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# A MEMETIC ALGORITHM APPLIED TO INDUCTION MACHINE PARAMETERS IDENTIFICATION BASED ON AN OUTPUT ERROR

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**Keywords: Identification; Genetic algorithm; Memetic algorithm; Hooke-Jeeves method; Induction machine.**

**Based on an output error, several evolutionary methods have been applied to identify the parameters of an Induction Machine (IM). The main drawback of these methods is their premature convergence in many situations. To overcome this issue and achieve a more accurate solution, this paper proposes a Memetic Algorithm (MA), which combines a Genetic Algorithm (GA) and a local search method. This approach uses the Hooke-Jeeves (HJ) method for the local search as a mutation operator.GA has proven good ability in global search. The HJ method has a good ability to refine the local search and achieve the optimal accuracy solution. The proposed MA, which maintains a tradeoff between exploration and exploitation strategies, is applied to minimize the related objective function to obtain the electrical and mechanical machine parameters. The validation of the method is confirmed by an experiment carried out on an (0.4 kW) IM with parameters estimated using the measured data. Using the estimated parameters, the computed transient and steady-state currents agree well with the measured data.**

## 1. INTRODUCTION

The induction machine (IM) is commonly used in-industrial and transport applications [1, 2]. It offers better performance than other ac motors. IM is an effective industrial solution in the field of high-performance drives. An efficient control of an IM needs a convenient model with accurate parameters. Different models consider the saturation or core loss effects [3–5]. Several methods of parameter identification based on the output error method [6,7] are proposed in the literature [8–11]. These methods vary by the nature of the input–output signals, the adopted IM model, and the used optimization method.

This paper aims to determine the parameters of an IM by the minimization of the quadratic error between the experimental current of the IM and the computed one from the adopted model. It is generally challenging to find the global optimum with deterministic methods. Fortunately, evolutionary methods are an approach for circumventing the problems of deterministic methods [12,13]. Many evolutionary optimization techniques, such as genetic algorithm (GA) [14], firefly (FA) [15], sunflower optimization algorithm (SOA) [16], and particle swarm optimization (PSO) [17], have been successfully applied to identify the parameters of IM. However, premature convergence is the main problem of these methods. To overcome this issue and achieve an accurate solution, this paper proposes a memetic algorithm (MA), which includes a hybridization between a GA and a local search method to reduce the probability of premature convergence. For this purpose, the Hooke-Jeeves (HJ) method is used as the local search method applied as a mutation operator. It is well known that GA has proven good ability in global search when it evolves through selection, crossover, and mutation operators. The last genetic operator is often cited as a key to allowing a “jump out” from local minima. Fortunately, the mutation operator is based on the HJ method, which might be the key to improving a local search and refining the accuracy of solutions. The proposed MA combines the abilities of global and local searching to maintain a good balance between exploration and exploitation strategies. On the other hand, MA can be evolved in another way, such as a GA exploring the search space to discover promising areas and providing a solution located within the attraction pool of the global minimum. Then, a local search uses the solution provided by the GA as an initial solution and continues the disruption process until the convergence criterion is satisfied [18].

Several memetic algorithms have been proposed in the literature [19-20]. The efficiency of a genetic search can be improved by hybridization with deterministic or stochastic search methods. In [21], a new minimum-time minimum-loss control algorithm for IM using a hybrid system (GA–PSO) is suggested to obtain high performance and efficiency under practical constraints on voltage and current. The hybrid PSO-Jaya optimization algorithm is proposed in [22] to extract the optimal unknown parameters of poly-phase IM from the nameplate data. Bosworth et al. [23] used the Fletcher-Reeves method as a mutation operator. In [24], the simulated annealing-inspired selection operator is introduced into the hybrid schema. The use of a biased binary crossing operator [25] based on the recruitment mechanism into the immune system [26] is discussed. Cheng et al. [27] proposed a new mutation operator based on the neighborhood search mechanism.

This paper proposes an MA for a parametric identification method through an output error. MA is a hybridization between a GA, and HJ used as a local search method operator that replaces the mutation, which is applied to an individual respecting the mutation probability. The proposed MA realizes a good exploration ability of GA and a good exploitation of the HJ method. To highlight the performance of the proposed MA, it is compared to a GA and HJ method separately from the IM parameters identification. Using only the starting current and the corresponding phase voltage, the electrical and mechanical parameters of an IM are determined simultaneously. This is achieved by minimizing the quadratic output error between the measured current and the computed one from the adopted model.

This paper is structured as follows: section 2 describes the GA incorporating the HJ method as a mutation operator. Section 3 presents the induction machine model. Section 4 introduces an identification method through an output error method. The procedure is used to determine simultaneously the electrical and mechanical parameters of an IM from measurements of the starting current and the corresponding phase voltage. Section 5 confirms the identification method by experimental results to show the MA's performance. Finally, section 6 draws some conclusions.

## 2. MEMETIC ALGORITHM

This section describes the HJ method, GA, and MA.

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### 2.1 HOOKE-JEEVES METHOD

The Hooke-Jeeves (HJ) method is a deterministic technique that does not require knowledge of the objective function and without derivatives calculation. It combines exploratory search and pattern search. The first two iterations of the HJ's procedure in a 2-dimensional space [28–30] are illustrated in Fig. 1.

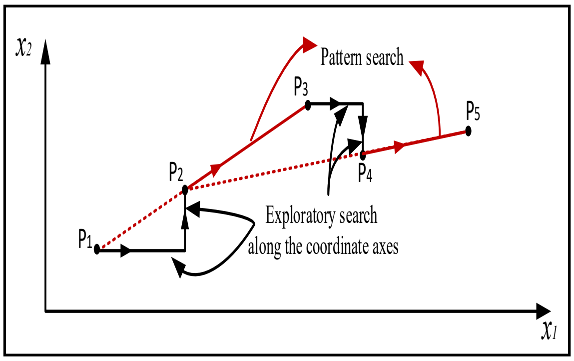



Fig. 1 – Illustration of the first two phases of the HJ method.

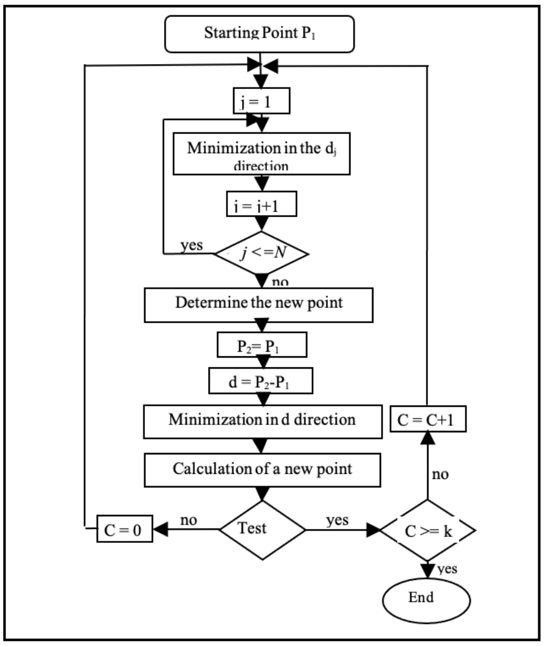



Fig. 2 – Flowchart of the HJ method.

The HJ's procedure is summarized as follows:

**Step 1:** Let $P_1$ be the initial point.
**Step 2:** An exploratory search along the coordinate axes leads to point $P_2$.
**Step 3:** A new pattern search along direction $P_1P_2$ leads to point $P_3$
**Step 4:** Starting from $P_3$, another exploratory search leads to $P_4$.
**Step 5:** A new pattern search along direction $P_2P_4$ leads to the next point $P_5$.
This iterative process repeats itself until the error test stops the program.

The flowchart of the HJ method is represented in Fig. 2.

### 2.2 GENETIC ALGORITHM

A genetic algorithm (GA) optimization process starts with a random population of many individuals evolving under specified selection rules to a state that minimizes the objective function. Each individual represents an IM, which is characterized by the following parameters vector $\mathbf{P} = [\sigma \quad T_s \quad L_s \quad T_s \quad J \quad B]^t$ and a value of an objective function which represents the output quadratic error between the measured current and the computed one from the adopted model of the IM. The elements of the vector **P** are called genes. All genes are bound to respect the search space. The new population is obtained iteratively by applying the genetic operators (Boltzman selection, continuous crossover, non-uniform mutation) and replacement strategy for the IM parameters identification [31].

The GA is combined with the HJ method as the mutation operator to hasten the algorithm's convergence and highlight the optimal solution accuracy. The following step describes the MA.

### 2.3 MEMETIC ALGORITHM

There are many ways of designing an MA because local search methods are also numerous. In this paper, hybridization is used to find in an MA the local search (HJ) operator that replaces the mutation for an individual according to the mutation probability.

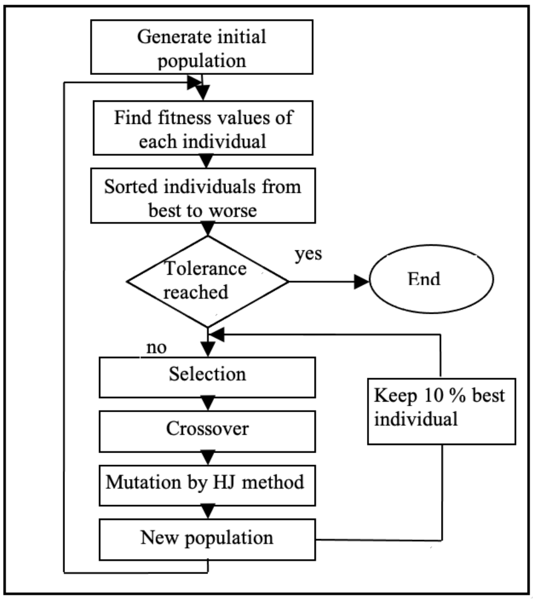



Fig.3 – Flowchart of the MA.

GA has proven good capacity to explore the search space, while the HJ method has a high-performance capacity to exploit the local search. The hybridization emergence comes from combining the advantages of GA's evolutionary and HJ's deterministic methods. Often, these methods are complementary because one detects good areas in the global search space while the other concentrates intensively on exploiting these areas of the search space. Thus, the interesting areas of the search space can be explored quickly by a GA and more exploited by the HJ method by refining the accuracy solution to maintain the trade-off between exploration and exploitation. The flowchart of the MA is illustrated in Fig 3.

## 3. **INDUCTION MOTOR MODEL**

Using the usual simplifying hypothesis, the saturation effect, core losses, and skin effect are neglected; only the first space harmonic is considered, and the air gap is constant. In the Park model, the dynamic equations of the IM [32] related to a reference linked to the stator are given by

$$\frac{\mathrm{d}X_1}{\mathrm{d}x} = A_1 X_1 + A_2 U \tag{1}$$

where $A_1$ and $A_2$ are respectively given by

$$A_1 = \begin{bmatrix} -\frac{1}{\sigma T_s} & \frac{1-\sigma}{\sigma} P_0 \Omega & \frac{1-\sigma}{\sigma . T_r} & \frac{1-\sigma}{\sigma} P_0 \Omega \\ -\frac{1-\sigma}{\sigma} P_0 \Omega & -\frac{1}{\sigma T_s} & -\frac{1-\sigma}{\sigma} P_0 \Omega & \frac{1-\sigma}{\sigma T_r} \\ \frac{1}{\sigma T_s} & -\frac{1}{\sigma} P_0 \Omega & -\frac{1}{\sigma T_r} & -\frac{1}{\sigma} P_0 \Omega \\ \frac{1}{\sigma} P_0 \Omega & \frac{1}{\sigma . T_s} & \frac{1}{\sigma} P_0 \Omega & -\frac{1}{\sigma T_r} \end{bmatrix} \tag{2}$$

$$A_2 = \begin{bmatrix} \frac{1}{\sigma L_s} & 0 & -\frac{1}{\sigma L_s} & 0 \\ 0 & \frac{1}{\sigma L_s} & 0 & -\frac{1}{\sigma T_s} \end{bmatrix}^{\mathrm{t}} \tag{3}$$

$$X_1 = [I_{ds} \quad I_{qs} \quad I'_{dr} \quad I'_{qr}]^{\mathrm{t}}, \tag{4}$$

where

$$I'_{dr} = \frac{I_{dr}}{L_r}; \qquad I'_{qr} = \frac{I_{qr}}{L_r}$$

$$U = [V_{ds} \quad V_{qs}]^t \tag{5}$$

The mechanical equation is given by:

$$J \frac{\mathrm{d}\Omega}{\mathrm{d}t} = T_{em} - T_l - T_{res}, \tag{6}$$

$T_{em}$ is the electromagnetic torque given by:

$$T_{em} = (1-\sigma) L_s \left( I_{qs} I'_{dr} - I_{ds} I'_{qr} \right), \tag{7}$$

And $T_{res}$ is the friction torque assumed to be:

$$T_{res} = B\Omega. \tag{8}$$

So, the mechanical equation becomes

$$\frac{\mathrm{d}\Omega}{\mathrm{d}t} = \frac{1}{J}(1-\sigma) L_s \left( I_{qs} I'_{dr} - I_{ds} I'_{qr} \right) - \frac{B\Omega}{J} \tag{9}$$

The machine is governed by the nonlinear eq. (1) and (9). So, the IM is completely characterised by the parameters vector $\mathbf{P} = [\sigma \quad T_s \quad L_s \quad T_s \quad J \quad B]^{\mathrm{t}}$, which can be determined from the measurement of the starting current and the corresponding simple voltage applied to the machine.

## 4. IDENTIFICATION METHOD

The method determines simultaneously the electrical and mechanical parameters of a mathematical model of the IM. So, the model can match the input–output behavior of the IM. This can be achieved by measuring the current and the corresponding voltage applied to the machine on transient from standstill to steady state. The used identification method is illustrated in Fig.4.

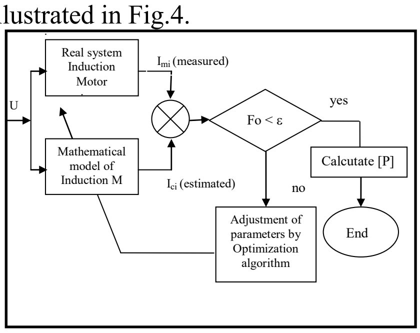



Fig. 4 – Identification process.

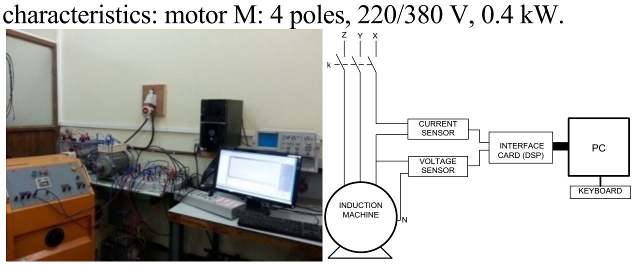
To estimate the vector of parameters $P = [\sigma \quad T_s \quad L_s \quad T_s \quad J \quad B]^{\mathrm{t}}$, the quadratic error $F_0$ between the measured values $I_{mi}$ and the computed ones $I_{ci}$ is obtained by the using Runge-Kutta algorithm from the adopted model at the same instants and is minimized by the GA, HJ, and MA

$$F_0 = \sum_{i=1}^{n} (I_{mi} - I_{ci})^2 \tag{10}$$

where $n$ is the number of the measured values.

## 5. EXPERIMENTAL RESULTS

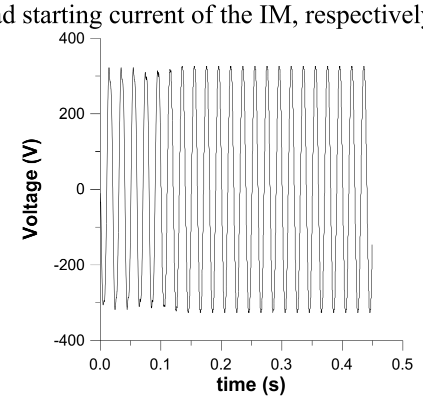
The experimental data is obtained from a transient test on a three-phase IM. A Dspace card simultaneously measures the start-up current and the corresponding phase voltage. The experimental setup is shown in Fig. 5. This experiment is carried out on a three-phase IM with the following characteristics: motor M: 4 poles, 220/380 V, 0.4 kW.



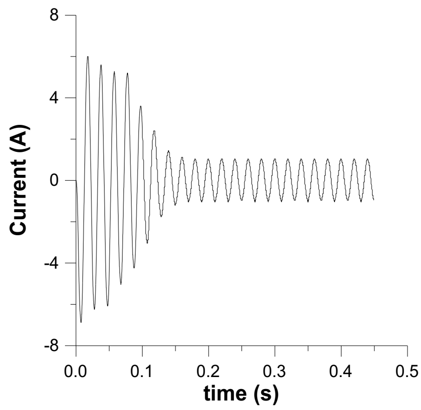

(a) (b)

Fig. 5 – (a) View of the experimental setup, (b) measurement setup.

The curves in Fig. 6 represent the measured voltage and the no-load starting current of the IM, respectively.




(a)




(b)

Fig. 6 – Motor M; (a) Voltage measured; (b) current measured.

The estimated parameters obtained using the measured data are given in Table 1. It can be noticed that the experimental results confirm well the fast convergence of the

MA and the optimal solution accuracy compared to the GA and HJ methods.

*Table 1*

Parameters resulting from the identification of motor M,

| **Parameters** | **GA** | **HJ** | **MA** |
|---|---|---|---|
| σ | 0.1073 | 0.112 | 0.1088 |
| *Tr* (ms) | 76.39 | 72.5 | 74.8 |
| *Ts* (ms) | 36.68 | 35.3 | 36.25 |
| *Ls* (mH) | 1026.67 | 984.021 | 1012 |
| *J* (kg.m$^2$) | 0.0041 | 0.0041 | 0.0041 |
| *B* (N.m.s/Rd) | 0.0031 | 0.0031 | 0.0031 |
| Number of iterations | 950 | 454 | **183** |
| Time computing (s) | 9908.453 | 29112.78 | **7784.51** |

The computed current is obtained by the estimated parameters. Figure 7 shows the superposition of the calculated current with the measured one both in transient and steady state.

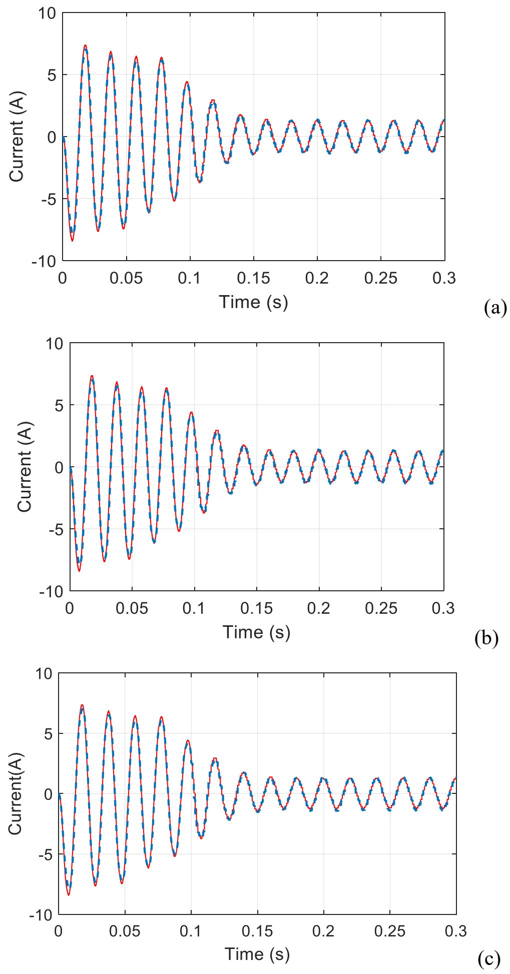
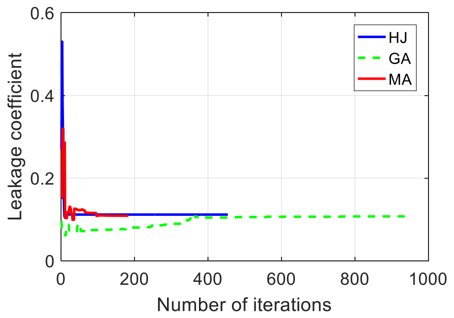



Fig. 7 – Superposition of the measured current and calculated one with the estimated parameters to motor M; (a) by GA; (b) by MA; (c) by HJ.

Calculated current — — — Measured current ———




(a)

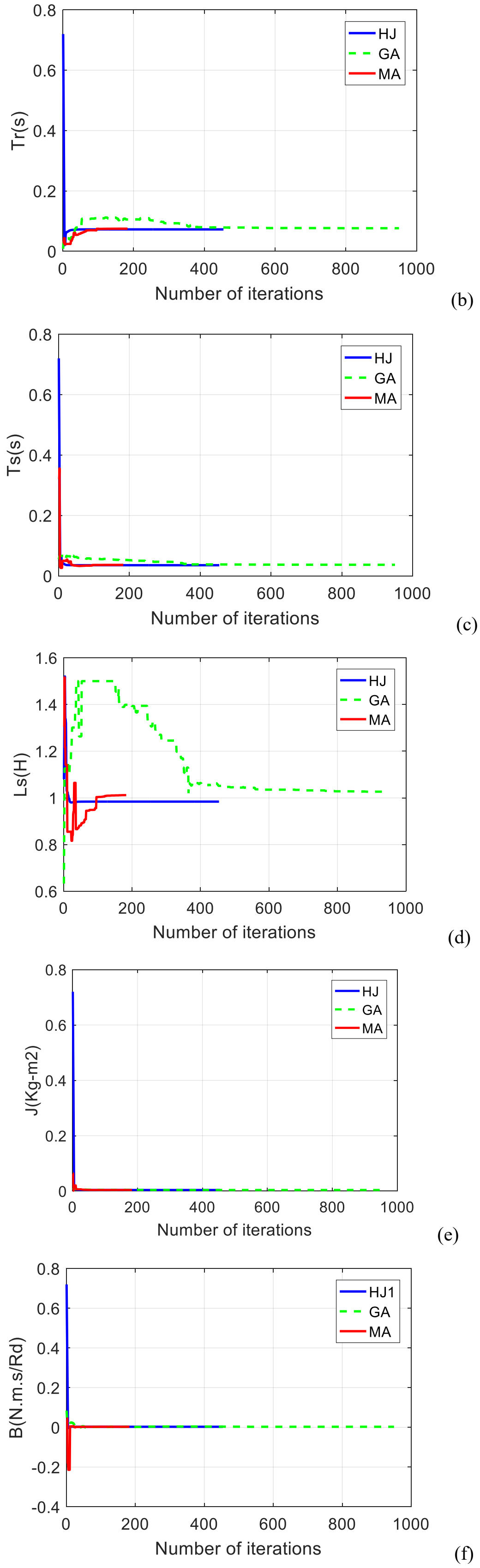



Fig. 8 – Parameters evolution of motor M; (a) of leakage coefficient; (b) of Tr; (c) of Ls; (d) of Ts; (e) of J; (f) of B.

Figure 8 illustrates the parameters' evolution versus the number of iterations for the motor M. This confirms the convergence for different algorithms.

## 6. CONCLUSIONS

This paper proposes a memetic algorithm to identify the induction machine parameters. MA is a hybridization between GA and HJ methods as a local search. To hasten the convergence, avoid the risk of premature convergence, and improve the estimated parameters accuracy, the hybridization approach is used as a local search (HJ) operator that replaces the mutation, which is applied to an individual respecting the mutation probability. The GA ensures the exploration of wider areas for locating the attraction pool of global optimum. The HJ method has a good ability to refine the exploitation and achieve the optimal accuracy solution. Then, a good balance between exploration and exploitation is achieved. Therefore, the electrical and mechanical parameters of an IM are determined simultaneously by using only the measured current and the corresponding phase voltage. This identification method is based on the output error and uses three optimization methods, GA, HJ, and MA, as minimization techniques. The validation of these methods is realized from an experiment carried out on an IM (0.4 kW) parameters estimation by measured data. The matching in the transient and steady state of computed currents with the measured ones confirms the accuracy of the identified parameters. The results show the superior MA versus GA and HJ to highlight the computing time and convergence speed performance.

### Nomenclature

| | | | |
|---|---|---|---|
| $V_{dr}$, $V_{qr}$ | d-q axes rotor voltage | $L_m$ | mutual inductance (H) |
| $V_{ds}$, $V_{qs}$ | d-q axes stator voltage | $L_s$, $L_r$ | stator and rotor inductances (H) |
| $I_{dr}$, $I_{qr}$ | d-q axes rotor current | | |
| $I_{ds}$, $I_{qs}$ | d-q axes stator current | $J$ | rotor inertia (kg.m$^2$) |
| $\varphi_{dr}$, $\varphi_{qr}$ | rotor winding flux linkages | $T_{em}$ | electromagnetic torque (N.m) |
| $\varphi_{ds}$, $\varphi_{qs}$ | stator winding flux linkages | $T_{res}$ | resistive torque (N.m) |
| | | $B$ | viscous friction coefficient (N.m.s/Rd) |
| $R_s$, $R_r$ | stator and rotor resistances (Ω) | σ | leakage coefficient |
| ω | mechanical velocity (Rd/s) | $T_r$ | rotor time constant (s) |
| | | $T_s$ | stator time constant (s) |
| $\omega_e$ | electrical velocity (Rd/s) | $P_o$ | number of pole pairs |

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