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Motor Speed Control Using PID Control with a Metaphysical Approach: A Comprehensive Analysis

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Abstract

Recent advancements in control technology have become integral to various industrial applications worldwide. Among these advancements, direct current (DC) motors are commonly utilized actuators in industrial systems due to their simplicity and reliability. DC motors exhibit a fast dynamic response but tend to experience steady-state errors, which can affect system performance. To address this challenge, it is crucial to implement an appropriate controller that optimally aligns with the inherent characteristics of DC motors. A Proportional-Integral-Derivative (PID) controller is widely recognized for its ability to provide fast response and effective speed control in DC motor systems. This study explores the application of a novel approach that integrates metaheuristic techniques, specifically Genetic Algorithms (GAs), to optimize the parameters of the PID controller. Unlike traditional PID tuning methods, such as trial and error, Ziegler-Nichols, or manual optimization, the metaheuristic optimization technique offers distinct advantages in achieving faster settling times and minimizing steady-state errors, while also reducing overshoot. The primary goal of this research is to enhance PID control efficiency for DC motors, particularly focusing on obtaining optimal gain parameters for improved performance in various industrial applications. The metaheuristic optimization approach applied in this study involves the use of Genetic Algorithms to fine-tune the PID gains, leading to superior control system performance. The results of this optimization are compared with conventional PID tuning methods through simulation using MATLAB/Simulink. The comparative analysis highlights the effectiveness of the proposed method in terms of quicker stabilization and improved steady-state accuracy.

Keywords: DC Motor, PID, and Metaheuristics

1. Introduction

In the era of Industry 4.0, control systems play a critical role in enhancing the effectiveness and efficiency of production processes across various industries. Specifically, within industrial plants, control systems are essential to ensure that operations are running smoothly and optimally. A plant, in this context, refers to a complex system of interconnected units that form a production line, making control systems integral to their functioning. For example, in the Ammonia production facility at Petrokimia Gresik, key plants such as chemical reactors, heaters, and boilers are continuously monitored and controlled. These plants are equipped with instruments that measure various operational parameters, which are then transmitted to the control room for real-time monitoring and regulation.

The advancement of control systems over time has brought about significant improvements, transitioning from traditional control mechanisms to more advanced, intelligent systems. Among these advancements, PID (Proportional-Integral-Derivative) control represents a significant development of conventional control methods, designed to optimize control performance and address specific challenges within industrial systems (Ogata, 2010). The Proportional (P) component of PID control is well-known for its ability to provide a quick response to input changes, enhancing system dynamics (Grassi et al., 2001). The Integral (I) component helps minimize steady-state errors, ensuring accuracy in the system's output over time (Khine et al., 2019). Meanwhile, the Derivative (D) component plays a key role in reducing overshoot and improving the system's stability, particularly during transient conditions (Ziegler & Nichols, 1993).

As industries increasingly adopt these advanced control strategies, the demand for more refined control systems has grown, driving further innovations (Kishor et al., 2006). This paper explores the application of these systems, particularly focusing on how PID controllers, when optimized with metaheuristic techniques, can significantly improve the performance of DC motors in industrial settings, leading to more reliable and efficient operations (Ferdinandus et al., 2018). This study also considers the shift from conventional control methods to intelligent control systems and evaluates the impact of these systems on production processes. By integrating advanced optimization techniques, such as Genetic Algorithms, this research aims to enhance PID control for better system stability, reduced errors, and faster response times.

2. Material and methods

2.1. DC Motor

Motor Speed Control Method Speed control method is applied to DC motor (Nugraha & Agustinah, 2018). DC motor speed control is primarily accomplished in two ways.

a. Anchor control
Method In this method, the motor speed is controlled by varying the armature voltage.
b. Field Control
Method In this method, the motor speed is controlled by varying the field current or stator current.

Physical Layout of DC Motors, the electrical equivalent circuit of the armature and bodyless rotor diagrams is shown in the figure below.

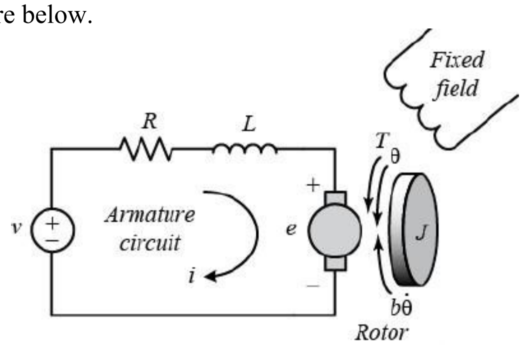

Figure 1. The electric equivalent circuit of the rotor

The input to the system is the supply voltage (V) applied to the motor armature and the output is the shaft speed. The rotor and shaft are considered rigid bodies. viscous friction model. The frictional moment is proportional to the angular velocity of the shaft.

Table 1. Parameter Motor

Rotor moment of inertia (J)	0.01 kg.m2
friction constant (b)	0.1 Nms
Electromotive force constant (Ke)	0.01 V/rad/sec
Motor torque constant (Kt)	0.01 Nm / Amp
Electrical resistance (r)	1 Ohm
Inductance (L)	0.5 H

Transfer function formula of feedback control system (Nugraha, 2017). The torque produced by a DC motor is proportional to the armature current and magnetic field strength (Bimbra, 1990) (Linsley, 1998). This example assumes that the magnetic field is constant. Therefore, the motor torque is proportional to the armature current i by a constant Kt as This is called an armature controlled motor.

$$T = Kt\ i$$

Description :
T = torque
Kt = instant factor
I = armature current

Back emf, e, is proportional to the angular velocity of the shaft by a constant factor Ke.

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$$e = Ke\theta$$

Description :
e = back emf
Ke = factor Constant
θ = velocity

In SI units, engine torque and rear constant are equal. H. Kt = Ke; therefore, we use K to represent both the motor torque constant and the rear constant (Anggono, 2011). Based on Newton's Second Law and Kirchhoff's Law of Stress, we obtain the following set of equations:

$$j\theta + b\theta = KI$$
$$L\frac{di}{dr} + Ri = V - K\theta$$

Description :
J = rotor moment of inertia
B = viscous motor friction constant
Ki = constant factor
L = electrical inductance
R = electrical resistance
V = voltage source

By applying the Laplace transform, the above modeling equation can be expressed in terms of Laplace variables.

$$s(Js + b)\theta(s) = KI(s)$$
$$(Ls + R)I(s) = V(s) - Ks\theta(s)$$

Eliminate Is) between the above two equations with the velocity as the output and the armature voltage as the input.

$$P(s) = \frac{\theta(s)}{V(s)} = \frac{K}{(Js+b)(Ls+R)+K2} \text{(rad/sec/V)}$$
$$P(s) = \frac{0.01}{(0.01s+0.1)(0.5s+1)+0.01^2}$$
$$P(s) = \frac{0.01}{0.005s^{2)}+0.006s+0.1001}$$

Feedback control systems are often called closed-loop control systems (Fitzgerald, 1992). In a closed-loop control system, an actuation signal, which is the difference between the input signal and the feedback signal, is sent to the controller to reduce the error and drive the system's output to the desired value (Berahim, 1994). The term closed-loop control always implies the use of feedback control measures to reduce system errors.

$$P(s) = \frac{0.01}{0.005s^{2)}+0.006s+0.1001}$$

2.2. Metaheuristic Optimization Method

Optimization is a critical aspect of numerous engineering and technical fields, often employing metaheuristic algorithms to address complex, non-linear, and multimodal problems (Mehta & Chiasson, 1998). Optimization is ubiquitous, ranging from the design of technological systems to economic planning, and even to non-technical applications such as scheduling vacations or determining optimal Internet routing. As resources whether time, money, or materials are typically limited, optimizing their usage becomes essential for achieving the most efficient and effective outcomes. In the engineering domain, optimization problems are frequently characterized by complex constraints and interactions, where achieving a perfect or globally optimal solution may be impossible due to conflicting goals or the absence of clear boundaries (Dubey & Srivastava, 2013).

Real-world optimization scenarios often involve highly nonlinear and multimodal functions, making them substantially more difficult to solve compared to simpler problems (Nugraha & Agustinah, 2017). For instance, in classical optimization problems, such as determining the minimum of a quadratic function like $f(x) = x^2$, the optimal solution is straightforward: the minimum value occurs at $f_{min} = 0$ when $x = 0$, given that the function is continuous and differentiable. By applying the first derivative $f'(x) = 0$, one can find potential solutions, and the second derivative $f''(x)$ can then be used to confirm whether the solution is a maximum or a minimum.

$$f1(x), \dots , fi(x), . . , (x), x = (x1, \dots , xd)$$

However, engineering optimization problems are often much more intricate. These problems frequently involve nonlinear, multimodal, and multivariate functions, where multiple local optima may exist. Furthermore, these functions may contain discontinuities, making it difficult or even impossible to calculate the necessary derivative information. In such cases, traditional optimization techniques, such as gradient descent or hill climbing, face significant challenges and limitations. As a result, metaheuristic methods such as Genetic Algorithms and Particle Swarm Optimization are commonly employed. These approaches do not rely on derivative-based methods, making them more suitable for solving complex optimization problems in real-world engineering applications.

In the context of this research, the optimization of PID controller parameters for motor speed control using a metaheuristic approach represents a significant advancement (Achmad & Nugraha, 2022). By applying algorithms like Genetic Algorithms, this study aims to identify optimal PID gains that minimize system overshoot and steady-state error, thus improving the stability and performance of the control system in DC motors. Given the nonlinear dynamics and varied operational conditions of DC motors, traditional optimization techniques often fail to provide satisfactory results, whereas metaheuristic algorithms offer a more robust solution. This approach demonstrates the importance of employing advanced optimization techniques in modern control systems, particularly within the field of engineering, where precision and efficiency are critical.

2.3. Genetic Algorithms

Genetic algorithms (GAs) are probabilistic global search methods that draw inspiration from the process of natural evolution. They are widely used for solving optimization problems, particularly in engineering and control systems. Initially introduced by John Holland in 1970 at the University of Michigan, GAs have evolved into a powerful tool for solving complex problems in various domains, including machine learning, robotics, engineering design, and control system optimization. With continuous advancements in computational power and algorithms, the applications of GAs have become increasingly attractive, especially in cases where traditional optimization methods struggle with high-dimensional or nonlinear problems.

Unlike traditional search methods, GAs begin with little or no prior knowledge of the problem solution. They rely on a process of iterative evaluation and selection, mimicking natural evolutionary operators such as selection, crossover (recombination), and mutation to converge towards an optimal or near-optimal solution. The algorithm is designed to explore the solution space by starting from multiple independent points (i.e., an initial population) and searching in parallel, which helps to avoid local optima—a common pitfall in traditional gradient-based optimization methods.

In particular, GAs are well-suited for nonlinear, multimodal, and complex optimization problems often encountered in engineering applications, where the problem landscape is riddled with local minima, making it difficult for traditional methods to find the best solution. GAs can navigate such complex problem spaces efficiently without encountering the challenges typically associated with methods that require gradient information or are sensitive to high-dimensionality, such as gradient descent. This capability makes GAs a robust alternative, especially in PID controller optimization, where the control parameters must be tuned to handle the dynamics of complex systems like DC motors.

A genetic algorithm operates based on six main components:

1. Coding technique: This refers to how solutions are represented as strings, often referred to as chromosomes. In the case of PID controller optimization, the chromosome might represent a vector of control gains (proportional, integral, and derivative gains).

2. Initialization method: The initial population of solutions is generated randomly, providing a diverse set of candidate solutions to explore.
3. Evaluation function: This is the fitness function used to evaluate the quality of a solution. In engineering applications, this could be a performance measure like overshoot, settling time, or steady-state error in the case of motor speed control.
4. Selection: The process of choosing the best-performing solutions (individuals) based on their fitness scores to "reproduce" and form the next generation.
5. Genetic operators: These operators include crossover (also known as recombination) and mutation, which mimic natural evolutionary processes. Crossover combines two parent solutions to create offspring, while mutation introduces small random changes to the offspring, allowing for exploration of new regions in the solution space.
6. Parameters: These include the population size, mutation rate, crossover rate, and number of generations (iterations) the algorithm runs. These parameters influence how effectively the GA searches the solution space.

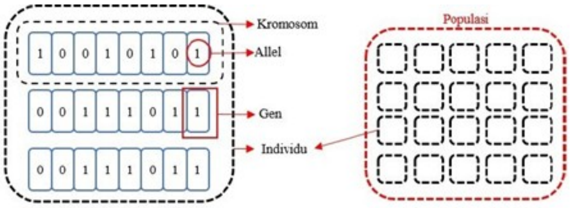

Figure 2. Genetic Algorithm Process

- Chromosomes: Represent potential solutions as strings or arrays of values.
- Alleles: Individual values in the chromosome that correspond to specific parameters of the solution, such as PID control gains.
- Individuals: A solution to the optimization problem represented by a chromosome.
- Population: The set of all candidate solutions that the algorithm evaluates in one cycle.
- Generation: The number of cycles (iterations) that the genetic algorithm executes to refine and improve the solutions.

Through this process, GAs have proven to be highly effective in finding optimal or near-optimal solutions to complex engineering problems, such as PID controller tuning for motor speed control, which can be challenging for traditional methods due to the nonlinearities and dynamic behavior of the system.

2.4. Matlab Modeling

From the system design described in the flow diagrams and mathematical models discussed in the previous chapter, we can begin to move to the realization in the form of simulation.

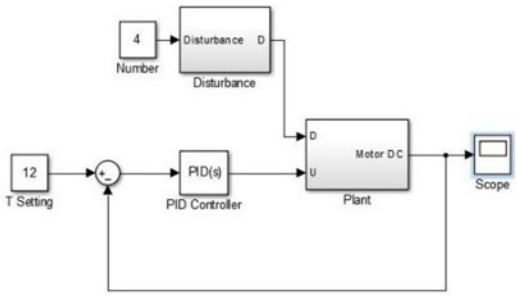

Figure 3. Simulation Modeling on Simulink

on the Simulink feature in the MATLAB program this process is called modeling.

2.5. PID

Controllers consist of proportional, integral, and derived actions. We usually refer to the Ziegler-Nichols PID tuning parameters. It is the most common and widely spread control algorithm. PID controller algorithms are primarily used in feedback loops (Nugraha, Ravi, & Tiwana, 2021). PID controllers can be implemented in various forms. It can be implemented as a standalone controller, as part of a Direct Digital Control (DDC) package, or even as a distributed control system "DCS". The latter is a hierarchically distributed process control system, widely used in processing plants such as pharmaceuticals and industrial petroleum refineries. Note that more than half of the industrial controllers in use today use modified PID or PID control schemes (Ivannuri & Nugraha, 2022). Below is a simple diagram showing the schematic of a PID controller. Such an arrangement is known as a parallel format.

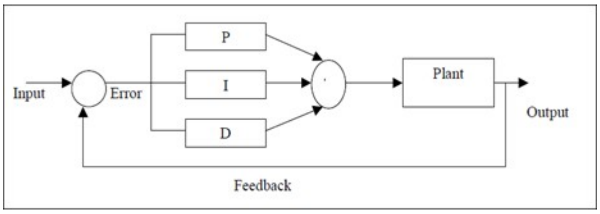

Figure 4. PID Controller Schematic – Non-Interacting Form

In proportional control,

$$Pterm = \text{Kp X Error}$$

It uses the proportion of system errors to control the system. In this action an offset is introduced in the system.

In Integral

$$I_{term} = \text{Kr x Error} \int Error\ dt$$

This is proportional to the number of errors in the system. In this action Action-I introduces a delay into the system. This removes the offset previously introduced by the P action.

In Derivative control,

$$D_{term} = K_D x \frac{d(error)}{dt}$$

This is proportional to the number of errors in the system. In this action Action-I introduces a delay into the system. This removes the offset previously introduced by the P action.

$$GC(s) = K\left(1 + \frac{1}{sTi} + sTd\right)$$

This can be illustrated below in the following block diagram

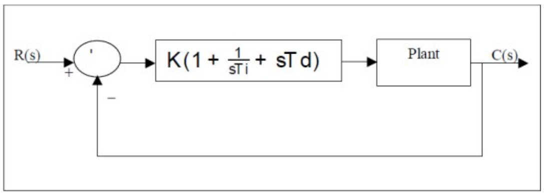

Figure 5. Block diagram of a Continuous PID Controller

Basically, what a PID controller does is act on a variable that is manipulated by an appropriate combination of three control actions: H. Control Action P, Control Action I, and Control Action D (Zakariz, Nugraha, & Phasinam, 2022). Action P is the control action proportional to the error in the drive signal, which is the difference between the input signal and the feedback signal. The I component is the control intervention proportional to the integral of the positioning error signal. Finally, action D is the control action proportional to the derivative of the actuation error signal. A sustainable PID can be achieved by integrating the three measures. This type of control is widely used in industries around the world. In fact, many studies, studies and applications have been discovered in recent years.

3. Results and discussion

3.1. Result

The research started by doing modeling in Simulink in MATLAB and analyzing the system response without a PID controller.

Table 2. DC Motor Response Without PID

No	*System Response*	*Rise Time (S)*	*Over Shoot (pu)*	*Settling Time (s)*	*Steady State (pu)*
1	DC Motor	1.02	0.0907	1.85	0.0908

Adjustments are then made according to the traditional method, the trial-and-error method, and Ziegler-Nichols as a comparison of the optimization method used

Table 3. DC motor response with PID tuning results using the conventional method

No	*System Response*	*Rise Time (S)*	*Over Shoot (pu)*	*Settling Time (s)*	*Steady State (pu)*
1	Trial And Error	0.014176	16.040	0.118	1.636
2	Ziegler Nichols	0.068865	15.256	1.138	1,636

After applying PID tuning using traditional methods, we started implementing a genetic algorithm for the PID controller. In this research experiment, he tested the application of the genetic algorithm to her PID controller nine times.

- Random population 20 is limited to 20 liters
- Random population 20 is limited to 40 liters
- Random population 20 is limited 60 liters
- Random population 30 limited to 20 liters
- Random population 30 limited to 40 liters
- Random population 30 limited to 60 liters
- Random population 50 limited to 20

In this experiment, we applied the Kp, Ki, and Kd parameter values to the output of the Simulink optimization and obtained the following results.

Description:

- Output red color literacy 60
- Output color Yellow literacy 40
- Output green color literacy 20

1. Population 20

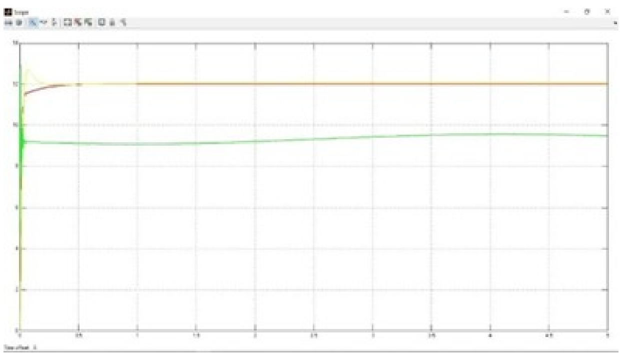

Figure 6. DC motor response with PID tuning results by experimenting 20 random

2. Population 30

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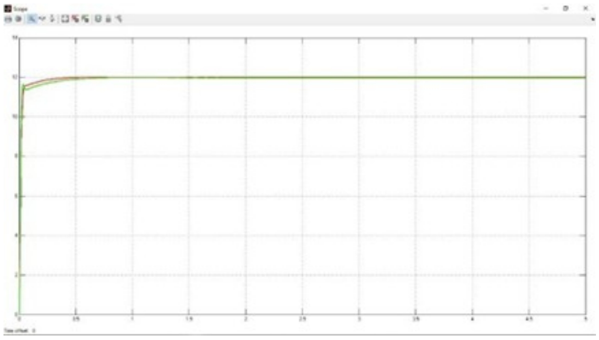

Figure 7. DC motor response with PID tuning results by experimenting 30 random

3. Population 50

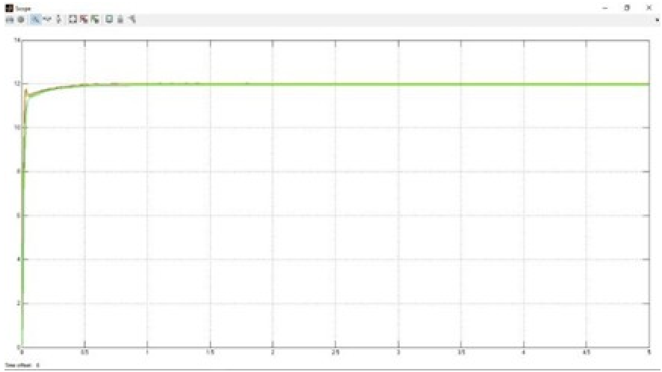

Figure 8. DC motor response with PID tuning results by experimenting 50 random

Experiment After an optimization experiment using a genetic algorithm, the system response results are compared with different previously applied methods in the next step.

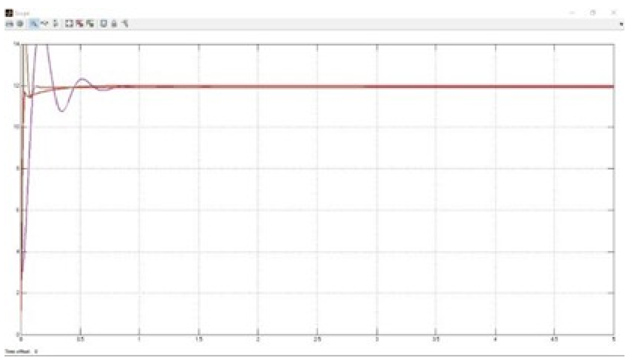

Figure 9. Comparison of DC motor response with PID tuning results Trial & Error, Ziegler Nichols and Genetic Algorithm Optimization

Description:

- Output red color Optimization of Genetic Algorithm
- Output color Purple Ziegler Nichols
- Output color Brown Trial and Error

Table 4. Comparation

No	*System Response*	*Rise Time (S)*	*Over Shoot (pu)*	*Settling Time (s)*	*Steady State (pu)*
1	Trial And Error	0.014176	16.040	0.118	1.636
2	Ziegler Nichols	0.068865	15.256	1.138	1.636

3	Optimation Algoritma Gen	0.442057	12.013	1.30	1.30

4. Conclusion

Here is the conclusion presented in key points, following research guidelines:

1. Settling Time Value: A settling time value of 1.30 seconds was obtained from testing the control system using simulations with a PID controller and tuning the genetic algorithm on a DC motor plant, using 50 random populations restricted to 60 liters.
2. Comparison with Other Methods: This settling time is longer than the Ziegler-Nichols method (1.138 seconds) and the trial-and-error method (0.118 seconds).
3. Advantage of the Algorithmic Optimization Method: Despite the longer settling time, the algorithmic optimization method (using the genetic algorithm) outperforms the other methods in terms of a smaller overshoot, which is only 12.013 compared to 16.040 for the trial-and-error method and 15.256 for the Ziegler-Nichols method.
4. Potential for Further Optimization: If the optimization were not limited by iteration constraints and allowed more time, the results could potentially be more optimal.

This conclusion highlights the comparison of settling times and overshoots from different methods, emphasizing the advantage of the algorithmic optimization method in reducing overshoot, even though its settling time is longer.

Credit authorship contribution statement

Author Name: Conceptualization, Writing – review & editing. **Author Name**: Supervision, Writing – review & editing. **Author Name**: Conceptualization, Supervision, Writing – review & editing.

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