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Data-driven Modeling and Control Strategy for DC Motor Performance Enhancement

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***Abstract*—** This investigation introduces a novel approach for data-driven control and optimization of direct current (DC) motors. The strategy utilizes MATLAB/Simulink to simulate the behavior of a DC motor, allowing for precise estimation of its dynamics. The motor's input voltage and resulting speed are crucial factors that are recorded and subsequently used for the system identification process. By utilizing the functionalities of the system identification toolkit, a systematic analysis of recorded data is performed, resulting in the transfer function for the motor. Utilizing a non-linear Autoregressive with Exogenous Inputs (NARX) network, trained simultaneously with the data, enhances the system's ability to make accurate predictions. This approach offers a clear benefit for engineers and researchers in this field by equipping them with a mechanism for real-time DC-motor monitoring and performance forecasting. Besides, the proposed data-driven approach aids in regulating the dynamics of the motor mimicked by the transfer function of the motor, whereas the Proportional-Integral-Derivative (PID) controller is based on the core ideas of classical control theory. Considering the complexity of the motor and non-linearity, the dual technique has been utilized in this research. The Genetic Algorithm (GA) uses controller gains to maximize motor performance and acquire optimized results under various operating conditions. This all-encompassing strategy not only ensures excellent control, but also emphasizes the adaptability and freedom of the proposed methodology. The simulation results and practical relevance for large-scale application in DC motor systems show the efficiency and robustness of the proposed control model, which surpasses standard techniques and is adaptive to dynamic features. The proposed control model demonstrates significant improvements in system response with optimized control parameters yielding faster rise time, reduced settling times, and minimal overshoot, highlighting its robustness and adaptability for large-scale applications.

***Keywords*—** DC motor; Genetic algorithm; Autoregressive with exogenous inputs network; PID controller; Machine learning; System identification.

1. INTRODUCTION

Model creation and application are standard procedures in several disciplines. A model is viewed through the prism of the mathematical relationship between system variables in the control and systems engineering domain. A dynamic system model can be applied to fault detection, control, prediction, optimization, and simulation [1]. The accuracy of system modeling is crucial to representing the dynamic of the system. System models can be modeled using two primary methods: physics-based modeling (analytical modeling) [2] and data-driven modeling [3]. Physics-based modeling, also known as analytical modeling, represents the system using differential, algebraic equations, transfer functions, or state-based representations

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relying on physics laws and principles [4]. On the other hand, data-driven modeling involves extracting data from a real or physical-based system and using system identification techniques to select a model structure [3] as shown in Fig. 1. This approach estimates parameters based on the relationship between input and output data. Data-driven modeling is especially advantageous when it is challenging to model the system dynamic mathematically, or the system behavior is unknown. In such cases, one does not need an in-depth understanding of the system to model it analytically [1]. This advantage of data-driven modeling forms the core motivation behind this research.

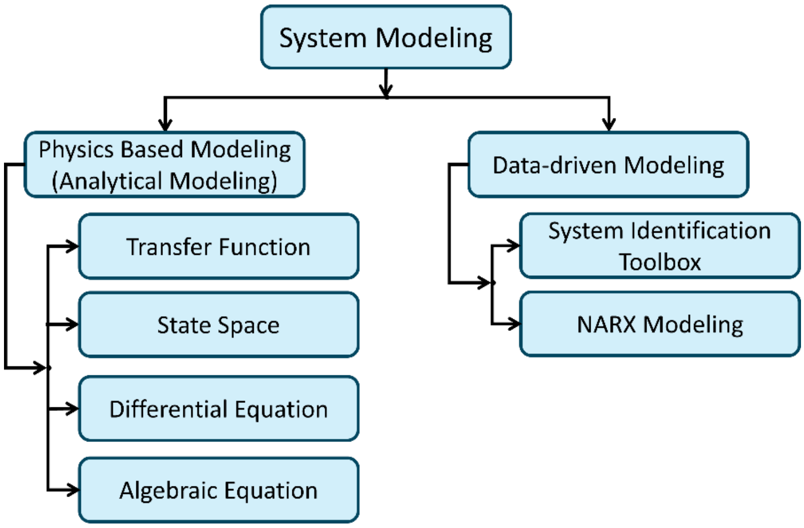

Fig. 1. System modeling approaches [3].

The research [5] discusses the use of System Identification (SI) modeling techniques to model underwater remotely operated vehicles (ROVs) for marine industries, specifically underwater exploration and surveying. MATLAB's SI toolbox was used for the analysis. Step and multiple-step inputs were recorded, and the model with the best fit was selected. The initial model showed a high percent overshoot and steady-state error, but a proportional-integral-derivative (PID) controller reduced these errors. However, the potential research gap is the lack of exploration of using metaheuristic algorithms to optimize the parameters of the controller, which could offer improved performance in a more dynamic underwater environment. To approximate the behavior of the DC motor, the research by [6] suggests a grey-box modeling approach that integrates qualitative and quantitative knowledge. The internal resistance and inductance values of the stator are fitted using linear regression to create the mathematical model. The aim is to find a correlation between the voltage applied to the armature and the rotational speed attained by the DC motor. The study emphasizes the value of system identification as well as its drawbacks. There is a limited exploration of alternative noise reduction techniques for improving measurement accuracy in DC motor systems.

The research [7] discusses the system identification process and Proportional-Integral controller design for a motor and presents appropriate results from open-loop tests. The article outlines the comprehensive process of developing a permanent magnetic DC motor prototype for speed control applications. The microprocessor is the primary module of the prototype; it also includes a transistor-based motor driving circuit and an infrared sensor for feedback. The prototype can accept analog and pulse width modulation inputs and has an adjustable output direct voltage. There is a lack of exploration of the PMDC motor prototypes under varying operational environments, which could impact their robustness in industrial applications [8].

The paper [9] presents the identification and instantaneous speed regulation of a DC motor using transient response analysis. It describes designing a PI speed controller that can accommodate shifting loads and counter-electromotive force and handle singularity at zero speed. Because the control system has enough tracking and regulating capabilities, it is suitable for engineering applications. The model with estimated parameters is verified by contrasting the model's response with that of the real motor. However, the research gap is due to a lack of consideration for the effects of magnetic saturation on the motor's performance and control system design. [10] employs fractional and first-order integer models to identify mathematical representations of a DC motor. The authors used the GA to optimize the fractional order models' parameters. The outcomes demonstrate that the fractional models have fitted better than the first-order integer model, with the least parameterized fractional model producing the best result. It only focuses on the direct method of closed-loop identification without exploring other methods for evaluating other fractional model structures. The project's objective [11] is to generate the input and output data through sensor placement and design to model a 350-watt brushless DC motor mathematically. Engine speed is the output data, whereas current and voltage are the measured input data. The System Identification Toolbox in MATLAB produces a mathematical model as a transfer function. There is a lack of investigation into the limitations and accuracy of the System Identification toolbox in various operating conditions. The study by [12] analyses using the adaptive Tabu-Search approach for PID speed controller design and system identification for brushless DC motors. The recommended design technique was compared with the conventional Ziegler-Nichols approach, which outperforms the traditional Ziegler-Nichols approach regarding speed output performance because it considers the control signal at every stage of the design process. There is a limited exploration of how the ATS method compares to other artificial techniques like genetic algorithms (GA) and particle swarm optimization (PSO) in diverse control scenarios.

Data-driven control is a system-based methodology that relies on real data rather than mathematical models to make choices and adjust control methods. It gathers real data via sensors or observations [13]. Modern industrial processes are becoming more complex, so controller design may not be possible even using readily available physical models. To overcome this problem, data-driven control theory and implementations have been created [3]. The PID controllers are extensively employed because of their robustness, practicality, and dependability. Process automation is essential in engineering and industry. These controllers feature an easily understood three-parameter structure (proportional, integral, and derivative), which has inspired more studies on tuning parameters and alternative designs to enhance their functionality [14]. Metaheuristic techniques have been investigated as an alternative to fine-tuning PID controller gains to maximize performance [15]. Non-linear, non-convex, and restricted problems can be resolved using the GA [16].

The study [17] shows how to use the GA to adjust a PID controller for droplet size control in microfluidics. This improves process response by lowering overshoot and settling time. There is a lack of exploration into the performance of the GA-tuned PID controller under varying operational conditions. It was discovered that the optimal objective function criterion for the GA yielded the lowest fitness value and the best system response [18]. There is a lack of experimental verification of the adaptive PID controller. To gain more precise control over stepper motor speed, the study by [19] suggests merging fuzzy PID parameters with GA. The technique increases the precision of motor speed control by improving response time, reducing overshooting, and shortening regulation times. However, there is a lack of exploration of the algorithm's performance in varying operational conditions. The study by [20] suggests a novel method for controlling the speed and position of a DC servo motor termed a GA-tuned PID controller. It was discovered that the suggested GA-tuned PID controller performs better in terms of time requirements like settling time and rising time compared to the ZN-tuned PID controller and PID controller in the literature. It lacks identification techniques and a data-driven approach. The study by [16] optimizes parameters. It enhances the performance of PID controllers in a Peruvian water tank facility using a simplified GA, demonstrating superior gains compared to MATLAB's auto PID-tune tool. A potential research gap in this paper is the lack of experimental testing of the GA-tuned PID controller in a multipurpose plant environment.

The study [21] assesses the effectiveness of non-linear autoregressive with exogenous inputs, a black-box modeling approach, on crosstalk modeling, especially on crosstalk brought on by random pulse width modulation. Measurement input and output data are used to build the NARX model, and its performance is contrasted with a Spice-based SACAMOS model. Despite being less flexible than the Spice model, it is shown that the NARX model accurately represents the signal on the victim cable with a minimal mean squared error value. The study is a first step in evaluating the behavior of electromagnetic interference and crosstalk in complex systems using the NARX framework. However, there is a limited evaluation of the NARX framework's performance in more complex systems under varying conditions beyond the fixed system and specific crosstalk scenarios studied. Some papers are tabulated in Table 1, targeting different application areas using SI and control algorithms for comparison purposes.

Table 1. Review of some relevant literature.

Ref.	Application area	Methodology	Advantages	Limitations
[5]	Remotely operated vehicle (ROV)	System identification (SI) and PID controller	Achieves 84.7% accuracy using SI	No metaheuristic algorithm was used
[6]	DC motor	Grey box modeling, linear and heuristic methods	84% fitness and low prediction error	Limited exploration of other noise reduction techniques
[14]	Automatic voltage regulator (AVR)	V-Tiger PID and PSO	V-tiger PID enhances transient response and robustness	Limited optimization techniques explored
[16]	Multipurpose water tank plant	PID tuning using GA	Superior control performance by GA-PID	No real-time testing
[22]	Li-ion battery	NARX and artificial neural network (ANN)	High accuracy and adaptability	Needs SOC calculation for each cell

It is evident from the literature material that has been evaluated that many studies have implemented various control strategies for DC motors: PID control [14], fuzzy logic controllers [23], neural networks [24], and sliding mode control, but still, there remains a lack of comprehensive approaches that integrate system identification with NARX modeling and GA optimization for the PID control. Existing studies focus on one or two aspects of DC motor control but do not leverage the combination of data-driven techniques, machine learning, and optimization algorithms to model and authenticate the system accurately and increase the control performance of DC motors under varying conditions. Traditional PID control is based on trial-and-error tuning, which consumes more time, and the response is also not very good. In contrast, fuzzy logic and neural networks provide improved responses. Still, they require significant computational resources and are difficult to tune. Stating the limitations of existing methods, there is a need for a more integrated and comprehensive approach that can accurately model the system dynamics and optimize the control parameters effectively. This research addresses this gap by combining data-driven system identification from real data of the Simulink Simscape model with NARX modeling. GA optimization offers a more robust, accurately modeled, and improved response for a DC motor control.

This study designs and develops the Simulink Simscape model of a DC motor and employs a DC motor input voltage and the corresponding speed as the input and output, respectively. The research uses the system identification procedure to accomplish the transfer function of data-driven DC motor control and authenticate it by comparing it with the standard DC motor transfer function using the same values utilized in the Simulink Simscape model. This study also utilized the NARX model to model the DC motor system. The results of the Simulink model, the transfer function obtained from the System identification toolbox, and the NARX model were compared to authenticate the results. This study also designs the PID controller, and its gains were optimized using a GA to improve the system's performance. The results illustrate how effective the suggested method is, and modeling and simulations are used to authenticate it.

The contributions of this research include:

- The validation of the obtained transfer function by comparing it with the general DC motor transfer function model.
- The training of the NARX model with the different levels of inputs from NARX (1,1) to NARX (5,5) to select the best out of the results.
- Complicated steps of input were chosen to ensure the robustness of the procedure.
- Reduction of error compared to that in the stated literature.
- The employment of a GA optimizes the gains of the controller and improves the efficiency of the result.

Following the introduction, the paper is organized as follows: Section II provides a detailed description of the system modeling process, including the design and simulation of the DC motor in Simulink. Section III focuses on the SI techniques used to identify and validate the transfer function of the DC motor. In Section IV, the NARX modeling approach and its application to DC motor control have been discussed. Section V presents the PID controller design and optimization using a GA. Finally, Section VI concludes the paper by summarizing the key findings and discussing future research direction.

2. FUNDAMENTAL MACHINE MODEL

DC motors are electromechanical devices that convert direct current electrical energy into mechanical energy. They come in various forms, including steppers [19], brushless [25], and brushed motors [26]. They are commonly utilized because of their high efficiency, low power consumption, and controllable design [23, 27]. DC motors have extensive applications in various fields of control systems, including robotics [28], transportation, and industrial applications, because of their efficiency and dynamic qualities [29]. On the other hand, issues like fluctuations in the dynamics of the load, disruptions, erratic and changing inputs, and unknown parameters might arise in a Permanent Magnet DC (PMDC) motor system [3]. PMDC motors are employed in several industries, including robotics and consumer electronics. Their parameters are crucial to get excellent performance in simulation models. The aging and depreciation of parameters cause them to change over time, which lowers performance. Various strategies have been employed to update motor settings to address this issue [30]. Accurate torque and position control are commonly achieved with DC servomotors [25, 27]. Additionally, their use is expanding in robotics because of their inexpensive cost, excellent control performance, and simplicity in construction [30]. As seen in Fig. 2, the properties of a DC motor include resistance, inductance, and the back electromotive force voltage.

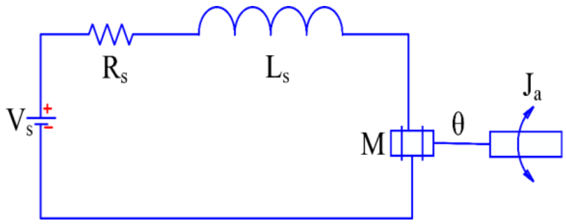

Fig. 2. Circuit diagram of a PMDC motor [31].

The mathematical model of the PMDC motor is provided below in accordance with Kirchhoff's law as shown in Eq. (1) below:

$$V_s - M = L_a\left(\frac{di}{dt}\right) + R_a i \tag{1}$$

where, R_a and L_a denote the resistance and electric inductance, respectively. V_s and i denote the input voltage and current of the DC motor, respectively. M represents the back electromotive force voltage, which is directly proportional to the motor's velocity [32].

$$M = K_a\dot{\theta} \tag{2}$$

given that, K_a represents the voltage constant of the motor and $\dot{\theta}$ denotes the angular velocity of the DC motor’s rotating shaft.

2.1. System Description

Data-driven control is a system-based approach whereby decisions and technique adjustments are made using actual data from sensors or observations. It addresses the challenge of designing controllers in complex industrial processes where physical models may not be readily available [13]. Figure 3 depicts a flow chart that shows a step-by-step procedure for generating data to be used in the system identification toolbox to produce the transfer function and to be used for training and testing the NARX model. After developing the model in MATLAB (Simscape), the motor's input voltage and corresponding output speed are saved. The data set (input voltage and output speed) are now used as variables in the system identification toolbox to generate the transfer function of the system. The same data set is also used to train and test the NARX model to get the responses.

2.2. Simscape Model

Creating mathematical equations based on physical principles to design complex multi-domain models is unnecessary because the blocks of the Simscape library correspond to real-world physical components [3].

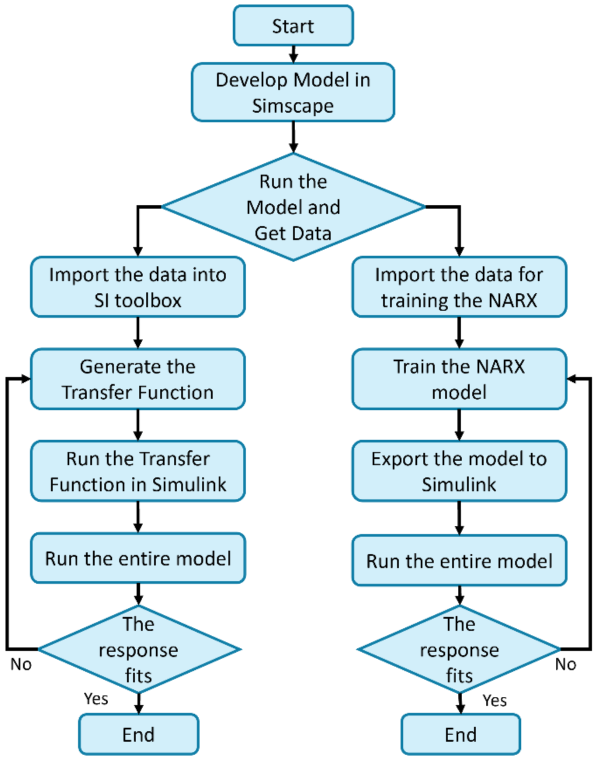

Fig. 3. Flow chart of the transfer function generation and the NARX model training.

Simscape is a part of Simulink that is used to create a component-based model of the systems. Figure 4 depicts the block diagram of the system model developed using Simulink (Simscape). The primary benefit of the Simscape model is its rapid modification capabilities without requiring knowledge of the system's equations.

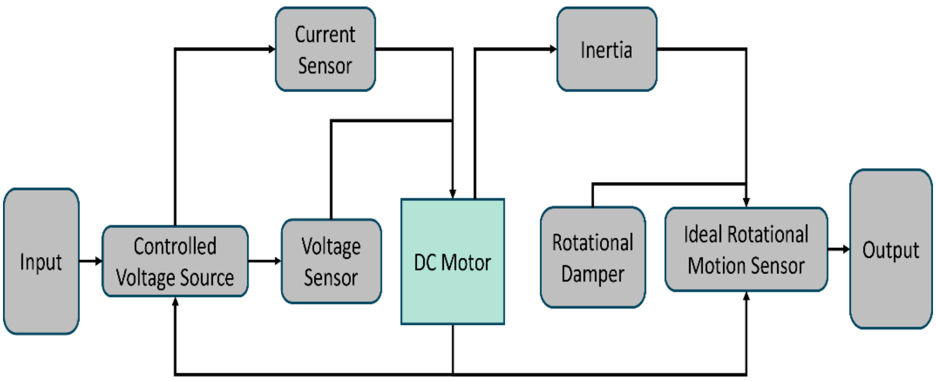

Fig. 4. Block diagram of the SIMSCAPE model.

Table 2 lists the DC motor components and their corresponding values. The damping coefficient (β) was chosen to be very small so that the damping would not significantly impede the motor's performance. Also, the moment of inertia (J) was selected very small so that the motor can quickly adapt to the control signals.

Table 2. List of the components used with their values [8].

Symbol	Component	Value
β	Damping coefficient	0.01 N.m/[rad/s]
J	Moment of inertia	0.01 kgm^2
L	Inductance	0.1 H
R	Resistance	1 Ω
K	Torque Constant	1

This type of PMDC motor has small values of the damping coefficient and moment of inertia used in various kinds of applications such as robotics (small-scale robots), academic projects, electromechanical actuators, computer fans, small pumps, hard disk drives, electronic toy cars, and drones. The values of the components were adopted from the experimental data presented in [8].

3. ALGORITHM BACKGROUND

3.1. NARX

The Non-linear autoregressive exogenous input (NARX) framework is utilized in time-series modeling [33]. It is a parallel arrangement of linear and non-linear blocks constructed based on the linear autoregressive exogenous input (ARX) framework in time series modeling [21, 34]. This framework modeled complicated non-linear behavior using a wavelet or sigmoid function. NARX networks can predict one-time series using the feedback input, the prior values of the same time series, and the external time series [35]. The standard architecture of the NARX is depicted in Fig. 5 below. The variables $x(t)$ and $y(t)$ represents the input and outputs, respectively, $w(t)$ represents the learned weight values connecting the neurons of the model, b is the bias term added to the weighted sum before applying the activation function. At the same time, the ratio $(1:2)$ indicates that there is one neuron at the output layer and 2 number of delays. Additionally, the 10 signifies the number of hidden layers in the model [24].

Linear models such as Auto-Regressive Moving Average (ARMA) and Linear Regression (LR) are widely used for time series prediction [22]. For short-term projections, Box and Jenkins' stochastic time series prediction model, ARMA, is entirely accurate [24]. ARMA, however, is inappropriate for non-linear systems, such as boilers in power plants. [36] presented the NARX model as a solution to this. NARX represents the following random processes:

$$y(k) = f[\, y(k-1), y(k-2\,), \dots, y(k-n)] \tag{3}$$

$$x(k), x(k-1), x(k-2), \dots, x(k-m) + \varepsilon_k \tag{4}$$

where, x is the externally determined variable, y is the variable of interest, and the error term is ε_k. An ANN may simulate the non-linear function f.

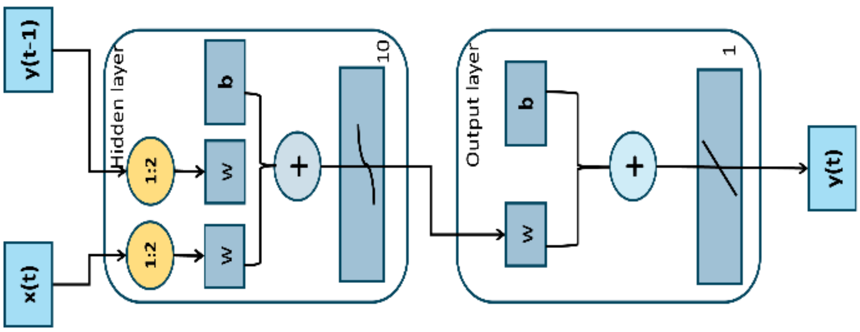

Fig. 5. NARX standard architecture [3].

3.2. The GA

The GA is a computational method that uses stochastic and adaptive search optimization. It is based on the process of intrinsic selection [20]. It has gained recognition as a highly effective and efficient method for solving optimization problems. It starts with an initial population with a certain number of chromosomes. Each chromosome represents a potential solution to the issue at hand, and its performance is assessed using a fitness function [37]. The simplified GA architecture is shown in Fig. 6.

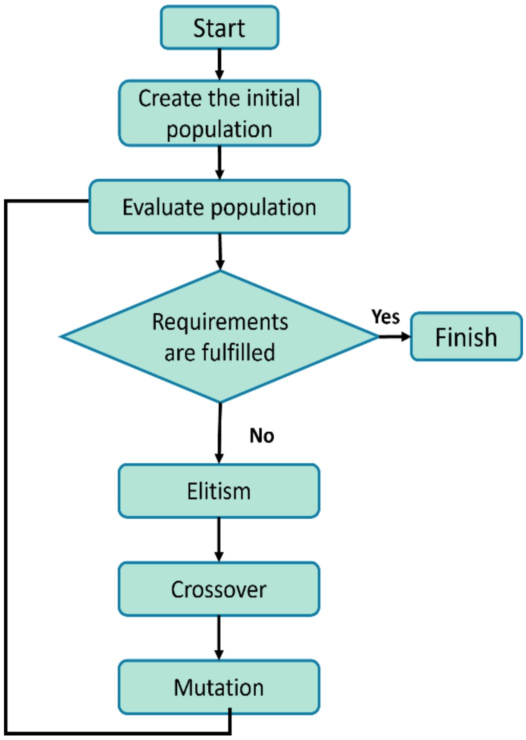

Fig. 6. A simplified flow chart of the GA [16].

The algorithm has three primary phases: Selection, Crossover, and Mutation. Using these three fundamental procedures allows for the generation of new individuals who may exhibit superior qualities compared to their progenitors. This method iterates through several generations until it reaches the optimal solution to the problem, at which point it ends [38, 39]. Metaheuristic methods have been put out recently to ascertain the PID controller gains. Compared to traditional approaches, the PID controller optimization process benefits from employing metaheuristic algorithms, which reduce tuning time and increase the possibility of finding optimal gains [40]. Metaheuristic algorithms are optimization strategies that imitate ethological, biological, chemical, or even physical events to solve complicated issues that are typically challenging for deterministic approaches to handle[41]. Though the most widely used categorization criterion is based on the many sources of inspiration, there is generally no one standard for categorizing metaheuristic optimization algorithms [42].

3.3. The PID Controller

A PID controller is an industrial control system's most common feedback controller. It is widely used because it is easy to implement and has a wide range of stability. The Schematic Diagram of PID is shown in Fig. 7. The PID block diagram demonstrates how the controller incorporates proportional, integral, and derivative actions to provide a control signal that minimizes the error over time, guaranteeing that the system's output achieves and sustains its desired setpoint [43]. The output of the controller is given by:

$$U(t) = K_P e_x(t) + K_i \int e_x(t)dt + K_d \dot{e}_x(t) \tag{5}$$

where $U(t)$ is the control signal, $e_x(t)$ is the error signal at a time t, and K_p, K_i, K_d are the proportional, integral, and derivative gains, respectively.

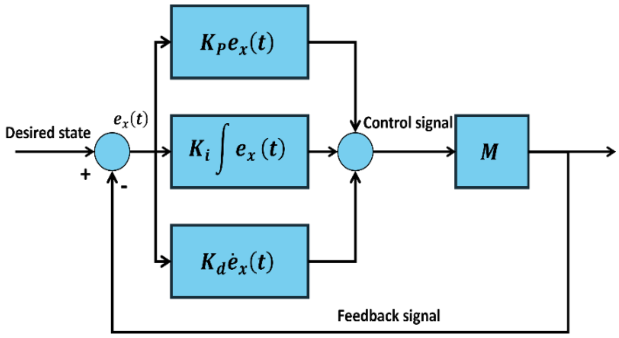

Fig. 7. Schematic diagram of a PID controller [17].

4. SYSTEM MODELING

4.1. Identification Procedure

System identification in MATLAB entails deriving an approximated mathematical model of a system from experimental data. The program offers built-in toolboxes for this procedure, covering preprocessing and estimating. The toolkit lets one choose mathematical operations for the algorithm and enter experimental data straightforwardly. It also serves to assess the performance of the projected system model. Several mathematical techniques in the System Identification Toolbox estimate models using input-output data [44]. The data undergoes preprocessing, which involves methods like filtering, detrending, and normalizing to remove any extraneous noise or bias. The toolkit offers several model structures, such as transfer functions, state-space models, and polynomial models. The user may select the most appropriate model structure by evaluating the system's characteristics [5]. The toolbox employs techniques like the prediction-error method (PEM) or subspace methods to estimate model parameters. This is achieved by reducing the discrepancy between the measured outputs and the expected outputs of the model. After evaluating the model, it may be verified using other approaches available in the toolbox, such as cross-validation or residual analysis, to confirm its accuracy [45].

The toolbox is employed to produce the transfer function of the modeled system. The data used is extracted from the Simscape model, where the input and output are the voltage and speed of the DC motor. Table 3 shows the performance parameters of the system identification toolbox after finding the transfer function extracted from the results generated by the toolbox. The toolbox calculates the parameters while generating the transfer function [46]. The system was simulated for 10s in a time step of 0.01, and the data set of 1000 samples was recorded.

Table 3. Performance parameters from the SI toolbox.

Parameters	Units [%]
Fit to estimation	96
Final prediction error (FPE)	1.053
Mean square error	1.042
Number of iterations	5

Figure 8 is a double y-axis plot that depicts the input of the system (in blue) and the respective system's response (in red). The input voltage and corresponding DC motor speed were measured and imported into the MATLAB workspace so that the system identification toolbox could access the information. The system identification toolbox was then used to generate the system's transfer function.

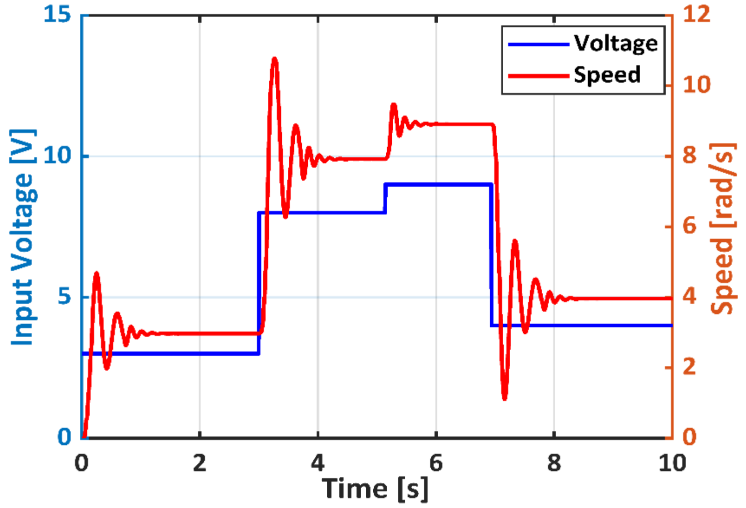

Fig. 8. Response of input voltage and output speed.

The transfer function generated is given by:

$$G(S) = \frac{975.5}{S^2+11.14S+985.7} \tag{6}$$

The transfer function was validated using the general transfer function relation of a DC motor, which is written in Eq. 4 as:

$$G(S) = \frac{\omega(s)}{V(s)} = \frac{K}{(Js+\beta)(Ls+R)+K^2} \tag{7}$$

Substituting the values of the components from Table 1, the transfer function is found to be:

$$G(S) = \frac{1000}{S^2+11S+1010} \tag{8}$$

As a result, the transfer function that results from using the system identification toolbox and the one that is calculated are approximately the same. This shows that the transfer function generated is an accurate representation of the system.

4.2. NARX Techniques

After getting the transfer function of the model, the NARX Neural Network is employed to identify the DC motor. The network was trained based on the Levenberg-Marquardt algorithm using the input voltage and output speed generated from the model. The training and testing parameters are represented in Table 4.

Table 4. The NARX training parameters.

Parameter	Value
Number of hidden layers	10
Simulation time	10 s
Time step	0.01 s
Delay	2 units

Figure 9 shows the blocks of the imported NARX model, transfer function, and DC motor Simscape model connected in parallel to compare their responses. The network was trained using 70% of the stored data, validated 15%, and tested using the remaining 15%. The NARX model was trained using different levels of input orders to obtain the best model. The range of input orders is from NARX (1,1) to NARX (5,5), with NARX (2,2) providing the best response after training. Figure 10 displays the varying voltage that is applied to the system in order to get the output. At the same time, the respective responses of the DC motor black box model, the transfer function, and the NARX model are depicted in Fig. 11.

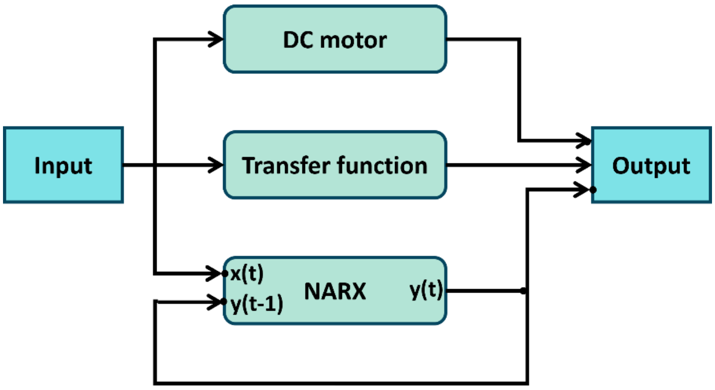

Fig. 9. Blocks of the imported NARX model, transfer function, and DC motor Simscape model for the response comparison.

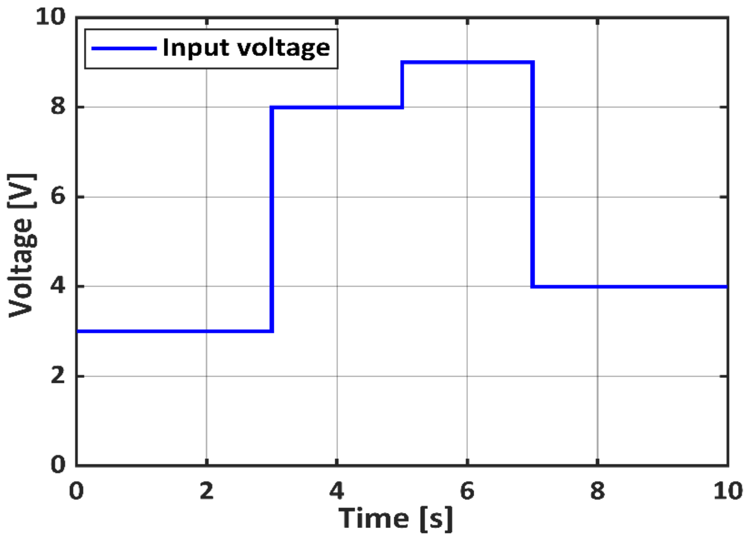

Fig. 10. Varying reference voltage given to the plant.

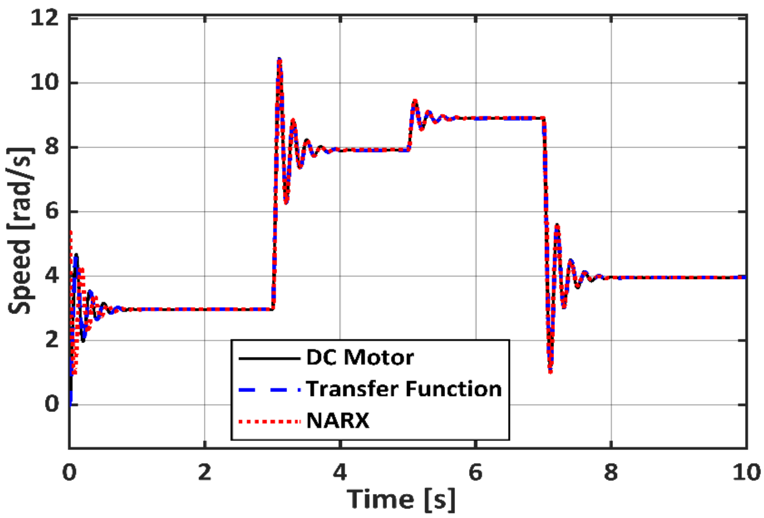

Fig. 11. Responses of the black-box model, transfer function, and NARX model.

5. CONTROLLER DESIGN

The PID is the most popular and efficient regulator that offers high precision for regulating various processes [4]. The output signal produced by the PID controller is computed using the following formula in Eq. (2). PID controllers are preferred due to their simplicity, reliability, and fast-rising time [47], which is used for the proposed model in this research. The controller coefficients must be configured for the plant model to be correctly regulated. Numerous tuning techniques, including the Ziegler-Nichols approach, a manual setup method, and an auto-tuning method in MATLAB, are used to tune the PID controller. Figure 12 illustrates the block diagram of the transfer function model with the PID controller.

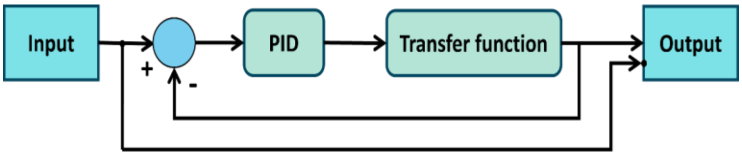

Fig. 12. Block diagram of the system with the PID controller.

The controller was tuned using an automatic tuning procedure, and a set of the PID gains and the respective Filter coefficient value were saved. Table 5 depicts the controller gains obtained (where N is the filter coefficient), and Fig. 13 shows the response received after the tuning.

Table 5. Controller gains obtained after tuning

Parameter	Value
K_P	8.45
K_I	27.51
K_D	0.56
N	64,550.57

Defining a fitness function is typically required when utilizing heuristic methods to optimize a problem. One way to gauge the optimum of specific solutions is to look at their fitness function [23]. Several fitness functions have been employed to adjust the PID controller settings. The rising time (T_r), overshoot (M_P), settling time (T_s), and steady-state error of the motor output is used to construct several fitness functions. This investigation uses the Integral Time Absolute Error (ITAE) function as the fitness function in [23, 38].

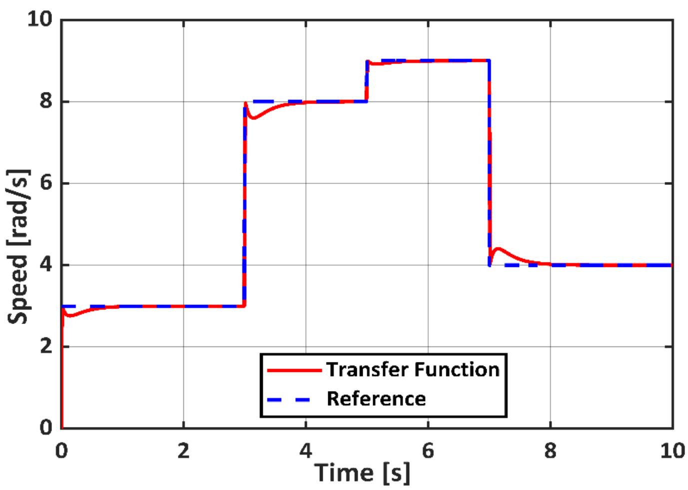

Fig. 13. Response of the system when PID is auto-tuned.

6. TUNING THE CONTROLLER GAINS USING THE GA

The response generated when the PID controller was automatically tuned has some overshot. A GA is utilized to get the optimized PID controller gains. Twenty-five generations are used with 50 populations, employing the minimization of ITAE as the objective function. Figure 14 shows a graph showing the best fitness of GA, with the best fitness value of 0.2936 and the mean fitness value of 0.2941. Table 6 shows the optimized controller gains obtained with the filter coefficient of N=63988 and the best ITAE value of 0.3102.

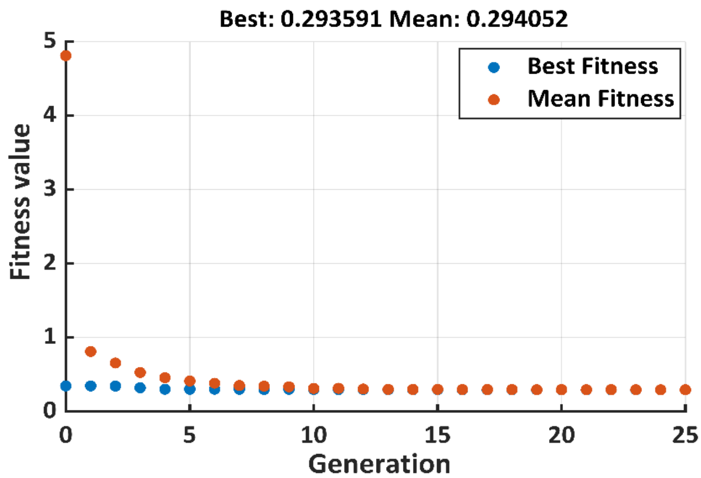

Fig. 14. Convergence graph of the best and mean fitness.

Table 6. Optimized controller gains obtained.

GA property	Value/method
Population size	50
Number of generations	25
Gains ($K_P, K_I, and\ K_D$)	95.007, 119.972 and 8.219
Filter coefficient (N)	63988
Objective function	ITAE

Figure 15 represents the output speed response obtained from the system when the controller is auto-tuned and when the controller is tuned using GA (by employing ITAE as an objective function). It can be observed from the graphical results that the best response (based on the given reference) is obtained when the PID parameters are tuned using GA.

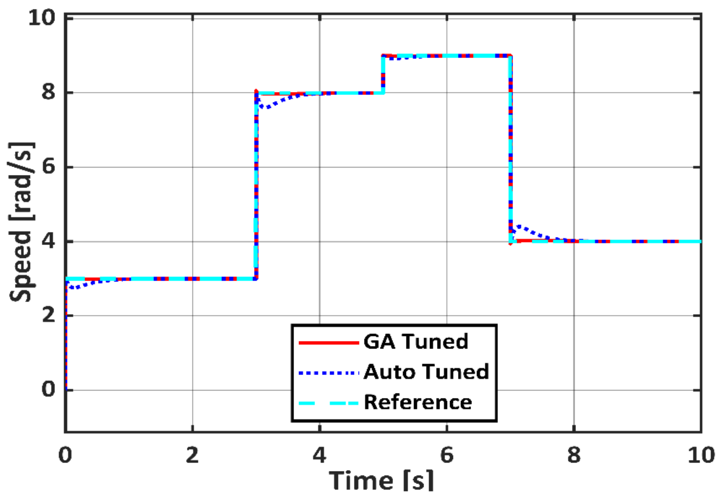

Fig. 15. The controlled transfer function response.

The performance indices obtained when the PID controller is auto-tuned and when it is tuned using GA are summarized in Table 7 below. With reference to the values of the performance matrices, there is a significant decrease in the settling time, the transient time, and the overshot of the system. Hence, it can be concluded that the response obtained when the PID was tuned with GA is more accurate.

Table 7. Performance metrics

Performance metric	Auto-tuned	GA-PID
Rise time [s]	2.001	2.000
Settling time [s]	1.889	1.042
Overshoot [%]	1.822	1.335
Transient time [s]	1.889	1.001

The suggested method successfully employs Simscape modeling, NARX neural network, PID controller, and GA to efficiently model, control, and optimize the DC motor system. The approach simplifies complex multi-domain systems and allows for quick updates without the need for complicated mathematical calculations by leveraging Simscape's component-based blocks. The model's dependability was confirmed by successfully determining a transfer function using System Identification MATLAB's toolbox, which closely matches theoretical assumptions. The NARX (2,2) neural network configuration performs well in handling non-linear behavior, providing enhanced predictive power and a more profound comprehension of the system's dynamics. The optimization of PID controller gains by GAs effectively minimizes Integral Time Absolute Error (ITAE) and improves system performance, surpassing auto-tuning approaches in lowering overshot and boosting stability. This method incorporates advanced modeling, prediction, and optimization techniques to create a precise and reliable control system for DC motors, therefore expediting the control design process and providing significant insights for future research. The findings underscore the efficacy of integrating data-driven methodologies with traditional control systems, significantly benefiting both industrial and academic applications.

7. CONCLUSIONS

This study successfully demonstrates the implementation of a comprehensive data-driven control technique that effectively modulates the behavior of DC motors across a variety of operating settings. Practical uses for the provided approach abound in control system design and offer great promise for academic study. It enables careful analyses of DC motor system underlying dynamics and controller design techniques. Control engineers and students especially need this resource with its simplicity of access and straightforward design. It offers a sensible way to grasp and succeed in the complexity of DC motor control.

In summary, the techniques and findings described in this context establish the basis for future data-driven control and optimization advancements. This will bring about a new age of improved efficiency and accuracy in DC motors. The findings, derived from continuous improvement and originality in the study, can significantly revolutionize the subject, stimulating progress and creativity across several industrial and academic fields. Notably, the GA-PID optimization resulted in significant performance improvements, achieving a rise time of 2.00 s, a settling time of 1.042 s, and reducing overshoot to 0.487%, demonstrating the effectiveness of the proposed control methodology.

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