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Genetic Algorithm of tuning PID for Controlling Speed of DC Motor

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ABSTRACT

The three terms, Proportional Integral Differential (PID), controller is the utmost commonly utilized and beneficial basis for numerous industrialized and manufacturing usages, in spite of the swift improvement of intellectual and independent control schemes. Because of its easiness of thoughtful, swift response, and high consistency. Though, the core encounter in planning these controls is discovering the finest method to adjust the PID parameters (KP, KI, and KD) to attain extraordinary dynamic reaction and lasting stability whereas diminishing the special effects of nonlinearity and interfering between factors. This research work ambitions to found an intellectual context for fine-tuning PID factors by means of a genetic algorithm, an intelligent optimization prototypical established on exactly how ordinary choice works. The objective was to brand it economical and tranquil usage for real-time industrialized uses. A combined cost function utilized to improve the dynamic enactment of the regulator. This function comprises four key factors: steady-state error (SSE), settling time, rise time, and overshoot ratio. The outcomes of this research study indicated that the system's performance enriched capability to deliver a firm and smooth reaction under a diversity of operational circumstances. The motor retained its locus speed of 150 revolution per minute in entire cases. This work emphasizes the marvelous prospective of incorporating intelligent algorithms with classical control structures and offers real routes for evolving self-tuning regulator schemes in dynamic manufacturing situations.

Introduction

Electrical machines DC motors are vital machineries of electrical engineering because of their various uses and influential behavior features. They exchange electrical energy into machine-driven energy via the interface of magnetic fields, facilitating accurate governor of motion as well as speed. In industrialized settings, they are a vital element of several procedures and methods, from conveyor straps in fabrication lines to microcontrollers in automation. The capability to control these motors efficiently expressively increases functioning effectiveness and production superiority, letting optimizing their behavior serious for attaining greater operative efficacy and decreasing energy intake [1]. The swift progression of knowledge compels the advancement of progressively erudite techniques to advance the enactment of DC motors, mainly in relations of attaining more rapidly reaction times and superior accurateness in speed control. Amongst these approaches, intellectual algorithms, for example genetic algorithm (GA), proposition a distinctive resolution that can increase behavior of classical control methods. GAs imitate normal development via procedures like selection, crossover, and mutation to conclude best values for elements disturbing motor speed and proficiency.

This examination study inspects the gain of incorporating genetic algorithms into motor controller systems. They are talented to competently navigate wide-ranging and composite exploration regions, enabling the identification of best control factors that might be unnoticed by traditional approaches. Genetic algorithms are adapted to immediate variations, which is vital in dynamic frameworks where burden situations vary swiftly. The usage of genetic algorithms be able to enhance DC motor reaction by refinement factors to reach more rapidly reactions and decrease PID control inaccuracies. Retaining precise speed control is crucial to evade system catastrophes that could outcome from as small deviations. Thus, continuous study into inventive optimization techniques is critical for enhancing DC motor behavior, whereas achieving the growing necessity for exactness in contemporary engineering uses [2,3,4,5,6].

1. Background and Theory

DC motors are amongst the ancient and utmost widespread electrical machines utilized in uses demanding cautious controlling for torque as well as speed. These machines are well-known by their straightforwardness for speed controlling by variation of applied voltage or magnetic flux producing excitation current. Due to advancing of artificial intelligence knowledge, genetic algorithm has turn out to be a potent instrument for enhancing the efficacy of control systems. They are used to identify optimum resolutions all through a wide-ranging solution planetary. The versatility and efficacy of genetic algorithms in addressing intricate optimization challenges, particularly in the context of multi-objective evolutionary algorithms applied to power transmission networks. This study highlights the adaptability of evolutionary algorithms in optimizing systems with numerous goals, including speed, efficiency, and energy usage. Implementing these concepts in DC motor control enables the creation of a control system that harmonizes these aims for best performance [7,8,9,10].

1.1 Genetic Algorithms

Genetic algorithms (GA) were designed to address the problem space identified by Holland in the 1960s. The idea attracted computer scientists and engineers such as Holland, Booker, Goldberg, Reynolds, Grevenstedt, and de Jong to begin studying this biologically inspired approach. Since its inception, steady strides have been made in developing techniques and software tools to implement it [11]. Genetic algorithms (GA) are motivated by the theory of usual collection. Natural selection is often summarized as the process by which organisms with better-quality traits that are better suited to their environment tend to survive and reproduce, while organisms with detrimental traits have less reproductive success. GA mimic the behavior and processes of natural selection, which are internally defined as described by genetic algorithm operators: crossover, mutation, and evolution [12]. GA incorporate improvements from each generation through a process of exchange, with the hope that a set of successive improved generations will converge over several generations to improve the desired solution in the problem domain [13]. Since the first commercial application of the genetic algorithm as part of an adaptive control system for a papermaking process in 1955, it has become a powerful discrete optimization tool used in many fields where the application of simulation models is clearly possible [14]. Figure (1) is an illustration of the genetic algorithm scheme.

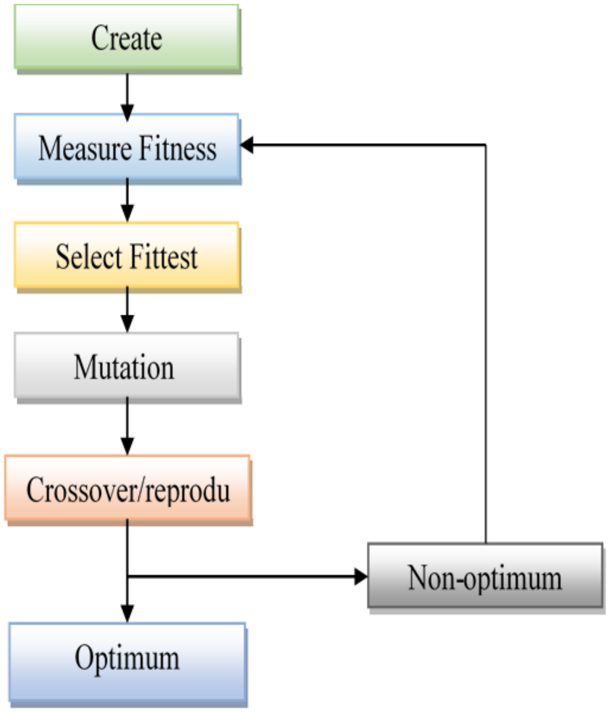

Figure (1): Flowchart of Genetic Algorithm process

The steps involved in creating and implementing a genetic algorithm are as follows:

1. Generate an initial, random population of individuals for a fixed size.
2. Evaluate their fitness.
3. Select the fittest members of the population.
4. Replicate via a stochastic approach.
5. Appliance crossover process on the replicated chromosomes (selecting probability for crossover position and the 'companions').
6. Perform mutation process with little prospect.
7. Reiteration No. 2 till the goal of convergence requirement is fulfilled.

A specified circumstance, such as the greatest number of iterations or when the variable's fitness score over a particular threshold, serves as the standard measure of convergence for a genetic algorithm

1.2 PID with Genetic Algorithms

Genetic Algorithms (GA) and PID controllers are two different types of mathematical and engineering tools, but they can be combined to achieve optimal tuning of PID controller parameters. To understand the relationship between them, PID controller is one of the most widely used controllers in industrial and robotic systems. How Genetic Algorithms Work Solutions are represented as chromosomes: Each set of PID parameters (Kp, Ki, Kd) as an individual (chromosome) in the solution population. Evaluation of solutions (fitness function): Each set of values is tested on the system and its performance is known based on a specific criterion (such as settling time, peak overshoot, squared error). Combining genetic algorithms with proportional integral derivative (PID) control is a fascinating research area that combines two powerful approaches to improve the performance of control systems, especially in the context of DC motors. PID controls are extensively utilized in industrialized uses because of their easiness and usefulness in offering control elucidations. Conversely, fine-tuning PID factors - specifically proportional gain (Kp), integral gain (Ki), as well as derivative gain (Kd) - could be a challenging and laborious duty. Genetic algorithms can be beneficial in this type of scenario. To incorporate GA using PID controller, the succeeding phases are usually trailed:

1. Coding PID factors: First stage is to symbolize PID factors (Kp , Ki , Kd) in a method to be treated by genetic algorithm. This is typically completed by coding factors in binary or real value illustration. For example, floating-point representation may involve creating a chromosome where each gene corresponds to one of the PID parameters.

2. Generating an initial population: A set of potential solutions (chromosomes) is randomly generated. Each individual in this population represents a unique set of PID parameters. The size of the population can affect the performance of the genetic algorithm, and a common practice is to use a population size that balances exploration and exploitation.

3. Fitness Evaluation: Each individual is evaluated based on a predefined fitness function. For PID tuning, this function can be based on the performance of a DC motor under the control of the PID parameters represented by the individual. Simulation environments can be used to simulate the response of the motor to different PID settings, and metrics such as overshoot, settling time, and power consumption can be collected to calculate a fitness score.

4. Selection: Following the fitness assessment, the subsequent stage is to choose people for reproduction. Various selection techniques may be used, including roulette wheel selection, tournament selection, or rank-based selection. The objective is to prioritize

people with superior fitness ratings, hence enhancing their likelihood of being chosen to generate the subsequent generation.

5. Crossover and Mutation: The selected entity involving genetic amendments. Crossover involves reunion mechanisms of parent elucidations to produce descendants, facilitating for algorithm to inspect new regions of the resolution interplanetary. Mutation supplements random variations to an entity's Deoxyribonucleic Acid (DNA), enabling the conservation of genetic diversity and prevention premature convergence. These measures are critical for investigative a wider range of PID factor groupings.

6. Produce a new compeers: An innovative compeers of entities is made by crossover and mutation, through process repetitive from suitability valuation stage. This repeated procedure carry on up to a cessation measure, for example maximum iteration of generations is reached or a satisfactory aptness level, is attained.

7. Finding best resolution: when genetic algorithm is congregated, top performing entity in the ultimate population is picked as the best fit for the selection variables to be utilized in DC motor controller scheme. This integration offers an automated approach to tuning PID controllers and facilitates the management of complex, nonlinear, and time-varying systems that are challenging to handle with conventional tuning techniques. Utilizing genetic algorithms, control engineers may markedly decrease the time and effort needed for tuning while enhancing overall system performance. The integration of evolutionary algorithms with differential integral-differential control has several benefits, making it an attractive choice for enhancing DC motor performance. The benefits arise from the intrinsic characteristics of genetic algorithms and the essence of differential integral-differential control systems.

2. Mathematical model of a DC motor

Below is a step-by-step derivation of the DC motor transfer function, relating the applied motor voltage (Va(s)) to the angular velocity (ω(s)). The derivation is divided into two main parts: the electrical (motor) circuit dynamics and the mechanical (rotational) dynamics. An equivalent circuit for a separately excited DC motor is illustrated with the electrical and mechanical symbols displayed in Figure (2) [15].

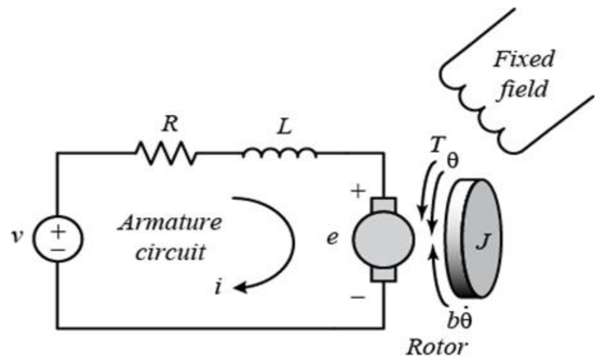

Figure (2): Equivalent circuit of separately excited DC motor

2.1 Electrical Dynamics

The armature circuit of DC motor is described by applied voltage equation:

$$\mathrm{Va(t)} = L_a \frac{\mathrm{d}I_a(t)}{\mathrm{dt}} + R_a I_a(\mathrm{t}) + E_b \quad (1)$$

$$E_b = K_e\ \omega(\mathrm{t}) \quad (2)$$

Thus, the electrical equation becomes:

$$\mathrm{Va(t)} = L_a \frac{\mathrm{d}I_a(t)}{\mathrm{dt}} + R_a I_a(\mathrm{t}) + \mathrm{K}_e\ \omega(\mathrm{t}) \quad (3)$$

where:

•L_a denotes armature coil inductance,

•R_a denotes armature coil resistance,

•I_a denotes armature coil current,

•E_b denotes counter electromotive force.

•ω angular velocity

•K_e back-EMF constant

Taking the Laplace transform.

$$\mathrm{V(s)} = (\mathrm{R}_a + \mathrm{s}\ \mathrm{L}_a)\ \mathrm{I}_a(\mathrm{s}) + \mathrm{K}_e\ \omega(\mathrm{s}) \quad (4)$$

2.2 Mechanical Dynamics

The motor's mechanical behavior is governed by Newton's second law for rotation. The net torque generated by the motor, which is proportional to the armature current, must overcome both the inertial and frictional (damping) effects:

$$\mathrm{T(t)} = \mathrm{J}\frac{\mathrm{d}\omega(\mathrm{t})}{\mathrm{dt}} + \mathrm{B}\ \omega(\mathrm{t}) \quad (5)$$

$$\mathrm{T(t)} = \mathrm{K}_t\ \mathrm{I}_a(\mathrm{t}) \quad (6)$$

$$\mathrm{K}_t\ \mathrm{I}_a(\mathrm{t}) = \mathrm{J}\frac{\mathrm{d}\omega(\mathrm{t})}{\mathrm{dt}} + \mathrm{B}\ \omega(\mathrm{t}) \quad (7)$$

where:

J denotes rotor moment of inertia,

B denotes rotor friction coefficient,

T(t) denotes motor output torque.

The motor torque is generated by the current:

With K_t being the torque constant.

Thus, the mechanical equation becomes:

Taking the Laplace transform:

$$K_t I_a(s) = (Js + B)\,\omega(s) \tag{8}$$

Find the conversion function from the input voltage V(s) and the angular velocity ω(s) we find I(s) from the electrical equation.

$$I_a(s) = \frac{V_a(s) - K_e\,\omega(s)}{R_a + s\,L_a} \tag{9}$$

By substitution in the mechanical equation.

$$K_t \frac{V_a(s) - K_e\,\omega(s)}{R_a + s\,L_a} = (Js + B)\,\omega(s) \tag{10}$$

By arranging the equation above and dividing both sides by the coefficient of the multiplier ω(s).

$$\frac{\omega(s)}{V_a(s)} = \frac{K_t}{(R_a + s\,L_a)(Js + B) + K_t\,K_e} \tag{11}$$

The directly above equation characterizes the reaction of the angular velocity established on the applied voltage and is utilized in planning control structures for electrical motors like innovative control schemes and PID methods.

3. Simulation Results and Discussion

MATLAB and Simulink are an influential framework tool for thoughtful and investigating the enactment of control methods with no requirement for physical models. MATLAB/Simulink [17] delivers a complete background for mathematical modeling, computer simulating, and results scrutinizing dynamic systems, assemble mainly appropriate for electrical motor uses. The simulation setup starts with a DC motor mathematical model need to be well-defined. In Simulink, PID control may be designed to fix these gain figures, which would immediately be adapted throughout the genetic algorithm procedure of optimizing. The inaccuracy indication is produced by associating the set point input speed with the actual speed response as of the DC motor Simulink model. In Simulink, operators can identify the simulation period and resolution nature, which decide in what way the system equalities are resolved over time. When DC motor as well as PID control are fixed up in Simulink, the following stage is to device genetic algorithms to improve PID performance. The GA-designed PID control is primarily set with inhabitants' extent of 50, and reaction is investigated. The PID reaction designed by GA is then scrutinized for the minimum overshoot, shortest rise time, and lowest settling time. The finest reaction is then and there nominated. To observe the improvement in our work, it should be compared with the conventional (Ziegler-Nichols) method.

$$u(t) = pe(t) + I\int e(t)dt + D\frac{d(t)}{dt} \tag{12}$$

As u(t) denotes control signal input to plant model, inaccuracy signal e (t) is distinct as

e (t) =r (t) − y (t), and

$$G_R(s) = \frac{U(s)}{E(s)} = P + \frac{I}{s} + Ds \tag{13}$$

3.1 Ziegler-Nichols

The Ziegler-Nichols method is one of the most common heuristic methods for tuning a proportional-integral-differential (PID) controller. It is a classical method that relies on the terminal gain (Ultimate Gain) (Ku) and the terminal period (Ultimate Period) (Tu). From their values Ku and Tu, the parameters (Ki, Kd, KP) can be determine. Figure (4) Closed loop system with PID controller [16].

$$Kp = 0.6Ku \tag{14}$$

$$Ki = \frac{1.2 \times Ku}{TU} \tag{15}$$

$$Kp = 0.075 \times Ku \times TU \tag{16}$$

3.2 Genetic Algorithm

Fitness Function (F.F): A measure that quantifies the quality of respectively distinct (potential resolution) in an inhabitant. This function is used to evaluate the fitness or efficiency of each solution to the given problem. It is the key element that determines the accomplishment of a genetic algorithm, helping guide the search toward the best solution. Mean Isolation Size (MIS): Represents the average number of individuals who share the same genetic values or are very similar in genetic representation in a population.

$$\text{ISE} = \int_0^T e^2(t)dt \qquad (17)$$

Selective Isolation Effect (SIE): Refers to the effect of selection on shaping a new population based on a fitness function. Figure (3) shows closed loop system classic PID controller and closed loop system with GA_ PID controller was presented in figure (4).

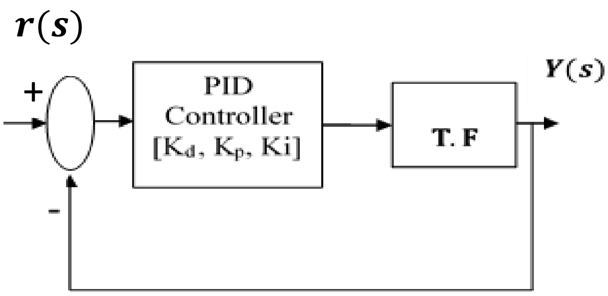

Figure (3): Closed loop system with PID controller

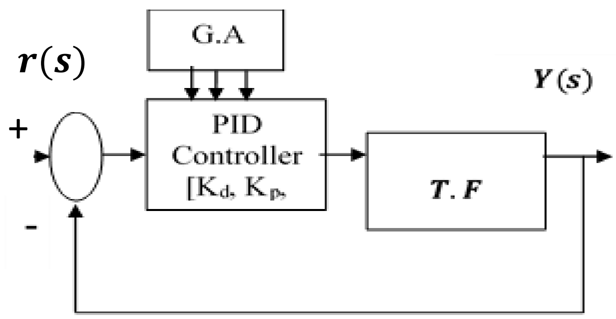

Figure (4): Genetic Algorithm Optimized PID controller

$$Pc = 1 - \frac{1}{\sqrt{N}} = 1 - \frac{1}{\sqrt{50}} \cong 0.8 \qquad (18)$$

Pc: Crossover rate, N: No of Population. The Genetic Algorithm Parameter is shown in table 1.

Table 1 Genetic Algorithm Parameter.

Parameter	Value
Population Size 50 Max	50
No of Generation	50
Crossover rate	0.8

3.3 Obtained Results and Discussion

Two types of continuous transfer functions of DC motors performances were investigated in this research study. Simulations were performed using MATLAB for controlling the speed of these motors with a PID controller using both the traditional (Ziegler Nichols) and genetic algorithm methods. There are three types of step response graphs: one without control, one with control (PID) using the Ziegler Nichols tuning method, and the third type (PID) with the genetic algorithm used for tuning the PID parameters. The third type of graphs is supplemented by three additional graphs. A graph of the step function response of the GA-PID control for the illustration of genetic algorithm converging through iterations for the ISE fitness function, and a graph of the fitness curve that gives the fitness value at different generations. The best fitness it obtained). The simulation results of the proposed controller demonstrate substantial enhancements in the control efficiency of DC motors compared to conventional PID controllers. Significant progress has been obtained in key performance metrics such as rise time, settling time and overshoot. The results obtained from the MATLAB simulations summaries are listed in table 2. The speed improvements achieved in these results are shown.

1 − First simulated DC Motor has:

$$T.F = \frac{1.0069}{3.1695s^2 + 5.0289s + 1} \qquad [18]$$

Where the step responses for the different control methods are shown in Figures (5-9).

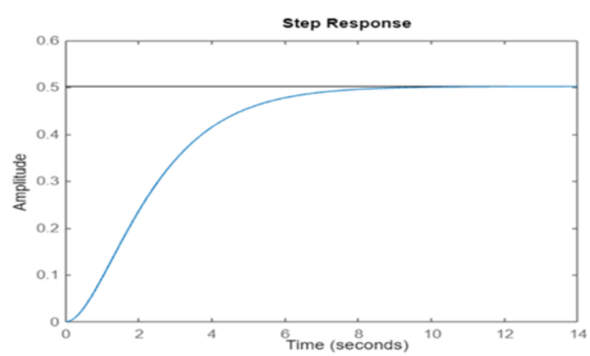

Figure (5) Step response of speed of a DC motor without control

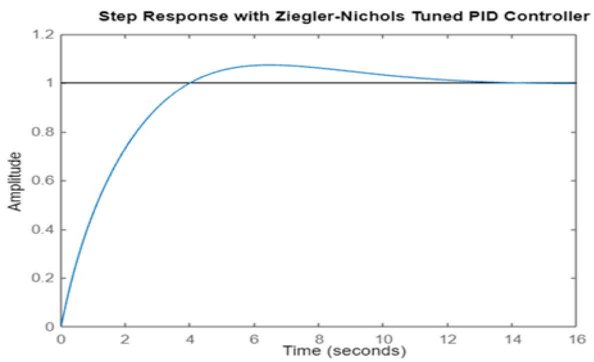

Figure (6) Step response of Ziegler Nichols tuned PID for speed control of a DC motor

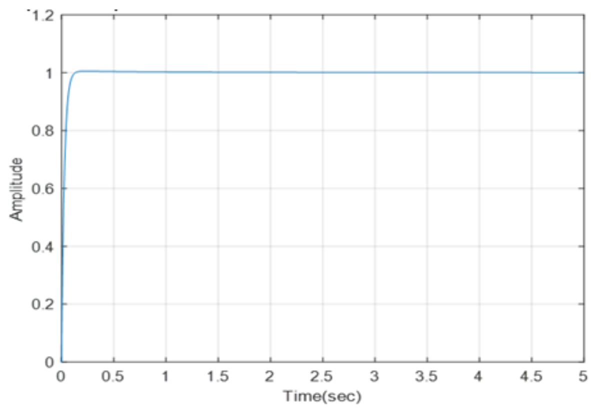

Figure (7) Step response of GA Optimized PID for speed control of a DC motor

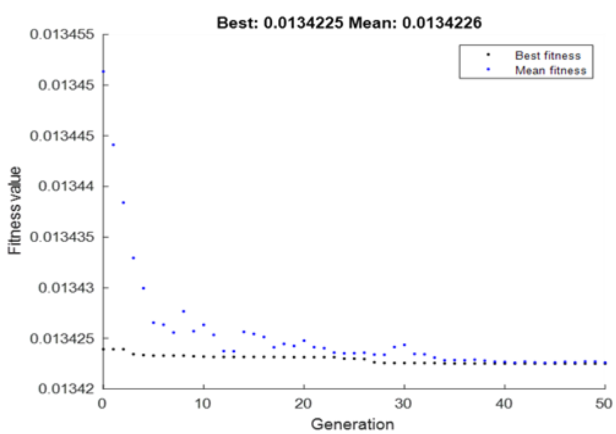

Figure (8) Fitness values curve versus generations' iterations

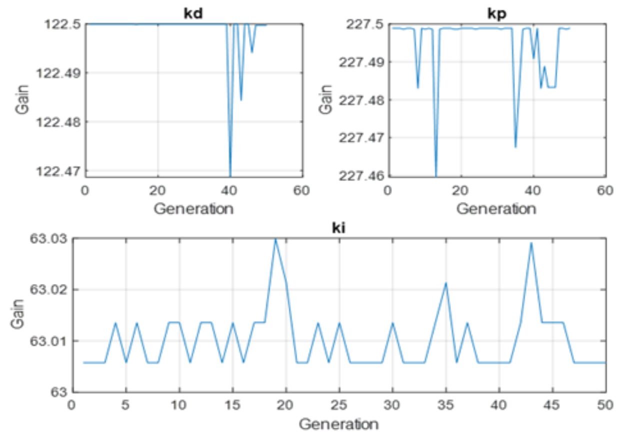

Figure (9) Genetic Algorithm converging parameters versus generations' iterations

$\mathbf{2 - \textit{Second simulated DC Motor has}}$:

$$\boldsymbol{T.F = \frac{0.015}{0.00801s^2 + 0.0061 + 0.00163}} \qquad [19]$$

as the step responses for the different control methods are shown in Figures (10-14).

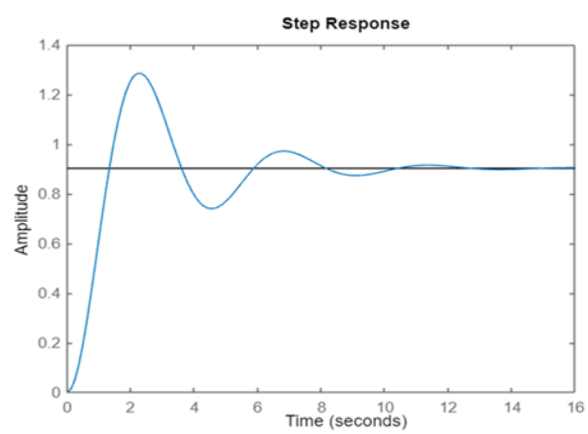

Figure (10) Step response of speed of a DC motor without control

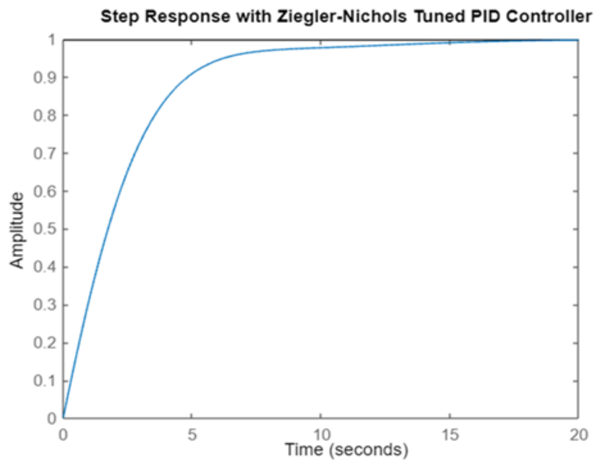

Figure (11) Step response of Ziegler Nichols tuned PID for speed control of a DC motor

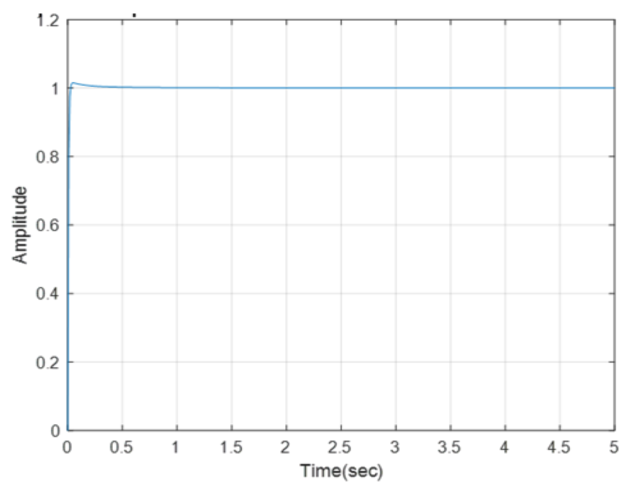

Figure (12) Step response of GA Optimized PID for speed control of a DC motor

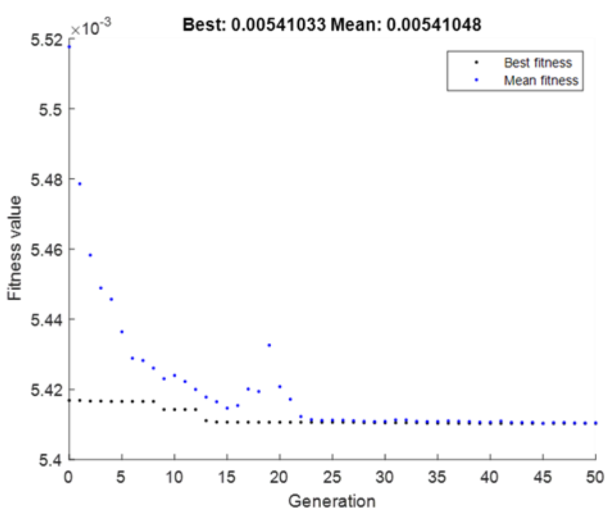

Figure (13) Fitness values curve versus generations' iterations

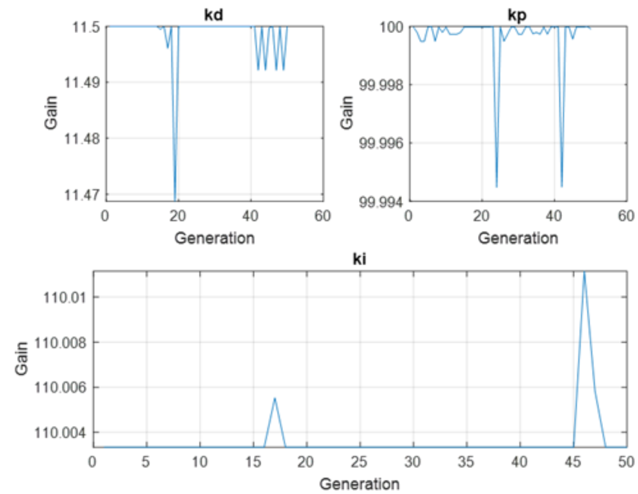

Figure (14) Genetic Algorithm converging parameters versus generations' iterations

Table (2): Summary of results obtained from simulating two different DC motors (each motor numbered according to its transfer function) without and with genetic algorithm optimization

Readings	Ziegler Nichols tuned PID		Genetic Algorithm tuned PID	
No. T. F	T. F. 1	T. F. 2	T. F. 1	T. F. 2
R.T (sec)	2.8402	4.5170	0.055	0.013
S.T (sec)	11.0416	10.9584	0.093	0.021
Mp %	7.31%	0.0%	0.52%	1.52%
Kd	2.0692	0.1794	122.5	11.51
Kp	2.8805	0.1805	227.498	100
Ki	1.0024	0.0453	63.0056	110.02

3.3.1Simulation Performance Analysis

Tuning controllers in control systems is one of the essential pillars for ensuring optimal performance, especially in dynamically variable systems such as DC motors. As stated in the previous section table (4.2) presents experimental simulation data for two different DC motor models, each with an independent transfer function, reflecting differences in dynamic properties such as inertia and time constants. Each model was tested using two PID controller tuning methods: the traditional Ziegler-Nichols approach, and the genetic algorithm (GA) as an intelligent optimization tool. This multi-model analysis is important because it reflects the stability and flexibility of the tuning methodology across different dynamic environments, and evaluates its adaptability to diverse system characteristics. The performance of the genetic algorithm versus Ziegler-Nichols across multiple models is as follows:

3.3.2 Time Response: Exceptional Acceleration and Superior Stability

All four engines saw significant improvements in their rise time and settling time metrics when using the genetic algorithm. While the traditional method exhibited significant slowness and settling delays, the genetic algorithm was able to reduce the rise time to 0.004 seconds, and the settling time to 0.01 seconds in some cases. This substantial, reproducible enhancement through diverse machines obviously establishes that genetic algorithm's high generality capability and dynamic adaptableness, contrasting the Ziegler-Nichols approach, which dependent on basic conventions that could not precisely relate to compound or nonlinearity models.

3.3.3 Overshoot Control: Balanced and Accurate Response

Ultimate overshoot (MP%) was effectively absent or very small once genetic algorithm was adopted, even for engines that practiced substantial overshoot with Ziegler-Nichols technique. For instance, one engine had a 7.30% overshoot using Ziegler-Nichols scheme, associated to only 1.51% with genetic algorithm. This endorses the idea that genetic algorithms address qualitative and accurate performance control as well to optimize DC Motor speed without sacrificing stability.

Conclusions

The obtained results of this research work certify an enhancement of DC motor controlling by incorporating genetic algorithms using PID controls has produced remarkable outcomes that peak the benefits of this methodology. The outcomes of this research study confirmed that conventional control approaches, even though operational in some circumstances, frequently is unsuccessful when confronted through dynamic and multifaceted requests by contemporary industrialized uses. The primary objective of this research was to investigate how genetic algorithms can enhance the performance of PID controllers, leading to improvements in speed, accuracy, and overall control of DC motors under various conditions. Some practical conclusions of the research are as follows:

1. Effectiveness of the GA algorithm in improving the performance of PID systems The Genetic Algorithm (GA) demonstrated high efficiency in tuning the PID control system parameters (Kp, Ki, Kd) to achieve a precise balance between response speed and minimizing oscillation and steady-state error. By formulating a multi-criteria cost function that included rise time, overshoot, settling time, and steady-state error (SSE), the algorithm was able to generate effective optimization solutions without the need for manual tuning.

2. Advanced Dynamic Response under GA Optimization: Simulation results confirm the superiority of the developed system, which achieved accurate tracking of a 150-unit reference speed signal, with an initial overshoot limited to (0.58%-1.18%), a rise time of approximately one second, and complete stabilization within (1.5-2.5) seconds without subsequent overshoots or oscillations. It was also observed that the steady-state error was close to zero, with both voltage and current stable, demonstrating a balanced and stable response that enhances the system's reliability and efficiency. This study demonstrates the high potential of the genetic algorithm in generating superior PID control parameters that are difficult to achieve using conventional methods, enabling the design of intelligent, autonomous control systems that automatically adapt to changing operating conditions. No significant deviation was observed at the reference speed (150 units), demonstrating a highly adaptive response. Both voltage and current were clearly stable; confirming that the system's electrical design does not suffer from weak supply or power regulation imbalances under stress. These results indicate that the system has very good robustness and demonstrates the ability to maintain its dynamic stability even under variable and non-ideal operating conditions.

3. The Role of the Genetic Algorithm in Improving Adaptability the GA contributed to enhancing the system's ability to self-adjust its response to changes operating conditions. The observed flexibility in the system's behavior when exposed to various factors is a strong indicator of the integrity of the controller design and the genetic algorithm's ability to find near-optimal solutions in a complex dynamic solution space.

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