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Identification of DC Motor Parameters using the ZOA Metaheuristic Algorithm with comparative study

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Abstract— In this work, the parameters of the direct current motor (DC motor) were estimated using its armature current and speed responses, employing a recent optimization algorithm known as the Zebra Optimization Algorithm (ZOA). ZOA is recognized for its high accuracy and fast convergence, as demonstrated in various recent studies. To evaluate its effectiveness, ZOA was applied to estimate the DC motor parameters and its performance was compared with two well-known algorithms: the Enhanced Opposition-Based Equilibrium Optimizer-Slim Mold Algorithm (EOSMA) and the Grey Wolf Optimizer (GWO). The results show that ZOA outperforms both EOSMA and GWO in minimizing the objective function, which reflects the estimation error of both armature current and speed. These findings confirm the superiority of ZOA in accurately identifying DC motor parameters.

Keywords— *DC Motor, Parameter Estimation, Zebra Optimization Algorithm (ZOA), Metaheuristic Algorithms, Grey Wolf Optimizer (GWO).*

I. Introduction

Accurate parameter identification of the DC motor is a fundamental aspect of modern control systems, predictive maintenance, and high-fidelity dynamic modeling. DC motor remains widely used in various industrial applications due to their simplicity, high starting torque, and ease of control. However, to ensure optimal performance and reliability, it is essential to determine motor parameters such as armature resistance, inductance, moment of inertia, and friction coefficients with high precision. Traditional identification techniques such as least squares estimation, recursive algorithms, and frequency response analysis have long been employed to address this problem. While effective under certain conditions, these methods often assume system linearity, require accurate mathematical modeling, and are highly sensitive to measurement noise and parameter fluctuations. Furthermore, classical methods tend to converge to local minima, particularly in systems that exhibit nonlinear or time-varying behavior.

Several previous studies have addressed the problem of DC motor parameter estimation using a wide variety of techniques. Among the conventional methods are curve fitting [1], constrained optimization [2], inverse problem methodologies employing conjugate gradient and regularization [3], and regression-based approaches [4]. In particular, the least squares estimation method has been extensively used due to its simplicity and effectiveness in static and linear environments [5]–[11]. In response to the limitations of classical methods, evolutionary algorithms such as Differential Evolution (DE) have been proposed as promising alternatives for nonlinear and complex systems [12], [13]. Moreover, heuristic and metaheuristic techniques have received growing attention due to their robustness and ability to avoid local optima. These include particle swarm optimization (PSO) [14], [15], ant colony optimization (ACO), artificial bee colony (ABC) algorithms [16], and nature-inspired approaches such as whale and bat algorithms [17], [18]. Among these, the Cuckoo Search (CS) algorithm has been particularly effective in estimating electrical and mechanical parameters of DC motors [19], [20]. Recent trends have further embraced intelligent algorithms and machine learning-based approaches, including parallel processing for real-time estimation [21] and adaptive learning methods aimed at reducing system uncertainties and accelerating the training process of neural networks [22]. Finally, several analytical approaches remain in use for parameter estimation, such as the motor transfer function method [23], the moment method [24], and algebraic techniques that estimate friction and inertia using voltage and angular position data from DC servo motors [25]. Other analytical models convert differential equations into algebraic forms using discrete-time sampling to identify continuous-time parameters [26]. Furthermore, parameter estimation has also been integrated with controller design, such as PI controller optimization in digital DC motor applications [27]. In addition, hybrid metaheuristic algorithms, such as the Equilibrium Slime Mould, have been explored for parameter identification in induction motors. These algorithms combine the strengths of different search strategies to optimize performance in complex systems, providing a promising solution for efficient motor parameter estimation [28].

One of the core contributions of this study lies in the introduction and application of the ZOA to the parameter identification problem in DC motor. Through a structured comparative framework, the performance of ZOA was evaluated alongside the EOSMA and the GWO. with the following key performance metrics: estimation accuracy, convergence speed, and robustness to initial condition variations. ZOA's superior exploration exploitation balance and adaptive behavior allow it to effectively navigate complex, non-convex optimization landscapes typically encountered in electrical machine modeling. These findings highlight the potential of ZOA as a powerful and reliable alternative to more established metaheuristic algorithms in the context of nonlinear system identification.

The organization of this paper is as follows: Section 2 presents the DC motor modeling. Sections 3, 4 and 5 describe respectively the EOSMA, GWO, and ZOA algorithms. Section 6 explains the parameter estimation of the DC motor using these algorithms. Section 7 discusses the results and compares the performance of ZOA with GWO and EOSMA.

II. DC Motor Modeling

DC motors, while no longer prevalent in electricity generation due to the advancement of semi-conductor rectifiers, remain extensively used in various applications such as automotive systems (including fans and power windows), household appliances, and portable electric tools often as universal motors. One of the key advantages of the DC motor is the simplicity of their mathematical modeling, which makes them highly suitable for analysis and control system design. To streamline the modeling process, several assumptions are typically adopted: temperature effects on resistance and inductance are neglected; iron losses and the influence of armature reaction are disregarded; all windings armature, compensating, and auxiliary are represented by equivalent resistance and inductance; and magnetic saturation is considered only in the stator yoke.

In this model, a preset DC motor with a rated power of 5 HP, a rated armature voltage of 240 V, a nominal speed of 1750 RPM, and a nominal current of approximately 17 A is used. The field voltage is specified as 150 V.

A. Electrical Model

The armature is represented by a resistor R_a , an inductor L_a, and a back electromotive force $E(t)$ connected in series. The voltage applied to the motor is given by:

$$u_a(t) = E(t) + R_a i_a(t) + \frac{L_a d_{ia}(t)}{dt} \tag{1}$$

The back EMF is proportional to the angular velocity:

$$E_{(t)} = k'.\Omega(t) \tag{2}$$

Where

$u_a(t)$ is the armature voltage, $i_a(t)$ is the armature current, Ω (t) is the angular speed and k' is the motor constant.

B. Mechanical Model

The electromagnetic torque generated by the motor is:

$$T_{em(t)} = k'.I_a(t) \tag{3}$$

The rotational dynamics are governed by:

$$j.\frac{d\Omega(t)}{dt} + f.\Omega(t) = T_{em(t)} - T_{R(t)} \tag{4}$$

Where: j is the moment of inertia, f is the viscous friction coefficient, $T_{R(t)}$ is the load torque.

III. Equilibrium Optimizer Slime Mould Algorithm.

The EOSMA is a hybrid metaheuristic algorithm that combines the strengths of the Slime Mould Algorithm (SMA) and the Equilibrium Optimizer (EO). It aims to balance exploration (global search) and exploitation (local search) to achieve fast convergence and high solution accuracy for complex optimization problems [29].

A. Main Update Equation.

At each iteration, the position of each solution, $\overrightarrow{x_{(\iota+1)}}$ is updated using one of the following three equation, based on random values:

$$\overrightarrow{x_{(\iota+1)}} = \begin{cases} \overrightarrow{x_{eq}(\iota)} + \left(\overrightarrow{x(\iota)} - \overrightarrow{x_{eq}(\iota)}\right).\vec{F} + \vec{j}.\frac{(1-\vec{F})}{\vec{\gamma}v}, rand < z \\ \overrightarrow{x_{eq,1}(\iota)} + \overrightarrow{va}.\left(\vec{w}.\overrightarrow{x_f(\iota)} - \vec{x_j}\right), & r < q \\ \overrightarrow{x(\iota)} + \overrightarrow{vb}.\overrightarrow{x(\iota)} & r \geq q \end{cases} \tag{5}$$

Where:

$\overrightarrow{x_{(\iota+1)}}$: Current solution position, $\overrightarrow{x_{eq(\iota)}}$: Random solution from the equilibrium pool, $\overrightarrow{x_{eq,1(\iota)}}$: Best solution in the equilibrium pool, $\vec{F}$: Equilibrium factor from EO, $\vec{\gamma}$: Random vector ∈ [0,1], $\vec{J}$: Density-related factor from EO, $\overrightarrow{x_{(\iota)}}$: Randomly selected slime mould positions, va: Adaptive coefficient, W: Weight factor from SMA, vb: Linearly decreasing value from 1 to 0, z: Experimental threshold (typically 0.03–0.06), q : Selection threshold based on fitness, *rand:* is a random number vector in the range [0,1],

B. Equilibrium Factor $\vec{F}$ Calculation (from EO):

$$\vec{F} = A_1.sign(\vec{r} - 0.5).\left(e^{-\vec{\gamma}T_1} - 1\right) \tag{6}$$

$$T_1 = \left(1 - \frac{i}{\max\_i}\right)^{\left(A_2.i/\max\_i\right)} \tag{7}$$

Where:

$A_1, A_2 \in [1,2]$: Control the balance between exploration and exploitation, i: Current iteration, max_i: Maximum number of iterations, *r:* is probability numbers in [0,1], T1: A time-dependent control parameter used to regulate the balance between exploration and exploitation during the optimization process.

C. Boundary Handling Equation.

To ensure that updated solutions remain within search limits:

$$\overrightarrow{x_{a,y(\iota+1)}} = \begin{cases} \frac{\left(x_{a,y(i)}+UB\right)}{2} & \overrightarrow{x_{a,y(\iota+1)}} \succ UB \\ \frac{\left(x_{a,y(i)}+UB\right)}{2} & \overrightarrow{x_{a,y(\iota+1)}} \prec UB \\ \overrightarrow{x_{a,y(\iota+1)}} & others \end{cases} \tag{8}$$

UB : it symbolizes the upper limits, a is population size, y indicates the number of dimensions.

IV.rGrey Wolf Optimizer

The GWO is a nature-inspired metaheuristic algorithm that mimics the leadership hierarchy and cooperative hunting strategy of grey wolves (Canis lupus). The wolf pack is divided into four ranks: alpha (α) as the leader and best solution, beta (β) as the advisor, delta (δ) with supporting roles (such as scouts and guards), and omega (ω) as the lowest-ranking members. The wolves' hunting process involves three main stages: tracking, encircling, and attacking the prey. In GWO, this process is mathematically modeled to update the positions of the wolves based on the top three solutions (α, β, δ), while the remaining wolves (ω) follow them. Each wolf updates its position according to the following formula [30]:

$$\vec{X}_{(k+1)} = \vec{X}_p(k) - \vec{A}.\vec{D} \tag{9}$$

Encircling prey: For a given iteration k, a prey located at $\vec{X}_p(k)$ is encircled by the grey wolves, which update their individual position $\overrightarrow{X_{(k)}}$ as follow:

$$\vec{D} = \left|\vec{C}.\vec{X}_p(k) - \overrightarrow{X_{(k)}}\right| \tag{11}$$

Control parameters:

$$\vec{A} = 2\vec{a}.r_1 - \vec{a}, \ \vec{C} = 2.r_2 \tag{12}$$

where:

Where a decreases linearly from 2 to 0, and $r_1, r_2 \in [0,1]$ are random numbers.

A. Guidance from Alpha, Beta, Delta.

α = best solution, β= 2nd best solution, δ = 3rd best solution. Wolves update positions relative to the three best solutions:

$$\begin{aligned} \vec{X}_1 &= \vec{x}_\alpha - \vec{A}_1.D_\alpha \\ \vec{X}_2 &= \vec{x}_\beta - \vec{A}_2.D_\beta \\ \vec{X}_3 &= \vec{x}_\delta - \vec{A}_3.D_\delta \end{aligned} \tag{13}$$

$\vec{x}_\alpha$, $\vec{x}_\beta$ and $\vec{x}_\delta$ are the position calculations of the alpha, beta, and delta wolves, and $\vec{A}_1$, $\vec{A}_2$ and $\vec{A}_3$ are the variables obtained using the equation, while D_α, D_β and D_δ are defined as follows:

$$\begin{aligned} \vec{D}_\alpha &= \left|\vec{C}_1.\vec{X}_\alpha - \vec{X}\right| \\ \vec{D}_\beta &= \left|\vec{C}_2.\vec{X}_\beta - \vec{X}\right| \\ \vec{D}_\delta &= \left|\vec{C}_3.\vec{X}_\delta - \vec{X}\right| \end{aligned} \tag{14}$$

B. Final Position Update

The new position is the average of the three leaders:

$$\vec{X}_{(k+1)} = \frac{\vec{X}_1+\vec{X}_2+\vec{X}_3}{3} \tag{15}$$

V. Zebra Optimization Algorithm

The ZOA is a nature-inspired population-based metaheuristic introduced by Trojovská et al. in 2022. It simulates the foraging and predator defense strategies of zebras to perform optimization by updating solution candidates (zebras) through two distinct behavioral phases (1, 2).

A. Phase 1: Foraging Behavior.

In this phase, the best solution in the population known as the pioneer zebra guides other zebras (solutions) toward its position. The update rule is:

$$x_{i,j}^{new,p1} = x_{i,j} + r.(PZ_J - I.x_{i,j}) \tag{16}$$

Then, the position is accepted only if it improves the objective:

$$X_i = \begin{cases} X_i^{new,p1}, & F_i^{new,p1} < F_i \\ X_i, & otherwise \end{cases} \quad (17)$$

Where:

$x_{i,j}$ is the current solution's coordinate, PZ_J is the pioneer zebra's component, $r \in [0,1]$ is a random number, $I = round(1 + rand) \in \{1,2\}$, F_i represents the objective function value before updating, Here, $x_{i,j}^{new,p1}$ denotes the updated coordinate of the solution in dimension generated during the foraging phase (phase 1).

B. Phase 2: Predator Defense Behavior

Here, zebras react to threats either by escaping predators or forming a defensive group. Based on a probability Ps:

$$x_{i,j}^{new,p2} = \begin{cases} x_{i,j} + R \,.\, (2r-1) \,.\left(1 - \frac{t}{T}\right).\, x_{i,j}, & P_s \le 0.5 \ (S_1) \\ x_{i,j} + r \,.\, (AZ_j - I \,.\, x_{i,j}), & P_S > 0.5 \ (S_2) \end{cases} \quad (18)$$

And update acceptance:

$$X_i = \begin{cases} X_i^{new,p2}, & F_i^{new,p2} < F_i \\ X_i, & otherwise \end{cases} \quad (19)$$

Where: $R = 0.001$ (a constant), t is the current iteration, T is the maximum number of iterations, AZ_j is the coordinate of the attacked zebra, P_S decides the strategy (escape vs. attack confusion), $x_{i,j}^{new,p2}$ is the updated coordinate of the solution in dimension generated during the predator-defense phase (phase 2).

These two phases repeat each iteration, allowing the algorithm to adaptively balance exploration and exploitation. At the end of optimization, the position of the pioneer zebra (best solution) is returned as the optimal result [31].

VI. Identification of Electrical Parameters Using the ZOA Algorithm

The fig. 1 illustrates the principle of applying the ZOA to identify the electrical parameters of the DC motor. The real armature current Ia and the real speed Ω are measured from the actual DC motor, while the estimated values $I_{a\,est}$ and Ω_{est} come from the DC motor model. The difference between the real and estimated values generates an error used to compute the objective function.

The ZOA algorithm adjusts the parameters of the DC motor model to minimize the objective function. This process repeats until the error is minimized, ensuring the model accurately replicates the real machine's behavior. We now proceed to the task of determining the parameters of the DC motor represented by the set of differential equations defined in:

$$\dot{x}_{est} = H(p_{est}, x_{est}, u) \quad (20)$$

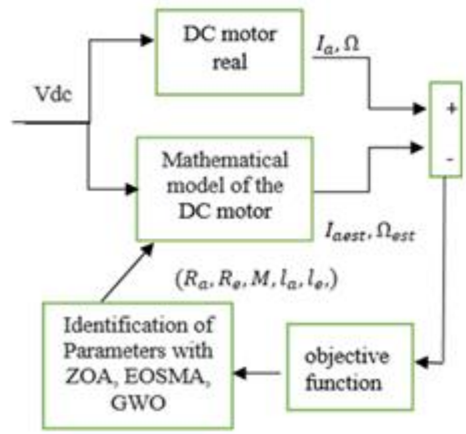

Fig. 1 Illustration of the ZOA, EOSMA and GWO algorithms applied to identify the electrical parameters of the DC motor.

where x_{est} is the variable vector of the mathematical model of the DC motor. H function represents a mathematical model of the DC motor. P_{est} represents the identification of the parameters of the DC motor.

$$p_{est} = [R_a, R_e, M, l_a, l_e]^t \quad (21)$$

$$x_{est} = [I_{a\,est}, \Omega_{est}]^t \quad (22)$$

Where l_a the armature Inductance, R_a is the armature Resistance, l_e is the field Inductance, R_e is the field Resistant, M is the mutual Inductance.

We can identify the optimal parameter vector $\widehat{P_{est}}$ based on the following equations:

$$F(\widehat{P_{est}}) = \min H(p_{est}), \qquad p_{est} \in R^n \quad (23)$$

$$F_{(\widehat{P_{est}})} = C_1(I_a - I_{a\,est})^2 + C_2(\Omega - \Omega_{est})^2$$

C_1, C_2 are the weights determine how much the current error and speed error matter in the objective.

$F_{(\widehat{P_{est}})}$: represents the objective function.

Table 1 summarizes the main parameter settings used for the ZOA, GWO, and EOSMA algorithms. To ensure a fair comparison, the population size and number of iterations were kept consistent across all three algorithms, set to 200 and 50, respectively. Each algorithm also includes specific parameters relevant to its design: for ZOA, the parameter R was set to 0.01 as recommended in the original study; the hybrid algorithm, we introduced the parameter z, which was empirically tuned, and the optimal value was found to be $z = 0.03$ based on validation performance [28].

TABLE I. PARAMETERS OF ALGORITHMS

	Algorithms		
Parameters	ZOA	GWO	EOSMA
Number of populations	200	200	200
Number of iterations	50	50	50
Z	/	/	0.03
R	0.01	/	/

Table 2. shows the search space boundaries for the parameters optimized by the ZOA, GWO, and EOSMA algorithms. These boundaries were defined for each parameter to guide the optimization process effectively and ensure meaningful results. The selected ranges are based on typical characteristics and design specifications of the DC motor.

TABLE II. THE RESEARCH SPACE OF OPTIMIZED PARAMETERS BY THE ZOA, GWO AND EOSMA ALGORITHM

	$R_a(\Omega)$	$R_e(\Omega)$	$l_a(H)$	$M(H)$	$l_e(H)$
lb	0	100	0.01	1	80
ub	3	200	0.1	3	150

lb it symbolizes the lower limits, *ub* it symbolizes the upper limits,

VII. RESULTS AND DISCUSSION

Table 3 presents the estimated parameters of the DC motor using three optimization algorithms: GWO, EOSMA, and ZOA. The parameters include the armature inductance l_a, external inductance l_e, mutual inductance M, armature resistance R_a, and external resistance R_e. The results indicate that while all three algorithms produce similar values for l_a and R_a, differences are noticeable in other parameters, particularly l_e, M, and R_e. Among the tested methods, the ZOA algorithm achieves the best accuracy in parameter estimation. This conclusion is supported by the objective function value, which reflects the optimization error. ZOA achieves an objective function value of 10^{-5}, significantly outperforming EOSMA (0.015) and GWO (0.0647). This demonstrates that ZOA is the most effective algorithm for accurately identifying the DC motor parameters.

Fig.2 illustrates the evolution of the objective function over successive iterations for the ZOA, EOSMA, and GWO algorithms. The plot clearly demonstrates that the ZOA algorithm achieves the fastest convergence, reaching a stable solution by approximately the 5th iteration. In contrast, the EOSMA algorithm converges around the 15th iteration, while the GWO algorithm requires up to 25 iterations to reach a similar level of convergence.

TABLE III. OPTIMIZED PARAMETERS OF THE MCC USING GWO, EOSMA AND ZOA ALGORITHM

	Algorithms			
Parameters	*GWO*	*EOSMA*	*ZOA*	*real*
L_a(H)	0.016	0.016	0.016	0.016
$L_e(H)$	113.27	110.07	112.5008	112.5
M (H)	1.1806	1.228	1.2362	1.234
$R_a(\Omega)$	0.78	0.78	0.78	0.78
$R_e(\Omega)$	150.26	149.33	149.999	150
Objective function	0.0647	0.015	10^{-5}	/

This performance highlights the clear superiority of the ZOA algorithm in terms of both convergence speed and solution quality. ZOA consistently attains lower objective function values more rapidly than its counterparts, making it particularly suitable for time-sensitive optimization tasks that demand high accuracy. Although ZOA may exhibit slightly higher computational demands, its ability to deliver high-quality solutions in fewer iterations underlines its robustness and efficiency. Consequently, it presents itself as a highly effective optimization technique, especially in applications where rapid convergence and precise outcomes are critical.

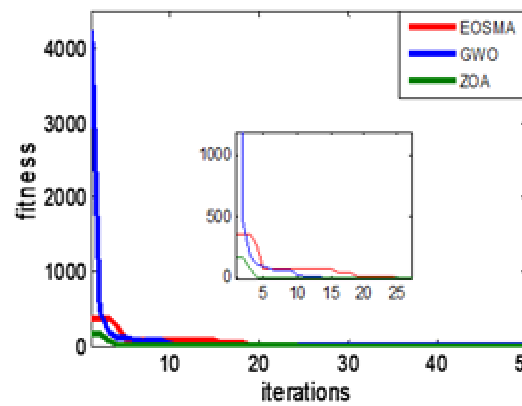

Fig. 2 Objective function.

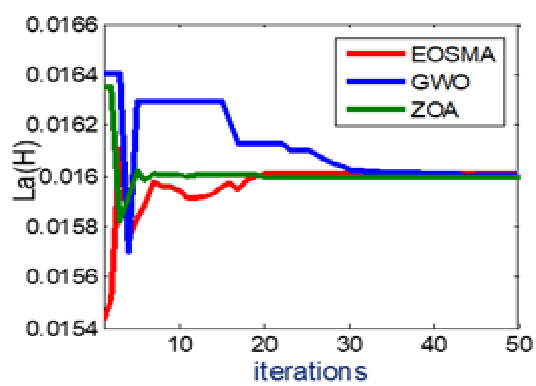

Fig. 3 Armature Inductance

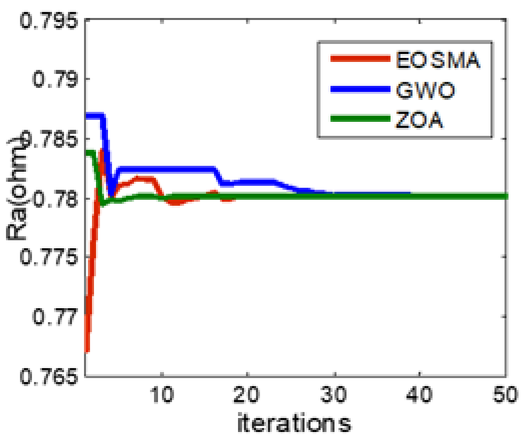

Fig. 4 Armature Resistance.

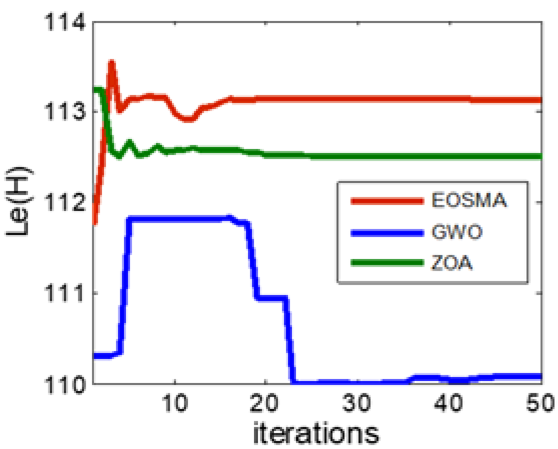

Fig. 5 Field Inductance.

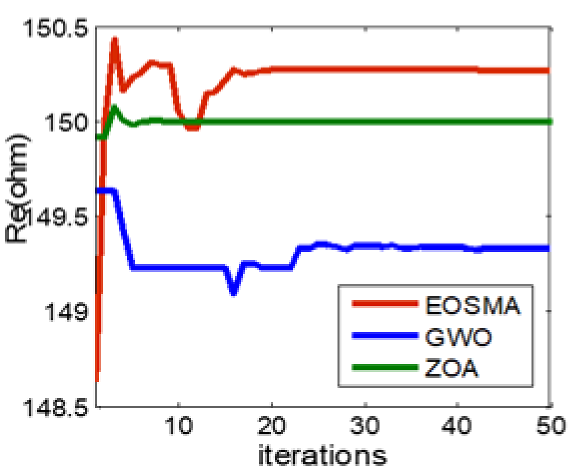

Fig. 6 Field Resistant

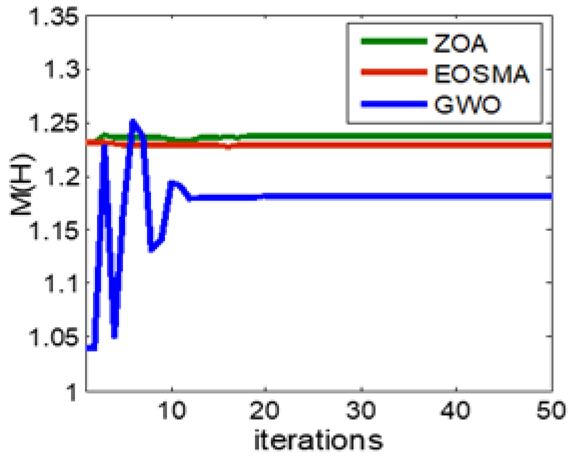

Fig. 7 Mutual Inductance

Fig. 3–7 illustrate the variation of the DC motor parameters over the course of the optimization iteration. The ZOA, EOSMA, and GWO algorithms perform the parameter search within the solution space defined in Table 2. Initially, each algorithm starts with randomly generated parameter values, resulting in high error rates at the beginning of the optimization process. As iterations progress, the ZOA algorithm shows early convergence, with its parameters stabilizing around optimal values by the 5th iteration. EOSMA begins to converge after approximately 15 iterations, while GWO demonstrates a slower convergence rate, requiring nearly 25 iterations to approach acceptable results. Upon completion of the optimization process, it is evident that the ZOA algorithm outperforms both EOSMA and GWO in terms of accuracy, convergence speed, and final solution quality. This superior performance is attributed to the effective minimization of its objective function, which reached a value of zero in the case of ZOA.

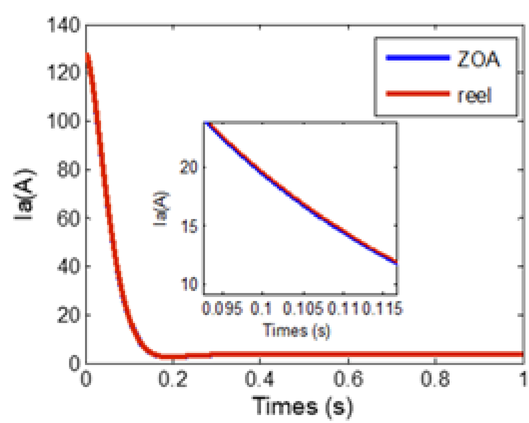

Fig.8 Comparison of DC motor Armature Current: Simulation (ZOA) vs Real System with Identified Parameters.

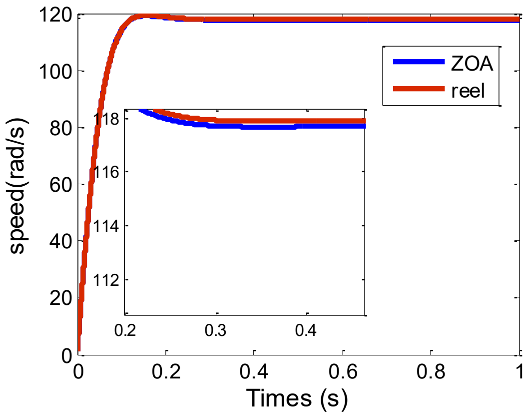

Fig. 9 Comparison of DC motor Speed Response: Simulation (ZOA) vs Real System with Identified Parameters.

Figures 8 and 9 illustrate a comparison between the simulation results using the ZOA-based model and real measured data for the DC motor in terms of speed and armature current responses. A high level of agreement is observed between the simulated and real responses, confirming the accuracy of the identified parameters and the effectiveness of the ZOA approach in representing the actual dynamic behavior of the motor. These results demonstrate the reliability of the proposed model in predicting motor performance under identical operating conditions.

VIII. CONCLUSION

In this work, the parameters of the DC motor were successfully estimated using the ZOA, based on measured armature current and speed responses. The proposed method was evaluated by comparing its performance with two other metaheuristic algorithms: EOSMA and GWO. The results clearly demonstrate that ZOA provides superior accuracy and faster convergence, achieving lower error values in both current and speed estimations. These findings highlight the effectiveness of ZOA as a reliable and efficient tool for parameter identification in electric motor systems. Future work may explore the application of ZOA in more complex systems or under varying load conditions.

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