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A Review on DC Motor Drive Controlling Schemes, Optimization Techniques and Future Trends

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ABSTRACT

Direct Current (DC) motors, pioneering electrical devices in the industry, are employed for high-power applications across a wide voltage range and various nominal speeds due to their easily controllable speed. DC motor drives find widespread use in fields requiring controllable variables, speed adjustments, and diverse operating states. The increased application of DC machines in industry can be directly attributed to the development and implementation of power electronics, given their advantageous characteristics such as high starting torque, responsive performance, and ease of linear control. Presently, their applications extend beyond electric vehicles, encompassing weak-power battery systems (toy motors) and electric traction in multi-machine systems. This paper offers a comprehensive review of numerous articles discussing diverse control schemes and optimization techniques employed in DC motor control, highlighting their advantages and driving mechanism strategies. Classical controller schemes (e.g., PI, PID, SMC) and AI-based optimization techniques (such as Artificial Neural Network (ANN), Genetic Algorithm (GA), Fuzzy Logic (FL), Simulated Annealing (SA), Firefly Algorithm (FA), Particle Swarm Optimization (PSO), Cuckoo Search (CS), Harmony Search (HS), and Grey Wolf Optimization (GWO)) have been thoroughly analyzed and discussed. Additionally, the paper summarizes the merits and drawbacks of these techniques. Points (up to 10) have been assigned to AI techniques based on computational complexity and convergence speed. The advantages of hybrid AI techniques over AI optimization techniques are also addressed. Furthermore, the paper delves into future prospects and trends related to the use of hybrid and enhanced optimization methods for DC motor control. Ultimately, the paper summarizes with observations, conclusions and recommendations.

Key Words: DC Motor, Classical Controllers, AI optimization Techniques, Hybrid AI techniques, Hybrid of Modified AI Optimization Techniques

I. Introduction

Numerous researchers have dedicated their efforts to investigating control schemes and optimization techniques applied to enhance the parameters of DC motors. A. P. Singh et al. [1] developed a PID controller design to supervise and regulate the speed response of a DC motor, utilizing a MATLAB program for calculation and simulation. In a similar vein, C. Copot et al. [2] devised fractional order PI and PD controllers for speed and position control of a DC motor, respectively. The closed-loop performances of these fractional order controllers were compared with their integer order counterparts. Sajad Hussain Mir et al. [3] proposed a fuzzy logic controller (FLC) for speed control of a separately excited DC motor (SEDC) within a MATLAB environment. Algreer et al. [4] addressed the design of a self-tuning PID controller, aiming to bridge the gap left by the Ziegler-Nichols tuning method for PID controller coefficients. Ms. R. P. Suradkar et al. [5] explored speed control of a DC motor employing both a conventional PI controller and a Fuzzy Logic Controller (FLC). I. H. Usoro et al. [6] sought to establish the impact of a fuzzy logic controller (FLC) and a Proportional-Integral-Derivative (PID) controller on the control performance of an industrial-type DC motor using MATLAB. Oti Stephen Ejiofor et al. [7] examined the intricacies of speed control for a DC motor through nonlinear joint control of armature voltage and field current, coupled with a proportional-integral controller. Mohammed Alhanjouri [8] proposed the use of Artificial Neural Networks (ANNs) for estimating and controlling speed in a separately excited DC motor, representing a crucial modern technique in control applications for enhancing efficiency. Boumediène Allaoua [9] suggested an intelligent controller for a DC motor drive using the Particle Swarm Optimization (PSO) method to optimize Proportional-Integral-Derivative (PID) controller parameters. Maad Shatnawi et al. [10] illustrated a robust method for designing current and speed controllers for a permanent magnet brushless DC motor (PMBLDCM), employing a simulated annealing algorithm to tune the parameters of a PI current controller and a PID speed controller. Zafer Ortatepe [11] presented software and implementation for proportional-integral-derivative (PID) tuning of a DC motor control system using a genetic algorithm (GA). Salam Ibrahim Khather [12] addressed the HS algorithm along with a dual Fuzzy algorithm to tune the parameters of a DC motor. Adam Pawlowski [13] introduced a method for determining PMDC motor parameters using the Grey Wolf Optimizer (GWO) for speed control. Omar Rodríguez-Abreo [14] proposed a metaheuristic cuckoo search algorithm modified for DC motors as a parametric estimation tool. E. S. Ali [15] proposed the use of the Firefly Algorithm (FA) to search for optimal Proportional Integral (PI) parameters for DC motor speed control by minimizing the time domain objective function.

II. DC Motor Model

The general equivalent circuit of the Permanent Magnet DC motor drive is illustrated in Fig. 1. As it can be noted from the diagram, Ra represents the armature winding resistance (Ω), La denotes the armature self-inductance (H), Ia signifies the motor armature current (A), and Va represents the applied voltage (V).

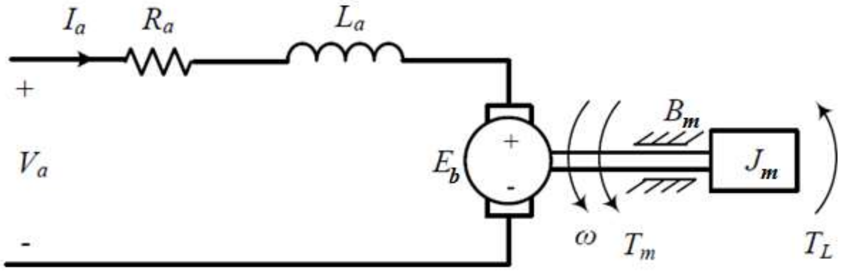

Figure 1: Simplified Equivalent Circuit Model for DC Motor Drive

From the equivalent circuit shown in Fig. 1, the armature DC voltage can be calculated by using electrical and mechanical equations.

a) Electrical Equations

From the equivalent electrical circuit depicted in Figure 1, it is evident that the armature inductance (La) and resistance (Ra) are connected in series with the induced (generated) voltage Eb (or Eg). This induced voltage acts in opposition to the source voltage and is commonly referred to as the back electromotive force (back emf). The back emf arises from the rotation of an electrical coil within the fixed magnetic flux lines of the permanent magnet. By applying Kirchhoff's Voltage Law (KVL) across the loop, we obtain Equation 1:

$$v_a(t) = R_a i_a\,(t) + \; L_a \frac{di_a(t)}{dt} + \; e_b(t) \qquad (1)$$

b) Mechanical Equations:

It can be inferred that different torque types are affecting the motor. In order to derive the mechanical equations, all torques are set to zero. The current flowing through the armature winding is directly proportional to the electromagnetic torque through a constant factor, expressed as:

$$T_m(t) = K_T i_a\,(t) \qquad (2)$$

Where; KT : the torque constant in NM/A

The generated motor torque should be equal to the load torque:

$$T_m(t) = \; J_m \frac{W(t)}{dt} + B_m\,.w(t) + \; T_L(t) \qquad (3)$$

The back-electromotive force, eb is related to the rotational angular velocity by the constant factor expressed:

e_b (t)=K_(b).ω(t) (4)

Substituting the equation (4) into equation (1) becomes:

$$v_a(t) = R_a i_a\,(t) + \; L_a\,.\frac{di_a(t)}{dt} + \; K_b\,.\,\omega\,(t) \qquad (5)$$

The motor torque equation also can be expressed as:

$$K_T\,.\,i_a\,(t) = \; J_m \frac{W(t)}{dt} + B_m\,.w(t) + \; T_L(t) \qquad (6)$$

For the easy analysis the time domain equations must be converted in to their corresponding frequency domain, this is done using Laplace's transform.

The Laplace's transform of the equations (5) and (6) becomes:

$$V_a(s) = R_a . I_a\,(s) + \; s.L_a\,.I_a(s) + \; K_b\,.\,\omega(s) \qquad (7)$$

$$K_T\,.I_a\,(s) = \; s.J_m.\,\omega(s) + B_m\,.\,\omega(s) + \; T_L(s) \qquad (8)$$

If the current, Ia is obtained from equation 8, and substituting that in to equation 7 yields:

$$V_a(s) = \omega(s).\;\frac{1}{K_T}[R_a . I_a\,(s) + \; s.L_a\,.I_a(s) + \; K_b\,.\,\omega\,(s)] \qquad (9)$$

Hence, the corresponding relationship between the rotor shaft speed and applied armature voltage is expressed by the transfer function in equation 10.

$$\frac{\omega(s)}{V_a(s)} = \frac{K_T}{(L_a\;s+R_a)(J_m\;s+B_m)+K_T K_b} \qquad (10)$$

Distributing the denominator term the equation 9 would final become:

$$\frac{\omega(s)}{V_a(s)} = \frac{K_T}{J_m L_a\ s^2 + (J_m\, R_a + B_m L_a)s + (B_m\, R_a + K_T K_b)} \tag{11}$$

As it could be inferred from the equation (9), the motor speed can be varied by controlling the armature voltage, Va or the armature current Ia.

Thus, the mathematical block diagram model of the DC motor drive can be illustrated as in figure 2:

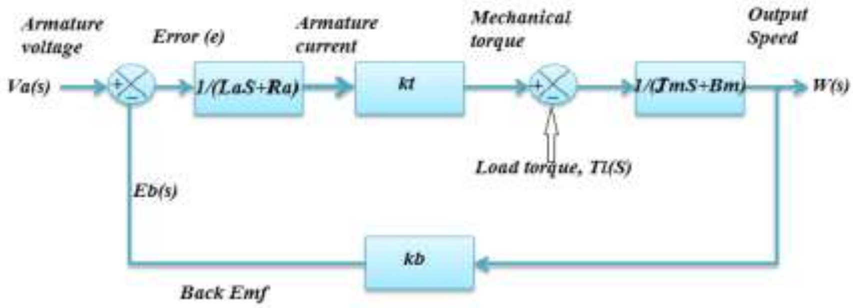

Figure 2: Mathematical block diagram model of the DC motor drive

III. Controlling Schemes and Optimization Techniques

Controllers and optimization techniques that are employed for DC motor (or any other motor) can be broadly classified as:

a. Classical (Conventional) or Heuristic Controller Schemes:

The classical controllers commonly employed for motor control include the PID controller, sliding mode control (SMC), and the On-Off (or Hysteresis) control. The PID control, originating in the late 19th century and evolving over time, is a classical control scheme that employs proportional, integral, and derivative terms to adjust the system's output based on the generated error, its integral, and its rate of change, respectively. Sliding mode control (SMC) is designed to force the system onto a sliding surface, enhancing robustness to uncertainties and disturbances. Essentially, the SMC adjusts the control input to maintain the system on the sliding surface. On the other hand, On-Off (Hysteresis) control, emerging in the early 20th century, involves switching the control action between two discrete states based on whether the system variable is above or below a reference or set-point [1-3, 5-7]. The merits and demerits of these classical controller schemes can be summarized in Table 1:

Control Scheme	**Merits**	**Demerits**
PI Controller	Simplicity, stability, and suitability for a wide range of applications	Limited performance in dynamic and nonlinear systems.
PID Controller	Enhanced performance in terms of response time, stability, and accuracy.	Complex tuning requirements, sensitivity to parameter changes, and potential for integral windup.
SMC	Robustness, insensitivity to parameter uncertainties, and disturbance rejection.	Chattering phenomenon, potential for high-frequency control input, and complexity in design.
On-Off (Hysteresis) Control	Simplicity, cost effective, stability, robustness, and low computational requirement.	Limited precision, overshoot and undershoot, poor performance in linear systems, inefficiency, limited applicability, and hysteresis effect.

b. AI based (Metaheuristic) Optimization techniques:

The Artificial Intelligence (AI) based optimization techniques, also called metaheuristic approaches are optimization algorithms inspired by natural or social behaviors that are applied to solve complex problems. These controllers are often used for tuning the parameters of DC motor controllers to achieve desired performance. The AI optimization techniques, Artificial Neural Network (ANN), Genetic Algorithm (GA), Fuzzy Logic (FL), Simulated Annealing (SA), Particle Swarm Optimization (PSO), Harmony Search (HS), Firefly Algorithm (FA), Cuckoo Search (CS), and Grey Wolf Optimization (GWO) are some among the bio-inspired optimization tools employed for DC motor control. Figure (3) shows the evolution period of these techniques [9 – 18, 20 – 22, 27, 28].

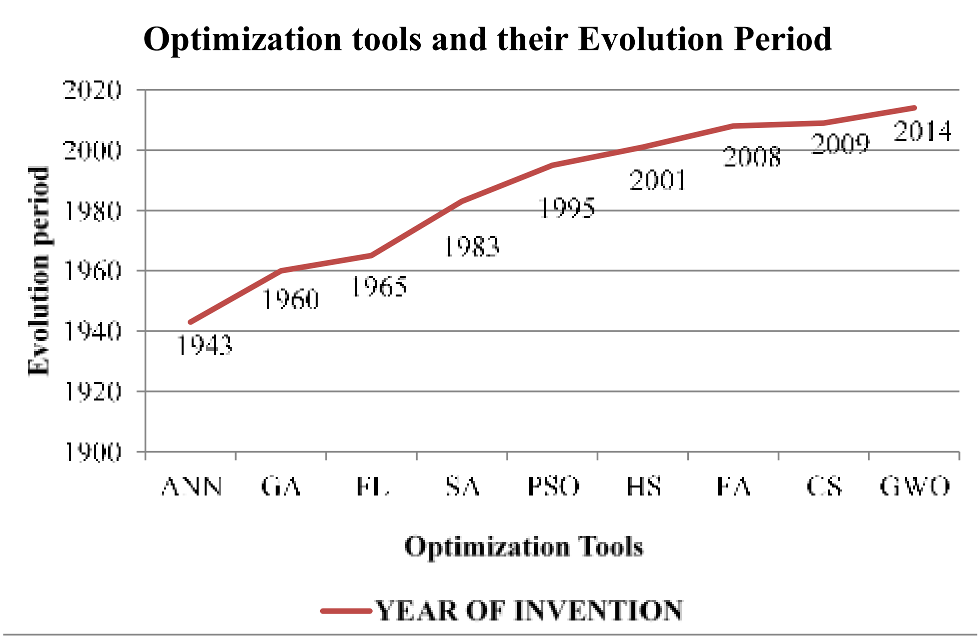

Figure 4: Evolution period of some of the Optimization techniques employed for DC motor control

The merits and demerits of the above optimization techniques employed for DC motor control is summarized in table 2.

Table 2: Merits and Demerits of the Optimization techniques employed for DC motor control [9 – 18, 20 – 22, 27, 28]

Optimization tool	Merits	Demerits
ANN	Adaptability, capability to learn from data, and suitability for systems with varying characteristics.	Complexity in structure and training, potential for overfitting, and requirements for sufficient training data.
GA	Global optimization, suitability for complex and nonlinear systems, and robustness.	Computational intensity, potential for slow convergence, and sensitivity to parameter settings.
FL	Robustness to uncertainties, adaptability, and suitability for systems with imprecise or nonlinear dynamics.	Difficulty in rule base design, potential for a large number of rules, and challenges in tuning.
SA	Global optimization, versatile, handle non convex spaces, and exploration and exploitation.	Computational intensity, sensitivity to parameters, no guarantee of global minimum, and local minima trapping.
PSO	Global optimization capabilities, simplicity, adaptability and parallelizability.	Premature convergence, dependency on parameters, Sensitivity to initial conditions,
HS	Global optimization capability, simplicity, and versatility.	Slow convergence, dependency on parameters, sensitivity to Initialization, limited handling of constraints, may Require fine-tuning.
FA	Global optimization capability, simplicity, and adaptability.	Slow convergence and sensitivity to parameters, to make informed decisions when applying it to specific optimization problems.
CS	Global optimization capability, fewer tuning parameters, simplicity, and adaptability	Limited exploration and sensitivity to parameters, longer convergence time
GWO	Global optimization, adaptability, fewer tuning parameters, simplicity, and parallelism.	Lack of guaranteed global optimum, sensitivity to parameters, convergence speed, limited exploration in early stages, limited adaptability to dynamic systems

Comparison among the aforementioned AI techniques used for optimizing DC motor parameters has been conducted based on the reviews. Two basic metrics have been chosen to proceed with the comparisons: convergence speed and computational complexity. Figure (4) depicts the comparison chart, scoring points up to 10 for fast convergence (10), moderate convergence (8), less moderate convergence (6), and slower convergence (4). Additionally, points are assigned for lower computational complexity (10), moderate computational complexity (8), high computational complexity (6), and the highest computational complexity (4).

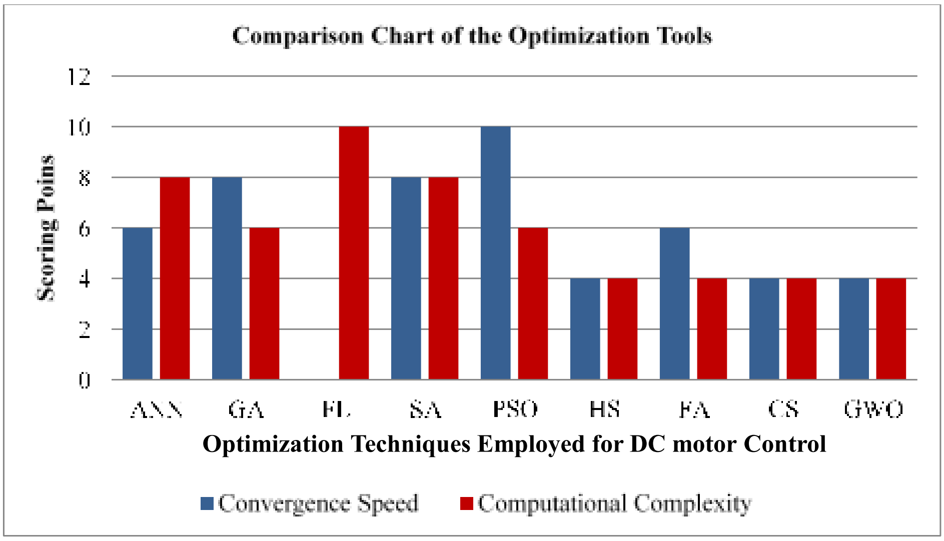

Figure 4: Scoring points of the optimization tools based on convergence speed and computational complexity

a. Hybrid AI techniques

A hybrid AI technique refers to the combination or integration of multiple artificial intelligence (AI) methods, models, or algorithms to address a specific problem or enhance overall system performance. The idea is to leverage the strengths of different AI approaches and create a synergistic solution that outperforms individual techniques. Here are a few common types of hybrid AI techniques, Neuro-Fuzzy (ANFIS), Genetic Algorithm with Fuzzy Logic (GA-FL), Particle Swarm Optimization with Neural Networks (PSO-NN), Particle Swarm Optimization with Fuzzy Logic (PSO-FL), and Particle Swarm Optimization with Grey Wolf Optimization (PSO-GWO). The advantages and shortcomings of the hybrid AI optimization employed for tuning of parameters to control DC motor can be summarized in table 3 [19, 23 – 26, 29, 30 – 33].

Table 3: Advantages and shortcomings of the hybrid AI techniques employed for DC motor control [19, 23 – 26, 29, 30 – 33]

Advantages of Hybrid AI Techniques	**Shortcomings of Hybrid AI Techniques**
Improved Performance: • Hybrid AI techniques combine the strengths of multiple approaches, leading to enhanced overall performance in terms of control accuracy, efficiency, and robustness.	**Increased Complexity:** • The integration of multiple AI techniques can result in a more complex control system, requiring sophisticated implementation and potentially making it challenging to understand and maintain.
Versatility: • Hybrid approaches can adapt to different operating conditions and requirements, making them versatile solutions for a wide range of DC motor control applications.	**Computational Overhead:** • Hybrid approaches may demand higher computational resources compared to individual techniques, which could be a limitation in real-time or resource-constrained applications.
Optimal Solution Exploration: • By integrating various AI techniques, hybrid systems can explore a broader solution space, increasing the likelihood of finding the optimal control strategy for specific DC motor scenarios.	**Training and Tuning Challenges:** • Designing and fine-tuning a hybrid AI system may be more complex than individual algorithms, requiring expertise in multiple domains and extensive training to optimize the system effectively.

Robustness to Parameter Variations: • The combination of different AI methods can improve the system's robustness, making it more resilient to variations in motor parameters, environmental conditions, and load changes.	**Dependency on Data Quality:** • Hybrid AI systems often rely on diverse datasets. The quality and representativeness of these datasets can significantly impact the overall performance, and obtaining suitable data may pose challenges.
Fast Convergence: • Hybrid AI techniques may leverage the strengths of different algorithms to achieve faster convergence rates during the optimization process, leading to quicker and more efficient control adaptation.	**Increased Implementation Time:** • Integrating multiple AI techniques and ensuring their seamless interaction may increase the implementation time, potentially delaying the deployment of the control system.

In summary, while hybrid AI techniques offer notable advantages in terms of performance and adaptability, their application involves addressing challenges related to complexity, computational requirements, and the need for comprehensive tuning and training. The decision to use hybrid AI approaches should consider the specific requirements and constraints of the DC motor control application.

IV. Future Trends

Anticipated future trends in optimization techniques for DC motor control may include:

- **Hybridizing modified version of the AI optimization techniques**: the modified PSO hybridized with MGWO for parameters of DC motor optimization offers a synergistic approach that combines the strengths of both algorithms, leading to improved performance in terms of convergence speed, solution quality, and adaptability to various optimization objectives and environments.
- **Machine Learning and Optimization Techniques:** Application of machine learning algorithms and hybrid optimization techniques may become more prevalent for tuning and optimizing DC motor parameters. These approaches can adapt to changing operating conditions and continuously optimize motor performance.

V. Observations

- Several authors explore hybrid AI techniques to enhance the overall performance of optimization problems.
- AI challenges necessitate the utilization of knowledge bases to store human expertise, operator judgment, especially in practical applications, accumulated experience over time, and dealing with factors such as network uncertainty and load variations.
- Others suggest that swarm intelligence holds greater potential for optimizing DC motor parameters, and it represents one of the most recent advancements in the realm of computational intelligence techniques.
- The hybrid approach boosts the robustness of the optimization process by integrating the adaptability of PSO to local changes and the resilience of GWO to global perturbations. This enhancement makes the algorithm more adaptable to diverse conditions encountered in DC motor applications.
- Fuzzy Logic, known for its ability to model human expertise and handle linguistic uncertainties, is integrated with MGWO to enhance the optimization process by incorporating domain knowledge and expert-defined rules for DC motor control.

VI. Conclusion

In this paper review, various DC motor control schemes and optimization techniques are examined. Classical controller schemes (PI, PID, and SMC) are compared with AI optimization techniques such as Artificial Neural Network (ANN), Genetic Algorithm (GA), Fuzzy Logic (FL), Simulated Annealing (SA), Firefly Algorithm (FA), Particle Swarm Optimization (PSO), Cuckoo Search (CS), Harmony Search (HS), and Grey Wolf Optimization (GWO). Additionally, Hybrid AI optimization techniques are evaluated in terms of their advantages and disadvantages, as well as their applications in DC motor parameter optimization and control. Each controller scheme and optimization technique has its own set of pros and cons. While hybrid AI techniques offer significant benefits in terms of performance and adaptability, their implementation involves addressing challenges related to complexity, computational requirements, and the necessity for comprehensive tuning and training. The decision to utilize hybrid AI approaches should carefully consider the specific requirements and constraints of the DC motor control application. Looking towards present and future trends, the adoption of modified (improved) Hybrid AI optimization tools, such as Improved PSO hybridized with MGWO, Improved PSO hybridized with ANFIS, and Modified GWO hybridized with GA, holds the potential to significantly enhance the overall performance of the DC motor drive.

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