorithm based PID (GAPID) controller, Automatic Generation Control (AGC)

I. INTRODUCTION

The primary goal of voltage control in a power system is to maintain equipment terminal voltage within an acceptable range following a disturbance. Framework On the other hand, system losses and the best use of the transmission system are directly linked to stability. Because of the imbalance between supply and demand, the power system's load fluctuates constantly, altering the operational environment.Small oscillations or swings brought on by the change in operating conditions cause voltage to collapse and steady-state power transmission across several networks to occur. (Prasertwong, Mithulananthan, and Thakur 2012)

An automated voltage regulator (AVR) is a type of voltage control device that can efficiently compensate for variations in power or terminal voltage from their normal states. The automated voltage regulator (AVR) in a single area power system regulates the amount of reactive power (steady-state power) that the generator produces or consumes in response to external stimulation. It is possible to effectively maintain the generator's terminal voltage close to its reference setting value by modifying the field current or generator excitation. To put it another way, regardless of the load circumstances on any given piece of power system equipment, the AVR maintains a constant voltage at its terminals (Wang and Du 2016).

Nonetheless, previous research (Demello and Concordia 1969; Stephenson and Ula 1977; De Oliveira 1989; Anderson and Fouad 2003) indicates that the synchronous generator equipped with AVRs has a tendency to cause negative damping in the system and deteriorate its dynamic performance during random load variations. In order to solve this issue, the power system stabiliser (PSS) becomes essential. These days, the majority of plants in linked systems use a mix of PSS and AVR for generator excitation control. When linearized around a certain operating point, PSS extends the dynamic stability of the power system and adds additional damping.

However, as the load (or operational) circumstances of the power system change, the performance of traditional PSS often degrades. Stated differently, the PSS-equipped linked systems are restricted to significant variations in load or a broad spectrum of operating circumstances (Chen and Malik 1997). Therefore, in order to prevent the impacts of random load changes, a control system must be developed. literature on preserving power system stability under various load scenarios. In order to meet the load or excitation conditions, the adaptive control mechanism (Zhang et al. 1993; Segal, Sharma, and Kothari 2004; Mahabuba and Khan 2009; Masrob et al. 2017) automatically tunes the unknown system parameters based on the most recent estimations.

Forming a continuously parameterized family of adaptive controllers to estimate the changing parameters is challenging,

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though. Additionally, they often perform poorly in the early stages of learning, have insufficient resilience, and react disappointingly to fluctuations in the plant. Nevertheless, robust control technique (Wang and Gu 2016; Mehta and Mehta 2012; Abdel Ghany 2008; Lee and Park 1998) is an effective method for developing controllers that primarily addresses uncertainties introduced by changes in model parameters or operating conditions in order to achieve a satisfactory level of robust performance or stability within limited modeling errors.

We have created an extended state observer in (Angu and Mehta 2017a) that functions as a disturbance estimator and a low-frequency damper in both parametric and external settings. An EROO that describes the practical design procedures for handling external disturbances under various operational situations is included in Angu and Mehta (2017b). In order to analyze the low-frequency oscillations linked to these designs, a linear model of a synchronous machine connected to an infinite bus via a transmission line was used. However, these two works do not address and illustrate the stability margins under parametric and external circumstances.

Gain margin (GM), phase margin (PM), and stability margins are the key metrics in characterizing feedback control system performance. GM and PM approaches are still regarded as crucial tools in classical control theory to evaluate robustness and quantify relative stability of closed-loop control systems, even in the face of new control technologies (Liceaga-Castro, Liceaga-Castro, and Siller Alcalá 2012).

They are easily estimated from Bode or Nyquist plots (Horowitz 1963), and it is easy to see how they vary as system parameters change. Using an EROO-based full state feedback control architecture, the resilience and relative stability of an isolated single area power system are examined in this work from the standpoint of the stated gain and phase margin. The goal is to control the terminal voltage within permissible limits in order to effectively sustain voltage across various networks of linked power systems. According to Anderson and Fouad (2003), the control approach entails creating a process for estimating signals and state feedback gains for parameter uncertainties and disturbances brought on by changes in load and demand for a predetermined loop condition.

i. For step load modification, there are no aberrations in VT in the steady-state.
ii. There must be critical stability margins of GM ≥ 6 dB and PM > 40 degrees.
iii. Sufficient stability and reaction time.

Typically, during the design phase, the AVR parameters for a certain operating state are fixed (Elgerd 1982). The fixed nominal operating state (OP1) of the plant is used to evaluate the estimation errors resulting from minor fluctuations (±10%) in its characteristics. These parametric uncertainties are thought to be used to conduct stability or robustness studies since they show the imprecision of the model's parameters. The purpose of the EROO's disturbance rejection property is to guarantee optimal command tracking and satisfying operations. In a stable state, the suggested controller exhibits zero estimate error and demonstrates resilience in the presence of perturbations. To illustrate the controller's effectiveness and performance, numerical results are given.

II. MODELLING OF THREE AREA

Modelling of single area system is combination of generator, speed governor, turbine and load.
This speed governor system mathematical model is represented in equation (1),
Equation 1 represents first order equation that means the higher order terms are neglected in this study because of negligible impact on stability analysis
Where Kgo and Tgo are the gain and time constant of governor system respectively

$$\frac{K_{Go}}{1+ST_{Go}} \tag{1}$$

The generator model system mathematical model is represented in equation (2), Equation 2 represents first order equation that means the higher order terms are neglected in this study because of negligible impact on stability analysis .Where Kg and Tg are the gain and time constant of generator system respectively

$$\frac{K_G}{1+ST_G} \tag{2}$$

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The Turbine model system mathematical model is represented in equation (3), Equation 3 represents first order equation that means the higher order terms are neglected in this study because of negligible impact on stability analysis
Where Kt and Tt are the gain and time constant of turbine system respectively

$$\frac{K_t}{1+ST_t} \tag{3}$$

The block diagram representation of a Single area system is shown in fig 1, this is obtained from mathematical models of speed governor system, turbine and generator system.

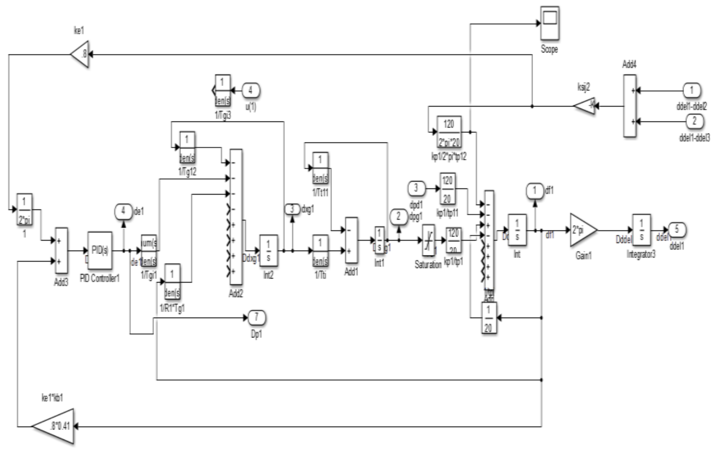

Fig.1. single area system.

III. DESIGN OF GA BASED PID CONTROLLER

a) Structure of PID controller

The structure of PID controller shown fig 2

A PID controller, which stands for Proportional-Integral-Derivative controller, is a widely used feedback control mechanism in engineering and industrial applications. It is designed to automatically regulate a system's output to achieve and maintain a desired set point. The PID controller continuously calculates an error value as the difference between the desired set point and the measured output of the system. Based on this error signal, it adjusts the control input to the system in order to minimize the error and drive the system towards the desired set point.

Proportional (P) Term: The proportional term produces an output that is directly proportional to the current error signal. In other words, it responds in proportion to the magnitude of the error. The proportional action helps in reducing the steady-state error and driving the system towards the set point.

Integral (I) Term: The integral term considers the accumulation of past errors over time and produces an output that is proportional to both the magnitude and the duration of the error. It helps in eliminating any residual steady-state error by continuously adjusting the control input to compensate for any long-term discrepancies between the desired setpoint and the actual system output.

Derivative (D) Term: The derivative term predicts the future behavior of the error signal based on its rate of change. It produces an output that is proportional to the rate of change of the error with respect to time. The derivative action helps in damping the system's response and improving its stability by anticipating and counteracting rapid changes in the error signal.

The combination of these three terms allows the PID controller to effectively control a wide range of dynamic systems, providing a balance between responsiveness, stability, and steady-state accuracy. However, tuning the PID controller parameters (proportional gain, integral time, and derivative time) is crucial for achieving optimal performance and stability in different applications.

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A methametical model of PID controller is represented in equation (4)

$$K_p + SK_d + \frac{K_i}{S} \tag{4}$$

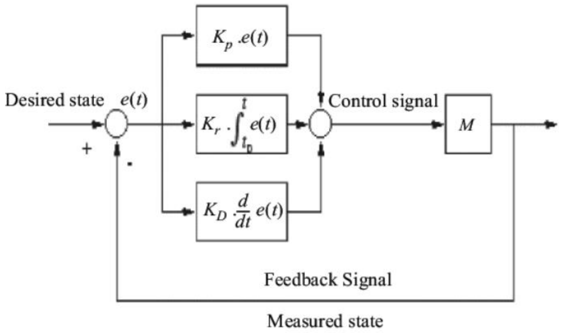

Fig 2. PID controller

(b) **Over view of genetic algorithm**
A genetic algorithm (GA) is a type of optimization algorithm inspired by the principles of natural selection and genetics. Developed by John Holland in the 1960s, genetic algorithms are widely used in various fields, including optimization, machine learning, and evolutionary computation.

Initialization: The process starts with an initial population of candidate solutions, often referred to as individuals or chromosomes. Each individual represents a potential solution to the optimization problem.

Evaluation: Each individual in the population is evaluated against an objective function, which quantifies how good or bad the solution is with respect to the problem being solved. The objective function guides the optimization process by providing a measure of fitness for each individual.

Selection: Individuals are selected from the current population to serve as parents for the next generation. Selection is typically based on the individuals' fitness scores, with fitter individuals being more likely to be selected. Various selection techniques, such as roulette wheel selection, tournament selection, or rank-based selection, can be used.

Crossover: During crossover or recombination, pairs of selected individuals exchange genetic information to produce offspring. This mimics the process of reproduction in natural evolution. Different crossover techniques, such as single-point crossover, multi-point crossover, or uniform crossover, are used to combine the genetic material of parents to create offspring.

Mutation: Mutation introduces random changes in the genetic material of offspring, thereby increasing genetic diversity within the population. This random perturbation helps prevent premature convergence to suboptimal solutions. Mutation typically involves flipping or altering individual bits or genes in the chromosome.

Replacement: The offspring generated through crossover and mutation are used to replace some individuals in the current population, forming the next generation. Replacement strategies can vary, including generational replacement (replacing the entire population with the offspring) or steady-state replacement (replacing a subset of the population with the offspring).

Termination: The algorithm continues to iterate through the selection, crossover, mutation, and replacement steps for a predetermined number of generations or until a termination criterion is met. Termination criteria can include reaching a satisfactory solution, reaching a maximum number of iterations, or stagnation of fitness improvement over successive generations.

(c)**Implementation of genetic algorithm for PID controller parameters**
Implementing a genetic algorithm (GA) for tuning the parameters of a PID controller involves defining the genetic representation of the controller parameters, designing fitness evaluation criteria, implementing genetic operators such as

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selection, crossover, and mutation, and integrating these components into the optimization process. Below is a basic outline of how you could implement a genetic algorithm for tuning PID controller parameters:

Define the Chromosome Representation: Each individual in the population represents a set of PID controller parameters. The chromosome can be encoded as a vector containing the values of the proportional gain (Kp), integral time (Ti), and derivative time (Td), or any other representation that suits your problem.

Initialize the Population: Generate an initial population of individuals with random PID parameter values within predefined ranges. This population serves as the starting point for the optimization process.

Evaluate Fitness: Evaluate the fitness of each individual in the population by simulating the PID controller's performance using the corresponding parameter values. The fitness function should quantify how well the controller performs in achieving the desired control objectives, such as setpoint tracking, disturbance rejection, or stability.

Selection: Use a selection mechanism (e.g., roulette wheel selection, tournament selection) to probabilistically choose individuals from the population based on their fitness scores. Fitter individuals are more likely to be selected for reproduction.

Crossover: Apply crossover or recombination operators to pairs of selected individuals to generate offspring. For PID controller tuning, you can use techniques like single-point crossover, multi-point crossover, or arithmetic crossover to exchange parameter values between parents.

Mutation: Introduce random changes in the parameter values of offspring to maintain genetic diversity and explore the solution space. Mutation can involve perturbing individual PID parameters by adding a small random value or applying more complex mutation strategies.

Replacement: Replace a portion of the current population with the offspring generated through crossover and mutation. You can use generational replacement or steady-state replacement strategies based on your preference.

Termination Criteria: Determine termination criteria to stop the optimization process. This could be reaching a maximum number of generations, achieving a satisfactory fitness threshold, or detecting stagnation in fitness improvement.

Repeat Steps: Iteratively repeat the selection, crossover, mutation, and replacement steps for multiple generations until the termination criteria are met.

Output the Best Solution: Once the optimization process concludes, select the individual with the highest fitness score as the solution. This individual represents the optimal PID controller parameters obtained through the genetic algorithm.

IV. RESULTS AND DISCUSSION

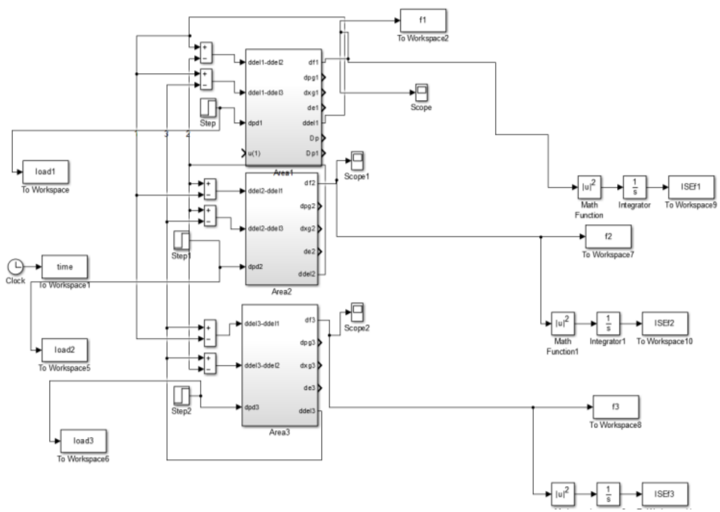

Fig-3 block diagram 3 area

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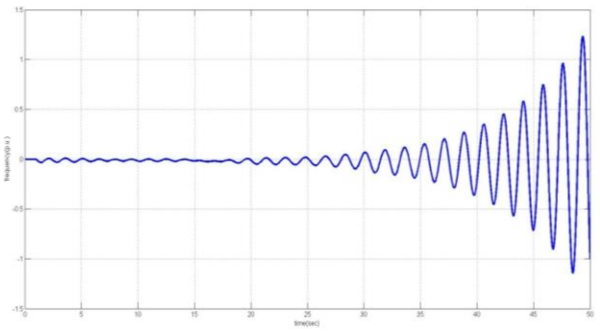

Fig.3. Without any controller

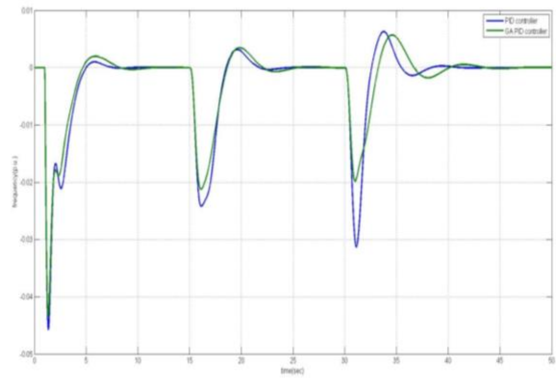

Fig.4. Frequency Response of Area 1 (without and with GAPID controller)

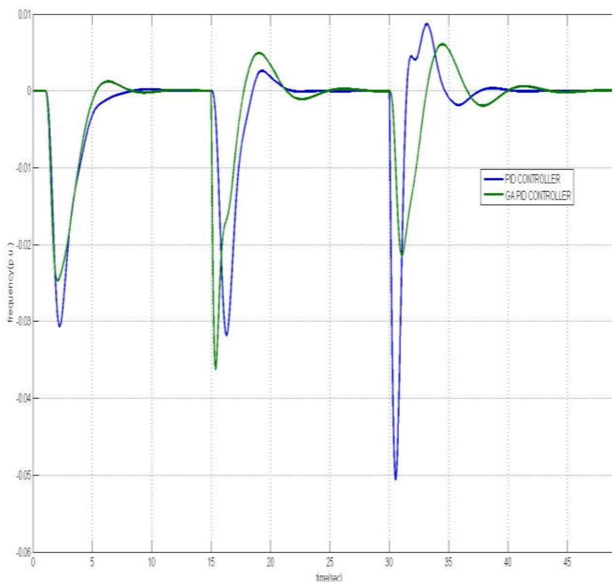

Fig.5. Frequency Response of Area 2 (without and with GAPID controller)

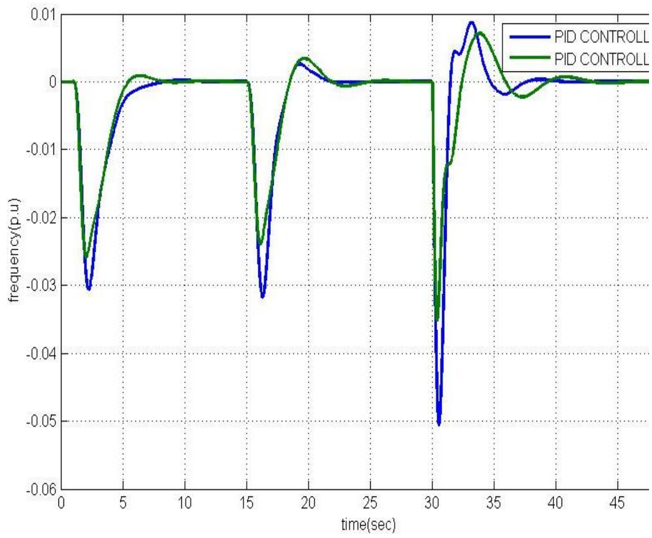

Fig.6. Frequency Response of Area 3 (without and with GAPID controller)

the three area test system block diagram is shown in figure 3. To test the effectiveness of the proposed controller, different disturbances at different areas are created. According to the figure.4 observed results, a step load application was produced by introducing a disturbance by raising the load at zero seconds. To evaluate the system's reaction, the frequency changes in areas 1, was tracked. The GA-PID controller showed a noticeable enhancement in all three performance measures when compared to the traditional PID controller. In particular, each area showed shorter settling periods and less peak overshoot for the GA-PID controller, suggesting a more effective and steady reaction to the load disturbance. In multi-area power systems, these results demonstrate how well the GA optimizes PID controllers for improved load frequency control, guaranteeing faster stabilization and fewer noticeable frequency variations.

According to the observed results in Figure 5, a step load application was created by generating a disturbance by increasing the load at zero seconds. To assess the system's response, the frequency of changes in Area 2 was monitored. When compared to the typical PID controller, the GA-PID controller outperformed the latter in all three performance measures. Each area had shorter settling durations and reduced peak overshoot for the GA-PID controller, indicating a more effective and consistent response to the load disturbance. In multi-area power systems, these findings show how well the GA optimizes PID controllers for better load frequency control, resulting in faster stabilization and fewer obvious frequency changes.

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According to the observed results in Figure 6, a step load application was created by generating a disturbance by increasing the load at zero seconds. To assess the system's response, the frequency of changes in Area 3 was monitored. When compared to the typical PID controller, the GA-PID controller outperformed the latter in all three performance measures. Each area had shorter settling durations and reduced peak overshoot for the GA-PID controller, indicating a more effective and consistent response to the load disturbance. In multi-area power systems, these findings show how well the GA optimizes PID controllers for better load frequency control, resulting in faster stabilization and fewer obvious frequency changes.

V. CONCLUSION

This study demonstrates the effectiveness of a Genetic Algorithm (GA)-based PID controller in enhancing the dynamic stability of a three-area interconnected power system. By optimizing the PID parameters using GA, the controller achieved superior damping of frequency and tie-line power oscillations compared to traditionally tuned PID controllers. The results confirm that GA provides a robust and efficient method for handling the non-linear, time-varying characteristics of modern power systems. The proposed approach not only improves the system's dynamic response but also ensures better resilience to load disturbances and system uncertainties. Overall, GA-based tuning offers a powerful and adaptable solution for Automatic Generation Control (AGC), contributing significantly to the stability and reliability of multi-area power networks.

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