



## Parameters Identification of Induction Motor with Hybrid Metaheuristic Algorithm: Equilibrium Slime Mould

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<https://doi.org/10.18280/jesa.580410>

### ABSTRACT

**Received:** 3 March 2025

**Revised:** 7 April 2025

**Accepted:** 14 April 2025

**Available online:** 30 April 2025

#### Keywords:

*parameters identification, IM, EOSMA, EO, SMA*

The identification of electrical and mechanical parameters is a crucial step in the modeling and control of industrial electric motors. Incorrectly identified parameters or those estimated with considerable error can lead to instability or biased control of the system. In this paper, we present a study to identify the electrical and mechanical parameters of an induction motor (IM) using two recent metaheuristic techniques: the Slim Mold Algorithm (SMA) and the Equilibrium Optimizer (EO). A hybrid algorithm, the Equilibrium Optimizer-Slim Mold Algorithm (EOSMA), combining the advantages of both techniques, is proposed and compared to other methods to demonstrate its effectiveness. The identification of the IM parameters is based on the optimization (minimization) of an objective function, which measures the error between the electrical quantities (stator current and motor speed) obtained from the simulation of a mathematical model and those measured during an experimental test. The results show that the electrical parameters identified by the hybrid EOSMA algorithm are more accurate than those obtained with the other two techniques in terms of convergence and precision, thus validating the effectiveness of the hybrid method.

## 1. INTRODUCTION

The IM is the most powerful and least expensive electrical machine on the market. It is an essential element in factories. The percentage of IM use in factories compared to other motors has reached around 80%. This prompted researchers to design a control unit based on the frequency converter control model [1]. In the control unit, the parameters of the IM must be known in order to diagnose its malfunctions. For this reason, researchers estimate IM parameters using a variety of methods, aiming to achieve accurate results.

A standard testing technique that involves direct current, no-load, and blocked rotor tests was introduced [2]. However, this method has a high error rate in estimating IM parameters, is time-consuming, and requires specialized calibration devices [3]. To address these challenges, a technique based on the Gauss-Seidel method that utilizes nameplate data to estimate IM parameters without interrupting the motor's operation was proposed [4-6]. Nevertheless, this technique is prone to errors, as IM parameters can vary due to operational conditions, temperature, and magnetic flux. To improve parameter estimation accuracy, the Iterative Least Squares (RLS) technique was introduced [7]. RLS is known for its ease of implementation, speed, and efficiency. It operates by minimizing the difference between real and estimated values. The impact of different environmental conditions on IM parameters was also studied using the RLS technique [8]. In recent years, various metaheuristic techniques have been

explored for estimating IM parameters. One technique combines numerical procedures and dimensionless analysis using Thevenin theory [9]. Another approach utilizes a particle swarm optimization algorithm and approximates rotor parameters as a function of speed [10]. An improved moth flame optimization algorithm was also developed [11]. A method that employs the Quantum Particle Swarm Optimization algorithm was proposed as well [12]. Additionally, linear induction motor parameter estimation based on the gray wolves optimization algorithm has been suggested [13]. Several methods based on the Kalman filter have been proposed to estimate IM parameters, although they are sensitive to the estimation of the initial state [14, 15]. Numerous researchers have applied different optimization algorithms using manufacturer's data sheets to estimate IM parameters [16-20]. In the last three years, new algorithms have emerged and been applied in various studies [11, 21, 22], including the EO and SMA algorithms used in variable neighborhood search for job shop scheduling problems [23], and in solving inverse kinematics and engineering design problems [24]. Recent work has applied modern EO and SMA algorithms to estimate IM parameters [25, 26]. These algorithms demonstrated faster convergence and higher accuracy compared to the PSO algorithm, which they outperformed in various evaluation scenarios.

In this paper, we contribute to identifying the electrical and mechanical parameters of IM based on experimental data of current intensity and speed, using a hybrid metaheuristic

algorithm that combines two algorithms: the EO and SMA. This combination, referred to as EOSMA, was introduced in 2022. The EOSMA algorithm has achieved great success and yielded better results in various research fields, but its application in estimating the parameters of IM has been limited. Therefore, in this work, we validated the EOSMA algorithm in estimating IM parameters by comparing it with the EO and SMA algorithms. The EOSMA algorithm produced more accurate results than both the EO and SMA algorithms, and it was characterized by rapid convergence and precise outcomes.

The following sections make up the organization of this work: Section 1 presents IM modeling. Section 2 provides a description of the new algorithms EOSMA, EO, and SMA. Section 3 provides a description of how to estimate IM parameters using algorithms EOSMA, EO, and SMA. Section 4 shows the results of estimating the IM parameters and comparing algorithm EOSMA with algorithms EO and SMA.

## 2. MODEL OF THE INDUCTION MOTOR

Modeling the IM is necessary to estimate its parameters. Therefore, a model closely matching the real IM was used, as validated in the frequency domain using the modified Park model SSFR [27]. Nonlinear mathematical equations were used for modeling an IM with reference to the rotor (d, q) axes.

$$\begin{pmatrix} u_{ds} = R_s I_{ds} + \frac{d\Phi_{ds}}{dt} - \omega_r \Phi_{qs} \\ u_{qs} = R_s I_{qs} + \frac{d\Phi_{qs}}{dt} + \omega_r \Phi_{ds} \\ 0 = R_r I_{dr} + \frac{d\Phi_{dr}}{dt} \\ 0 = R_r I_{qr} + \frac{d\Phi_{qr}}{dt} \end{pmatrix} \quad (1)$$

with

$$\begin{pmatrix} \Phi_{ds} = (M + L_s) I_{ds} + M I_{dr} \\ \Phi_{qs} = (M + L_s) I_{qs} + M I_{qr} \\ \Phi_{dr} = (M + L_r) I_{dr} + M (I_{ds} + I_{dr}) \\ \Phi_{qr} = (M + L_r) I_{qr} + M (I_{qs} + I_{qr}) \end{pmatrix} \quad (2)$$

Then the machine's nonlinear equations can be written as follows:

$$\begin{pmatrix} u_{ds} = R_s I_{ds} + (M + L_s) \frac{dI_{ds}}{dt} + M \frac{dI_{dr}}{dt} - \omega_r (M + L_s) I_{qs} - \omega_r M I_{qr} \\ u_{qs} = R_s I_{qs} + (M + L_s) \frac{dI_{qs}}{dt} + M \frac{dI_{qr}}{dt} - \omega_r (M + L_s) I_{ds} + \omega_r M I_{qr} \\ 0 = R_r I_{dr} + (M + L_r) \frac{dI_{dr}}{dt} + M \frac{dI_{ds}}{dt} \\ 0 = R_r I_{qr} + (M + L_r) \frac{dI_{qr}}{dt} + M \frac{dI_{qs}}{dt} \end{pmatrix} \quad (3)$$

where,  $R_r, R_s$  rotor resistance and stator resistance,  $L_s, L_r$  stator inductance and rotor inductance.

It can be done to complete the motor's differential equations

with the movement equations expressed by (4) and (5).

$$j \frac{d\omega_r}{dt} = C_{em} - C_r - F\omega_r \quad (4)$$

$$C_{em} = \frac{3}{2} M (I_{qs} I_{dr} - I_{ds} I_{qr}) \quad (5)$$

where,  $j$  represents the moment of inertia of the IM under study,  $C_{em}$  its electromagnetic torque,  $F$  its viscous friction,  $C_r$  its load torque.

Figure 1 illustrates the mathematical model of a three-phase IM in the dq reference frame. The model was developed using the Simulink environment and is based on the dynamic equations of the motor transformed into the rotating reference frame. The three-phase voltages ( $V_a, V_b, V_c$ ) are converted into dq components using the Park transformation, which simplifies the analysis by reducing the system to two dimensions. The model includes both the electrical circuits of the motor and the mechanical equations that relate the generated torque to the rotor dynamics. A small simulation time step (0.0001 s) is used to ensure high accuracy in the transient response analysis.

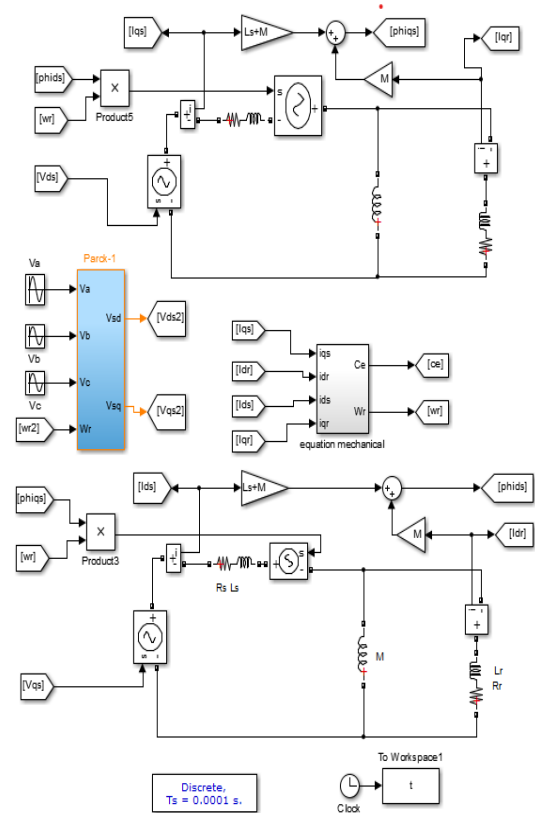


Figure 1. Simulink block diagram of the IM [27]

### 2.1 SMA

SMA is a new algorithm based on metaheuristics proposed by Li et al. [28]. Slime mold is a living organism that thrives in cold and humid environments. It spreads and reproduces in areas with abundant food. Slime mold moves toward food by detecting its scent, thereby spreading and enveloping itself around the food source. A mathematical model corresponding to this natural phenomenon was simulated using three different equations.

$$\vec{x}_{(i+1)} = \begin{cases} rand.(ub-lb)+lb & rand < z \\ \vec{x}_{B(i+1)} + \vec{va} \cdot (\vec{w} \cdot \vec{x}_{f(i)} - \vec{x}_{j(i)}) & r < q \\ \vec{vb} \cdot \vec{x}_{(i)} & r \geq q \end{cases} \quad (6)$$

where,  $i$  is the number of iterations,  $\vec{x}_{(i+1)}$  represents the position of the new mold particle,  $\vec{x}_B$  is the location with the currently identified high concentration of food odors,  $lb$  it symbolizes the lower limits,  $ub$  it symbolizes the upper limits,  $\vec{x}_{f(i)}$  and  $\vec{x}_{j(i)}$  it is two randomly selected individual mold locations.  $rand$  and  $r$  is a variable number from 0 to 1,  $\vec{va}$  is a variable number in the interval  $[-d, d]$ ,  $\vec{vb}$  decreases linearly from 1 to 0,  $d$  is defined as follows:

$$d = \arctan h \left( i - \frac{i}{\max\_i} \right) \quad (7)$$

where,  $\max\_i$  is the number of maximal iterations.  $\vec{w}$  is the transfer coefficient from the mold particle to the food location, and this factor changes from particle to particle depending on the value of the target function.  $\vec{w}$  is defined on:

$$\vec{w}_{(Sidx(n))} = \begin{cases} 1 + r \cdot \log \left( \frac{Bf - s_{(n)}}{Bf - wf} + 1 \right) & n < \frac{m}{2} \\ 1 - r \cdot \log \left( \frac{Bf - s_{(n)}}{Bf - wf} + 1 \right) & n > \frac{m}{2} \end{cases} \quad (8)$$

where,  $n = 1, 2, \dots, m$ .

$m$  is the number of mold particles,  $r$  is a random numerical variable between 0 and 1,  $Bf$  represents the best value of the objective function for each iteration,  $wf$  represents the worst value of the objective function,  $s_{(n)}$  represents the value of the objective function for each mold particle,  $Sidx$  represents the sequence of sorted objective function values.

$$q = \tanh \left| s_{(n)} - FI \right| \quad (9)$$

where,  $FI$  represents the optimal value of the objective function calculated over all iterations. The transmission and spread of slime mold is based on three different equations:

When  $rand < z$ , one equation is used.

When  $r < q$ , another equation is used.

When  $r \geq q$ , a third equation is used.

It is set to  $z = [0.03 - 0.06]$  range in the SMA.

## 2.2 Equilibrium optimizer algorithm

The EO algorithm is inspired by modern physics and is based on the principle of balancing mass and volume, as proposed in recent research [29]. The concept is described by the following equation.

$$\vec{c}_1 = \vec{c}_{eq} + \vec{F} \left( \vec{c}_0 - \vec{c}_{eq} \right) + \left( 1 - \vec{F} \right) \frac{\vec{j}}{(\vec{\gamma} \cdot \vec{v})} \quad (10)$$

where,  $\vec{c}_1$  represents the updated solution,  $\vec{c}_0$  represents the

preceding solution,  $\vec{c}_{eq}$  indicates the best solution,  $\vec{F}$  is a coefficient applied to weigh local and global search efforts.  $\vec{j}$  represents the density development rate in the test volume,  $\vec{\gamma}$  is the variable of probability numbers in  $[0, 1]$ .  $v=1$  indicates unity of volume. There are five candidate solutions in the balance basin. The four most intriguing solutions discovered thus far are listed below, with the second representing the central location (average concentration) of these four contender solutions, as illustrated:

$$\begin{aligned} \vec{c}_{eq, pool} &= \{ \vec{c}_{eq,1}, \vec{c}_{eq,2}, \vec{c}_{eq,3}, \vec{c}_{eq,4}, \vec{c}_{eq,ave} \} \\ \vec{F} &= A_1 \cdot \text{sign}(\vec{r} - 0.5) \cdot (e^{\vec{j} T_1} - 1) \\ T_1 &= \left( i - \frac{i}{\max\_i} \right)^{\left( A_2 \cdot \frac{t}{\max\_i} \right)} \end{aligned} \quad (11)$$

where,  $A_1 \in [1, 2]$  and  $A_2 \in [1, 2]$  represent the fixed global search force coefficient. The larger  $A_1 \in [1, 2]$  the greater the exploration capacity and the lower the exploitation capacity, and vice versa. The  $\vec{j}$  value is expressed as:

$$\vec{j} = \begin{cases} 0.5r_1 (\vec{c}_{eq} - \vec{\gamma} \vec{c}) \vec{F} r_2 \geq jp \\ 0 & r_2 \leq jp \end{cases} \quad (12)$$

where,  $r_1$  and  $r_2$  are probability numbers in  $[0, 1]$  and where  $jp=0.5$  is the random probability of generation.

## 2.3 Proposed a new hybrid metaheuristic algorithm EOSMA, for IM parameters identification

The EOSMA algorithm is a recently proposed method representing a hybrid of the SMA and EO algorithms. This hybrid algorithm was developed to enhance the performance of metaheuristic solutions, aiming to achieve high convergence speed and solution accuracy. By integrating the strengths of SMA and EO, the algorithm provides a robust approach for finding optimal solutions. It employs strategies that accelerate the convergence process, enabling it to reach optimal solutions in a shorter time while maintaining high accuracy in solving complex problems. Additionally, EOSMA combines global search mechanisms (exploration) with focused search mechanisms (exploitation), ensuring comprehensive coverage of the search space and improving solution quality. The algorithm operates using mathematical equations derived from the unique features of SMA and EO, performing heuristic searches through iterative steps where solutions are gradually refined through the interaction of both algorithms' components [23].

$$\vec{x}_{(i+1)} = \begin{cases} \vec{x}_{eq(i)} + (\vec{x}_{(i)} - \vec{x}_{eq(i)}) \cdot \vec{F} + (1 - \vec{F}) \frac{\vec{j}}{(\vec{\gamma} \cdot \vec{v})} & rand < z \\ \vec{x}_{eq,1(i)} + \vec{va} \cdot (\vec{w} \cdot \vec{x}_{f(i)} - \vec{x}_{j(i)}) & r < q \\ \vec{x}_{(i)} + \vec{vb} \cdot \vec{x}_{(i)} & r \geq q \end{cases} \quad (13)$$

where,  $\vec{x}_{(i)}$  is the location of the equilibrium point,  $\vec{x}_{eq(i)}$  is a solution chosen at random from the equilibrium pool with



$$\dot{x}_{est} = F(P_{est}, x_{est}, u) \quad (16)$$

where,  $x_{est}$  is the variable vector of the mathematical model of the IM.  $F$  function represents a mathematical model of the IM.  $P_{est}$  represents the identification of the parameters of the IM.

$$P_{est} = [R_s, R_r, M, l_s, l_r, j, f]^T \quad (17)$$

$$x_{est} = [I_{abcest}, \Omega_{est}]^T \quad (18)$$

$$u = [u_{abcs}]^T \quad (19)$$

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

$$S_{(P_{est})} = \min S_{(P_{est})} \quad P_{est} \in R^n \quad (20)$$

$$S_{(\widehat{P_{est}})} = \sum \left| \frac{I_{asest} - I_{as(exp)}}{I_{asest}} \right| + \frac{1}{3} \left| \frac{\Omega_{est} - \Omega_{(exp)}}{\Omega_{est}} \right| \quad (21)$$

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

### 3.2 The IM experiments tests

The characteristics of the IM used in the experiment are shown in Table 2.

Table 3 summarizes the main parameter settings used for the SMA, EO, 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 300, respectively. Each algorithm also includes specific parameters relevant to its design: for SMA, the parameter  $z$  was set to 0.03 as recommended in the original study; EO uses a control parameter  $jp$ , set to 0.5 based on prior literature. For EOSMA, the hybrid algorithm, we introduced the parameter  $k$ , which was empirically tuned, and the optimal value was found to be  $k = 0.2$  based on validation performance.

**Table 2.** Characteristics of the IM used in the experiment

Parameter	Value
P nominal power	1 KW
V nominal voltage	380 V
$I_N$ nominal current	2.5 A
$F_s$ the feed frequency	50 HZ
COS $\phi$ power factor	0.83
$N_N$ the nominal speed	2780 tr/min
The coupling	$\Delta$

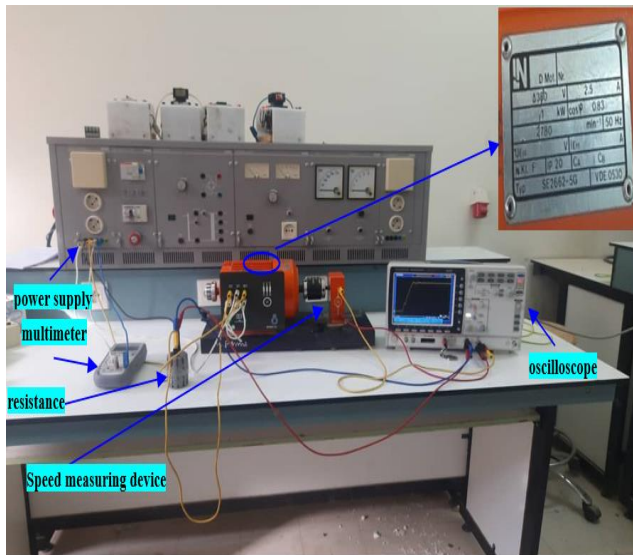
**Table 3.** Parameters of the algorithms

Algorithms	SMA	EO	EOSMA
Number of population	200	200	200
Number of iterations	300	300	300
$z$	0.03	/	/
$jp$	/	0.5	/
$k$	/	/	0.2

Table 4 shows the search limits of the algorithm. Search limits are set for each parameter to ensure accuracy in the search. These limits were chosen based on the induction motor data plate.

**Table 4.** The research space of optimized parameters by the EOSMA, EO, and SMA algorithms

	$R_s(\Omega)$	$R_r(\Omega)$	$l_s(H)$	$M(H)$	$l_r(H)$	$J(kg.m^2)$	$F(Nm/s)$
$lb$	10	5	0.001	0.5	0.001	0.0001	0.0001
$ub$	30	20	0.5	4	0.5	0.1	0.1



**Figure 3.** Experimental tests of IM data extraction

Figure 3 illustrates the experimental setup used to extract

current and speed data from a no-load IM. The IM was powered by a stable three-phase 380 V supply and operated under no-load conditions. The experiments were conducted in a laboratory environment at a constant ambient temperature of approximately 28°C. Voltage stability was maintained throughout the tests using a regulated power source. The current was measured using a cathode-ray oscilloscope connected in series with a 1-ohm resistor, while motor speed was measured using both a tachometer and the oscilloscope. The acquired current and speed signals were transferred to a computer in Excel format for further processing and analysis in MATLAB. The experimental data obtained from this setup was matched with the mathematical model to accurately estimate the parameters of the IM.

## 4. RESULTS AND DISCUSSION

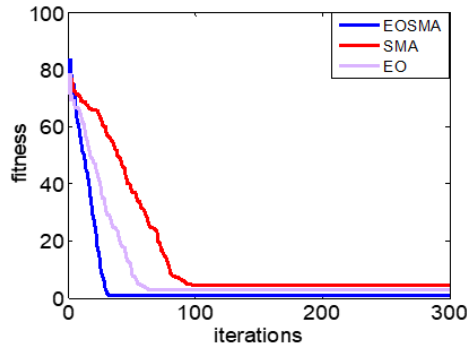
The table shows the results of the IM parameters obtained from the algorithms EOSMA, EO, and SMA. The results of the algorithm EOSMA are very accurate compared to the other algorithms, EO and SMA, because the objective function of EOSMA is better than EO and SMA, as shown in Table 5.



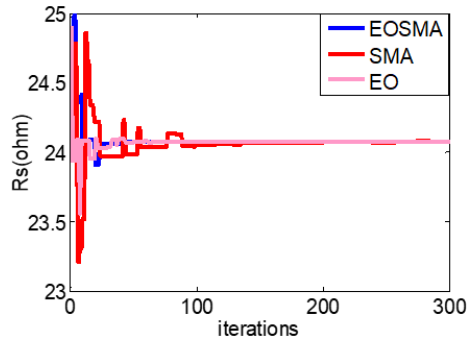
**Table 5.** Identified parameters of IM with EO SMA EOSMA algorithms

Algorithms Parameters	SMA	EO	EOSMA
$L_s(H)$	0.059	0.077	0.056
$L_r(H)$	0.045	0.026	0.043
$M(H)$	1.69	1.62	1.66
$R_s(\Omega)$	24.076	24.073	24.075
$R_r(\Omega)$	14.01	13.13	13.51
$J(kg.m^2)$	0.0008913	0.0008911	0.000795
$f(N.m.s)$	0.00027082	0.00027084	0.00024
Objective function	4.003	3.102	0.8

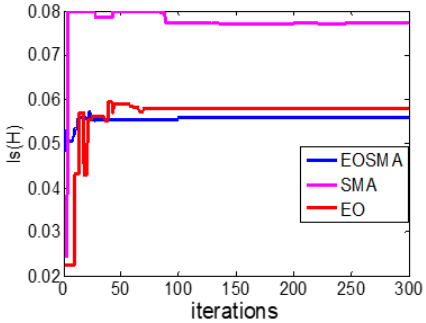
Figure 4 presents the progression of the objective function over successive iterations for the EOSMA, EO, and SMA algorithms. It is evident that EOSMA achieves convergence by approximately the 40th iteration, compared to the EO algorithm, which converges around the 60th iteration, and the SMA algorithm, which converges by the 80th iteration. These results clearly indicate that EOSMA not only converges more rapidly but also achieves superior objective function values. This comparison underscores the effectiveness of EOSMA in terms of both convergence speed and solution quality. The hybridization of SMA and EO successfully combines the strengths of both algorithms—balancing exploration and exploitation—to produce more accurate and efficient optimization outcomes. From a computational standpoint, while EOSMA may incur a slightly higher processing cost due to the integration of two algorithmic frameworks, its accelerated convergence often offsets this overhead. In practice, the algorithm requires fewer iterations to reach optimal or near-optimal solutions, which can lead to significant time savings overall. Therefore, despite its marginally higher computational demand, EOSMA proves to be a robust and efficient choice, particularly for applications that demand high precision and rapid convergence.



**Figure 4.** Objective function

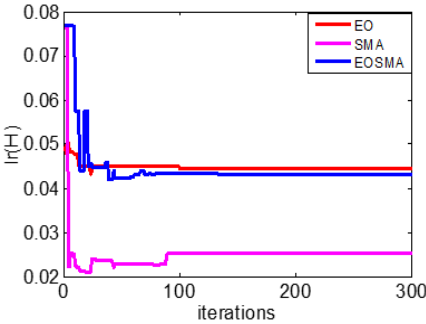


**Figure 5.** Stator phase resistance

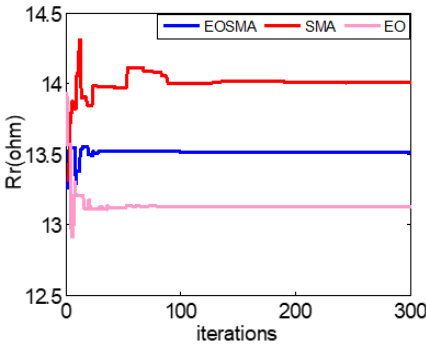


**Figure 6.** Stator inductance

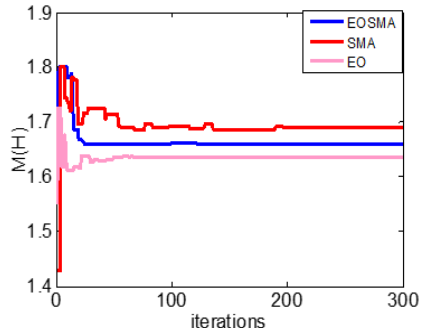
Figures 5-11 show the changes in IM parameters as a function of iterations. EOSMA, EO, and SMA search for IM parameters in the research space indicated in Table 4. At the beginning of the iteration, the algorithms provide random parameters, and the error rate of the parameters is large. After 80 iterations, the parameters begin to converge to the correct results. After the research is completed. We conclude that algorithm EOSMA obtained better and more accurate results because the objective function EOSMA is minimized (objective function EOSMA: 0.8).



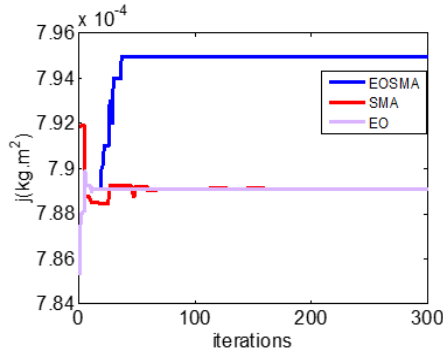
**Figure 7.** Rotor inductance



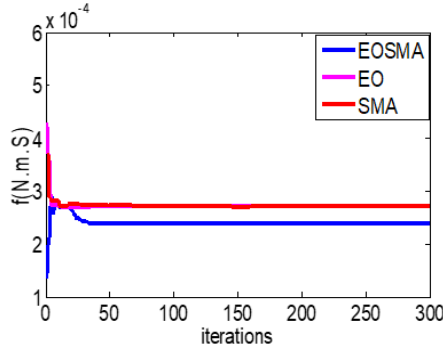
**Figure 8.** Rotor phase resistance



**Figure 9.** Mutual inductance

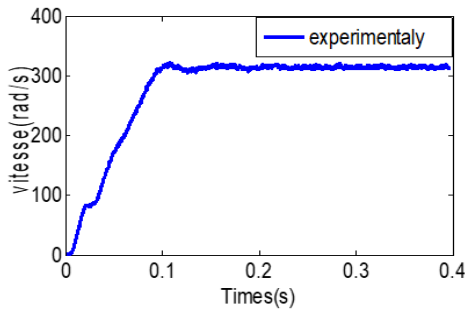


**Figure 10.** J moment of inertia of the IM

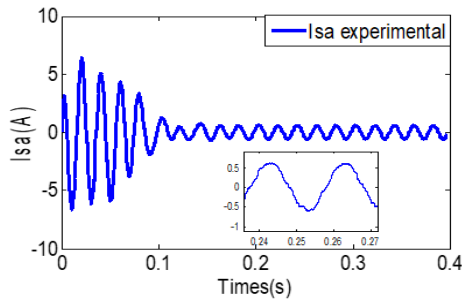


**Figure 11.** Coefficient of friction f

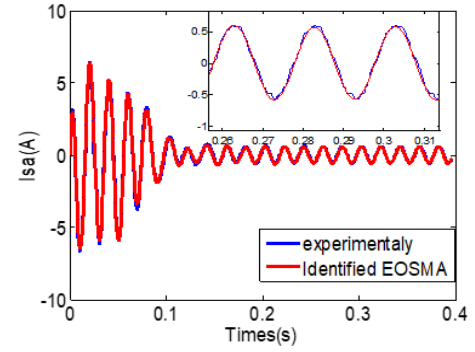
Figures 12 and 13 illustrate the evolution of angular velocity and current intensity over a short time interval. The upper curve shows a rapid increase in angular velocity, stabilizing around 300 rad/s, indicating efficient dynamic system performance. The lower curve displays damped oscillations in the current signal, reflecting transient behavior due to electromagnetic interactions. These results contribute to understanding the system's dynamic response and evaluating its accuracy.



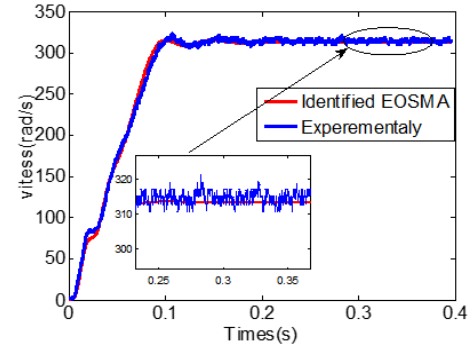
**Figure 12.** Experimental speed



**Figure 13.** Experimental stator current



**Figure 14.** IM stator current obtained from simulation and experimental with identified parameters based on EOSMA



**Figure 15.** IM speed obtained from simulation and experimental with identified parameters based EOSMA

Figure 14 shows the difference (error) between the current intensity obtained from the mathematical model of the IM and the experimental model of the IM. Likewise, Figure 15 shows the difference (error) between the speed obtained from the mathematical model of the IM and the experimental model of the IM. These results obtained with precision prove by evidence the usefulness and validation of the EOSMA algorithm for the identification of the IM parameters.

## 5. CONCLUSION

In this research, the parameters of the IM were estimated based on experimental data regarding current intensity and the speed of the IM, using a recent algorithm known as EOSMA. The EOSMA algorithm is a hybrid approach that is distinguished by its accuracy and speed of convergence, as demonstrated in several recent studies. Therefore, we tested it for estimating IM parameters and compared its performance with the EO and SMA algorithms. The EOSMA algorithm outperforms the EO and SMA algorithms based on the objective function indicating the error between the current speed obtained from the mathematical model and those obtained from the experimental data.

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