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Analyzing, controlling, and dynamically modeling a standalone wind-diesel power system using a GA-PID controller

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Abstract: This work focuses on the modeling, control, and dynamic analysis of a small, isolated electric power system consisting of a diesel engine and a wind turbine generator. A time-domain dynamic study of an electric power system utilizing simplified models of its constituent parts takes into account the wind turbine's pitch controller and the diesel engine's speed regulator. Wind gusts, rapid ramp changes, and random noise components comprise the wind disturbance model. The diesel generator supplies the additional power required by the load, while the wind turbine generator is always operated at its rated capacity. Two control schemes—proportional-integral (PI) and proportional-integral-derivative (PID) controllers—are employed in this work to improve the wind-diesel power system's dynamic performance in the face of load and wind disturbances. The diesel generator provides the extra power needed by the load, while the wind turbine generator is always run at its rated power. Two control schemes—proportional-integral (PI) and proportional-integral-derivative (PID) controllers—are employed in this work to improve the wind-diesel power system's dynamic performance in the face of load and wind disturbances. Genetic algorithms (GA) and other optimization approaches are used to optimize the gain parameters of PI and PID controllers. The results of the simulation are shown, and the dynamic performance of the wind-diesel power system is compared for various PI and PID controller optimum gain settings that were determined using GA.

Keywords: PID controller, Genetic Algorithm based PID (GAPID) controller,

I. INTRODUCTION

A well-planned electrical power generation system is required to meet a continuously increasing power demand. The most environmentally friendly energy source is electrical energy, which is produced by burning traditional fossil fuels, nuclear energy, and, where feasible, hydro resources. All of them contribute to a variety of environmental issues, as well as other downsides. As a result, in order to meet the growing need for electrical power for industrialization while minimizing environmental degradation, it is critical to consider both electrical power generation and environmental issues simultaneously. Wind energy is one solution for suitable places remote from centralized electrical energy delivery systems. Because wind power changes at random, a backup power supply is required to meet the load demands. The diesel and wind power generation system is one example of a hybrid system that combines several energy sources. Because the diesel system acts as a buffer, the wind and diesel power combination is extremely reliable [1]. WTG systems' output power can be regulated using a variety of classic methodologies, including the state space approach, robust control, and optimal control. Scott et al. [2] studied the dynamic behavior of an autonomous system composed of wind turbine generators and diesel engines. Their findings suggest that changing the control parameter values can improve the damping of the power system. The authors of [3] used a standard proportional-integral-derivative (PID) controller installed on the diesel system and a programmable smoothing load to examine the dynamic modeling and analysis of wind-diesel power systems. Power system stabilizers are often developed utilizing a PID controller to optimize power system dynamics. In order to reduce power and frequency changes during load disturbance circumstances, Tripathy et al. used a magnetic energy storage unit in the isolated wind-diesel power system. The authors investigated the autonomous wind-diesel power system in a variety of scenarios in [5], [6]. They have included an implementation of their algorithm in addition to the mathematical model.

Das et al. [1] conducted a dynamic analysis of a freestanding wind-diesel hybrid power system. The authors of [7] used a fuzzy logic controller for an isolated wind-diesel hybrid power system. When using a fuzzy logic controller in an isolated wind-diesel power system, a significant amount of heuristic information is necessary.

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The authors of [8] explored the dynamic features of autonomous wind-diesel systems by integrating an examination of the fundamental modes with controller parameters. According to the literature review, many researchers have considered the dynamic performance analysis of wind-diesel power systems to be an interesting topic [9], [4], [8-13], and [1]. The majority of the research focused on the analysis of wind-diesel systems dealing with small autonomous installations, without regard for wind speed and wind power modeling details. Furthermore, the research has not addressed or investigated the tuning of controller gain settings to improve the wind-diesel system's dynamic behavior to withstand wind disturbance.

The purpose of this work is to investigate the performance analysis and dynamic modeling of an isolated wind-diesel power system by optimizing the controller gain parameters using two optimization techniques: genetic algorithm (GA). The specific areas of concern are:

1) Simulate a standalone power system consisting of a diesel generator and a wind turbine generator (WTG).
2) The dynamic performance of a freestanding wind-diesel power system will be investigated using proportional-integral (PI) and proportional-integral-derivative control (PID) approaches.
3) To compare the wind-diesel power system's dynamic reactions to PID and PI control systems.

II. MODELLING OF WIND-DIESEL SYSTEM

The mathematical modeling specifics of various wind speed components, wind power, and wind-diesel power systems are presented in this part. Providing a state-space model of the wind-diesel system is the primary goal.

A. Wind speed

To examine the dynamic behaviors of the wind-diesel power system, a wind disturbance model that incorporates base wind, gusting, ramp wind, and random noise is used. Wind speed influences the wind turbine generator's output power. Below is a full discussion of the mathematical model for the various wind speed components [10].
The equation serves to describe the mathematical model for wind.

$$V_W = V_{WB} + V_{WG} + V_{WR} + V_{WN} \quad (1)$$

where KB is a constant and this component of wind is constant component present in the model of wind speed.
The mathematical model for gust wind is expressed by

$$V_{WG} = \begin{cases} 0, & for\ t < T_{gust1} \\ V_{cos}, & for\ T_{gust1} < t < T_{gust1} + T_{gust} \\ 0, & for\ \ t > T_{gust1} + T_{gust} \end{cases} \quad (2)$$

B. Wind power

The wind turbine generator is characterized by the power coefficient Cp and wind velocity. The power coefficient Cp is again characterized by tip speed ratio and blade pitch angle. The wind blade dynamics are approximated by the following non linear functions.
Mathematically, tip speed ratio is expressed as

$$\gamma = \frac{V_W}{\omega_B} \quad (3)$$

The power coefficient is written as:

$$C_P = \frac{1}{2}(\gamma - 0.0228\beta^2 - 5.6)e^{-0.17\gamma} \quad (4)$$

The wind power is expressed as:

$$P_W = \frac{1}{2}\rho A_B C_P V_W^3 \quad (5)$$

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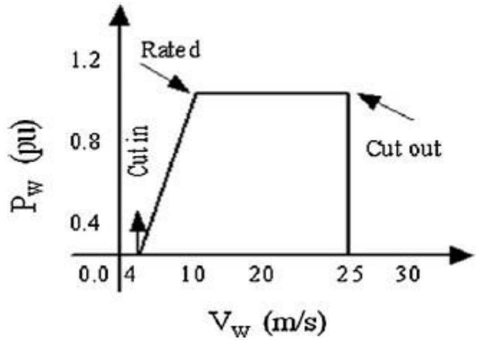

Fig. 1: Characteristic curve of wind speed vs wind power

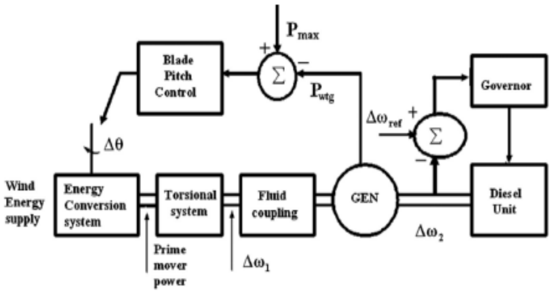

Fig. 2: Conceptual model of wind-diesel isolated power system

C. Model of wind-diesel system

The wind-diesel hybrid model consists of the wind speed model, diesel generator model, blade pitch control of wind turbine and wind turbine generator model as sub systems [9], [4], [1]. A minimum wind speed is required during the start up and synchronization. The diesel generator dynamics are controlled by speed control governor of diesel. The conceptual model of the wind diesel isolated power system is shown in Fig. 2. The uncertainty in the wind speed is modelled by taking gust, ramp wind and random noise as discussed in the previous section. The diesel generator drives the synchronous generator and develops the reference grid for the induction generator which is coupled to the wind turbine. The output power of wind turbine generator can be controlled by changing the pitch angle of the blades of the wind turbine generator using a hydraulic pitch actuator.

III. DESIGN OF GA BASED PID CONTROLLER

a) Structure of PID controller

The structure of PID controller shown fig 3

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.

A methematical model of PID controller is represented in equation (5)

$$K_p + SK_d + \frac{K_i}{S} \qquad (5)$$

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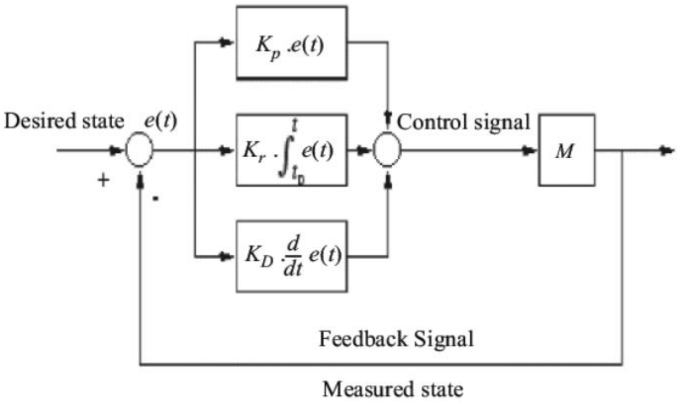

Fig 3. PID controller

(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 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:

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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

This section presents the results of wind-diesel power system simulations using proportional-integral and proportional-integral-derivative controllers. The major purpose is to compare dynamic performance for optimal control benefits acquired using GA technique. MATLAB is used to execute the algorithms and optimize the PI and PID controller parameters for wind-diesel power systems, which employ GA technique. To investigate dynamic performance, MATLAB Simulink is used to build a model of an isolated wind-diesel power system. Figure 4 shows the developed MATLAB simulink model. Figure 5 shows the MATLAB Simulink model for wind speed, a subsystem of Figure 4.
Table I shows the optimum gain parameters of PI and PID controllers determined using GA as the objective function in (27). Figure 6 depicts the dynamic responses for WTG frequency, diesel frequency, WTG output power, and diesel generator output power.

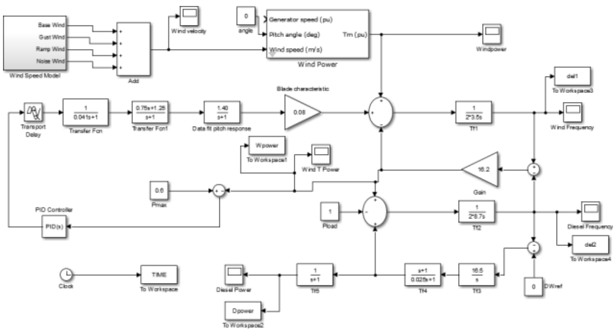

Fig. 4: MATLAB simulink model for an isolated wind-diesel power system

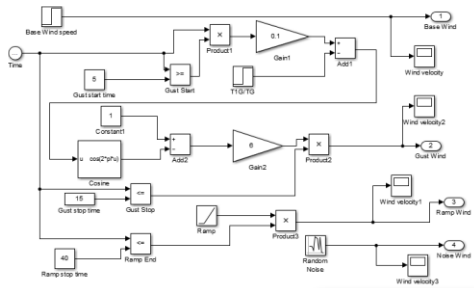

Fig. 5: MATLAB simulink model for wind speed

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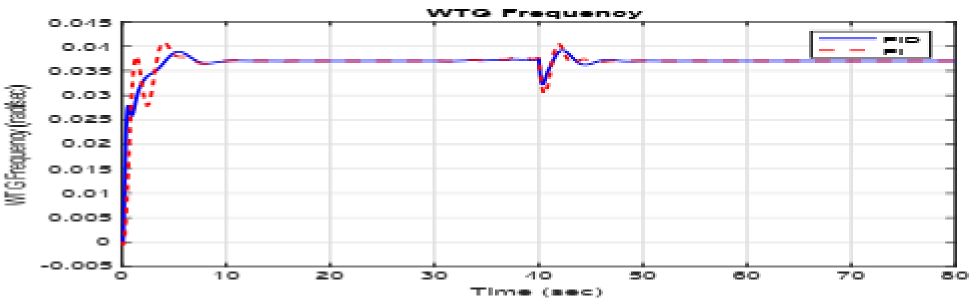

Fig.6. WTG frequency

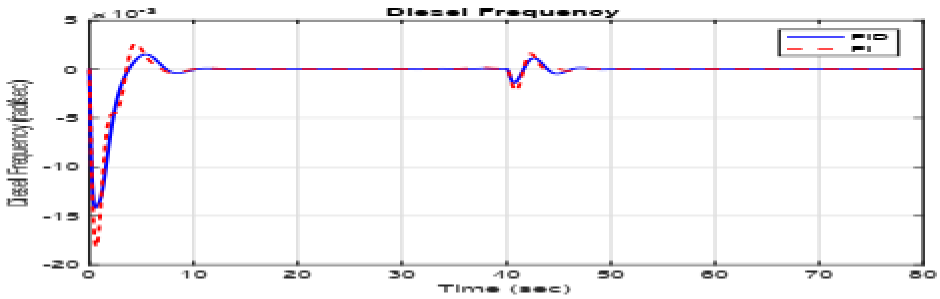

Fig.7. Diesel frequency

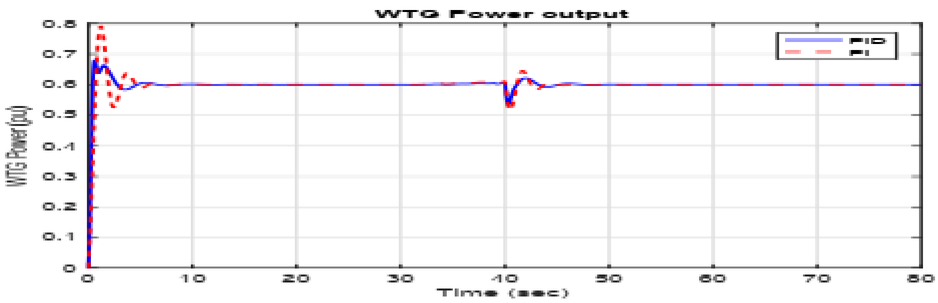

Fig.8. WTG Output power

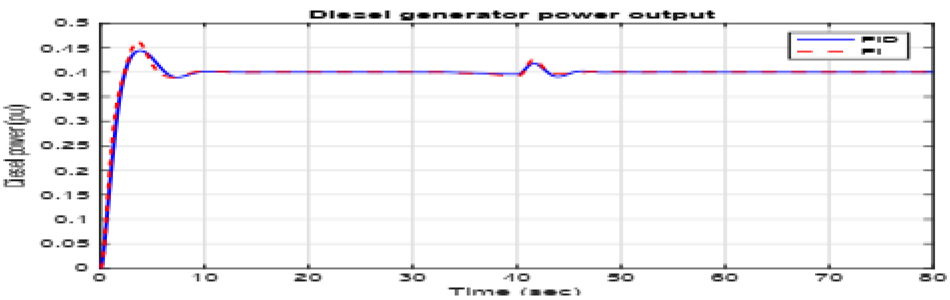

Fig.9. Diesel Power

Form the figures 6 to 9, it is clear that the oscillations in power and frequency are effectively reduced by GA based PI controller when compared with conventional PI.

V. CONCLUSION

This work simulates and investigates the dynamic performance of a wind-diesel power system in isolation, using proportional-integral and proportional-integral-derivative controllers. The controller gain settings are maximized using genetic algorithms. The performance analysis reveals that controller gain settings optimized using genetic algorithms yield extremely similar dynamic responses.

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