New Objective Function for Identifying the Parameters of an Induction Machine Using Hybrid Particle-Based Gravitational Search Algorithm

Anant Oonsivilai*, Apichai Rojwongwiriya, and Ratchadaporn Oonsivilai

***Abstract*— *At present, the agricultural industry is using more induction machines than previously in place of the traditional diesel engine. We identify useful parameters in the design of the control system of the induction machine. The conventional methods used to identify the parameters of the induction machine are a no-load test, a DC test, a locked rotor test, and a retardation test. This paper presents a new objective function for the identification of the parameters of the induction machine using hybrid particle swarm based gravitational search algorithm techniques (PSO-GSA). The integral of squared error (ISE) is used as the objective function of the hybrid particle swarm based gravitational search algorithm techniques. The conventional objective function for identifying the parameters only considers the stator current and rotor speed. The new objective function in the identification of parameters also includes consideration of the electromagnetic torque. A comparison is made between the results obtained by the new objective function and the old objective function. The simulated results show that the new objective function is more effective for this task than the old objective function at short iterations*.

***Keywords*— Parameter identification, induction machine, hybrid particle based gravitational search algorithm.**

1. INTRODUCTION

Induction machines are popular because they are cheap, efficient and reliable [1]. Usually, the equivalent circuit per phase at steady state is used to describe the behavior of the three-phase induction motor. In addition, in simple control, precision is ignored, so steady-state behavior is analogous to the behavior of the dynamic state of the induction machine.

Nowadays, the development of the controllers of induction machines using steady-state parameters is not adequate. As a result, there is a challenge in identifying the precise parameters for the control of the induction machine unit. However, identifying these parameters is not easy and requires many steps [2].

To identify parameters of induction machine, two successive tests, namely, the locked rotor test and the no-load test with synchronous speed should be carried out to determine stator resistance. These tests take a very long time and require multiple measurements which might result in errors. Some tests are not feasible or difficult to do in the case of tests at synchronous speed, which may involve problems with the fan and gearbox, and the locked rotor test when machine is connected to system.

This paper presents effectiveness of a new objective function for identifying the dynamic parameters of an induction machine compared with the conventional objective function for identifying the parameters which only considers the stator current and rotor speed.

This article has the following format. Section II presents the model simulation of an induction machine. Section III presents a method of identifying the parameters using hybrid particle swarm based gravitational search algorithms. Section IV presents the results of identifying the parameters. Finally, conclusions are drawn in Section V.

2. MODEL SIMULATION OF AN INDUCTION MACHINE

The induction machine model used in this research is expressed in a stationary reference frame with the assumption that the linearity of the magnetic circuit and loss of iron is ignored Flux linkage equations and stator current equations are used in the model as follows [3].

$$\psi_{qs}^{s} = \omega_b \int \left\{ v_{qs}^{s} + \frac{r_s}{\omega_b L_s}\left(\psi_{mq}^{s} - \psi_{qs}^{s}\right) \right\} dt \tag{1}$$

$$\psi_{ds}^{s} = \omega_b \int \left\{ v_{ds}^{s} + \frac{r_s}{\omega_b L_s}\left(\psi_{md}^{s} - \psi_{ds}^{s}\right) \right\} dt \tag{2}$$

$$\psi'^{s}_{qr} = \omega_b \int \left\{ \frac{\omega_r}{\omega_b}\psi'^{s}_{dr} + \frac{r'_r}{\omega_b L'_r}\left(\psi_{mq}^{s} - \psi'^{s}_{qr}\right) \right\} dt \tag{3}$$

$$\psi'^{s}_{dr} = \omega_b \int \left\{ -\frac{\omega_r}{\omega_b}\psi'^{s}_{qr} + \frac{r'_r}{\omega_b L'_r}\left(\psi_{md}^{s} - \psi'^{s}_{dr}\right) \right\} dt \tag{4}$$

$$\psi_{mq}^{s} = L_M \left(\frac{\psi_{qs}^{s}}{L_s} + \frac{\psi'^{s}_{qr}}{L'_r} \right) \tag{5}$$

$$\psi_{md}^{s} = L_M \left(\frac{\psi_{ds}^{s}}{L_s} + \frac{\psi'^{s}_{dr}}{L'_r} \right) \tag{6}$$

$$\frac{1}{L_M} = \frac{1}{L_m} + \frac{1}{L_s} + \frac{1}{L'_r} \tag{7}$$

$$i_{qs}^{s} = \frac{\psi_{qs}^{s} - \psi_{mq}^{s}}{\omega_b L_s} \tag{8}$$

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$$i_{ds}^{s} = \frac{\psi_{ds}^{s} - \psi_{md}^{s}}{\omega_b L_s} \quad (9)$$

where

v_{qs}^{s} : stator voltage q axis in the stationary reference frame

v_{ds}^{s} : stator voltage d axis in the stationary reference frame

ψ_{mq}^{s} : mutual flux linkage q axis in the stationary reference frame

ψ_{md}^{s} : mutual flux linkage d axis in the stationary reference frame

r_s : stator resistance

r'_r : rotor resistance

L_s : stator inductance

L'_r : rotor inductance

L_m : mutual inductance

ω_r : rotor speed

ω_b : base speed

The electromagnetic torque equation and speed equation is shown as follows.

$$T_{em} = \frac{3}{2}\frac{P}{2\omega_b}\left(\psi_{ds}^{s} i_{qs}^{s} - \psi_{qs}^{s} i_{ds}^{s}\right) \quad (10)$$

$$\frac{2J\omega_b}{P}\frac{d\left(\omega_r / \omega_b\right)}{dt} = T_{em} + T_{mech} - T_{damp} \quad (11)$$

where

P : number of poles

J : machine inertia

T_{mech} : mechanical torque

T_{damp} : damping torque.

3. IDENTIFYING THE PARAMETERS USING HYBRID PARTICLE SWARM BASED GRAVITATIONAL SEARCH ALGORITHMS

Hybrid particle swarm based gravitational search algorithms are smart to deal with global optimization with many variables. The normal mathematical method cannot obtain a globally optimal solution. Such a method takes a long time and requires a high-performance computer. At present, these issues have been exhausted, making hybrid particle swarm based gravitational search algorithm more popular.

Particle Swarm Optimization

Particle swarm optimization imitates the behavior of living together in a herd. The behavior of the particle in the herd is consistent or in the same direction. The key to this behavior is the direction and speed of each particle. The direction of all the herd will run towards the best fit [4-13].

The particle swarm optimization formula is as follows.

$$v_i^{iter+1} = v_i^{iter} + rand_i\left(p_i^{best} - p_i^{iter}\right) + rand_i\left(g_{best}^{iter} - p_i^{iter}\right) \quad (12)$$

$$p_i^{iter+1} = p_i^{iter} + v_i^{iter+1} \quad (13)$$

where

p_i^{iter} : position of the particle i at iteration $iter$

v_i^{iter} : velocity of a particle i at iteration $iter$

p_i^{best} : position of the particle i at best iteration

g_{best}^{iter} : position of the best particle at iteration $iter$

$rand_i$: uniform random value in the range [0,1] to randomize the next position of a particle i

Particle swarm optimization will look at all the particles with the same mass. And the direction of the particles depends on the $v_i^{iter}, p_i^{best}, g_{best}^{iter}$ in search space as shown in Fig. 1.

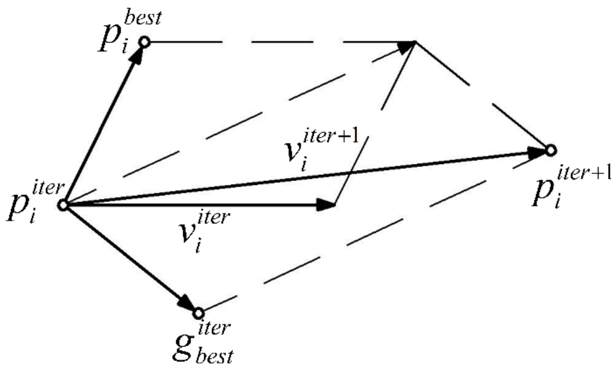


Fig.1. Particle swarm optimization in search space

Gravitational Search Algorithm

GSA is inspired by the law of gravity. Each particle in the system pulls in other particles with a force that changes with mass and is conversely relative to the separation between two particles. All these particles pull in each other by gravity. This force causes the movement of all particles to the largest particle. Heavy particles move slower than lighter particles.

Each particle has two specific values: position and mass. The position of a particle is in the boundary of the search space, and the mass of a particle is determined by the objective function. So, the particle is pulled in by the heaviest particle. The heaviest particle will be the best value in the search space [14-16].

The system has all N particles. At iteration $iter$ of gravity between particle i and j is given by the following equation.

$$F_{ij}^{iter} = G^{iter}\frac{M_i^{iter} \times M_j^{iter}}{\left(R_{ij}^{iter}\right)^2}\left(p_j^{iter} - p_i^{iter}\right) \quad (14)$$

where

M_i^{iter} : mass of a particle i at iteration $iter$

M_j^{iter} : mass of a particle j at iteration $iter$

p_i^{iter} : position of the particle i at iteration $iter$
p_j^{iter} : position of the particle j at iteration $iter$
R_{ij}^{iter} : distance between the particle i and j at iteration $iter$
G^{iter} : gravitational constant at iteration $iter$

The gravitational constant and mass of the particle is calculated as.

$$G^{iter} = G_0 \times \exp\left(-\alpha \times iter / Maxiter\right) \tag{15}$$

$$m_i^{iter} = \frac{obj_i^{iter} - worst^{iter}}{best^{iter} - worst^{iter}} \tag{16}$$

$$M_i^{iter} = \frac{m_i^{iter}}{\sum_{n=1}^{N} m_n^{iter}} \tag{17}$$

where

α : descending coefficient
G_0 : initial value respectively
obj_i^{iter} : objective function value of particle i at iteration $iter$
$best^{iter}$: minimum of the objective function value (case minimization) at iteration $iter$
$worst^{iter}$: maximum of the objective function value (case minimization) at iteration $iter$
$iter$: current iteration
$Maxiter$: maximum number of iterations

The resultant force of a particle is calculated by the following equation.

$$F_i^{iter} = \sum_{j=1, j\neq i}^{N} rand \cdot F_{ij}^{iter} \tag{18}$$

where $rand$ is uniform random value in the range [0,1]

According to the law of movement, the acceleration varies with the force and is inverse to the mass. So, the acceleration of all the particles and the gravitational search algorithm formula can be shown by the following equation

$$a_i^{iter} = \frac{F_i^{iter}}{M_i^{iter}} \tag{19}$$

$$v_i^{iter+1} = rand_i \times v_i^{iter} + a_i^{iter} \tag{20}$$

$$p_i^{iter+1} = p_i^{iter} + v_i^{iter+1} \tag{21}$$

where

p_i^{iter} : position of the particle i at iteration $iter$
v_i^{iter} : velocity of a particle i at iteration $iter$
a_i^{iter} : acceleration of the particle i at iteration $iter$
$rand_i$: uniform random value in the range [0,1] to randomize the next position of a particle i

The gravitational search algorithm will look at all particles with a different mass, causing every particle to affect the direction of one particle as shown in Fig. 2.

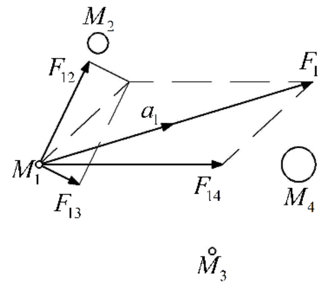


Fig.2. Resultant force and acceleration for the gravitational search algorithm.

Hybrid Particle Swarm best Gravitational Search Algorithm

The PSO-GSA concept is obtained from the hybridization methods used for heuristic calculations [17]. Hybridization methods are divided into two algorithms, high-level or low-level with relay or teamwork method as homogeneous or heterogeneous. In this paper, we use low-level heterogeneous hybrid teamwork to hybridize PSO with GSA. Low-level is the integration of both functions. Teamwork is the simultaneous operation of two algorithms. Heterogeneous is using two different algorithms to obtain results [18,19].

PSO-GSA is the compound of the velocity equations of PSO and GSA as shown in the following equation.

$$v_i^{iter+1} = rand_i \times v_i^{iter} + c_1 \times a_i^{iter} + c_2 \times rand \times \left(g_{best}^{iter} - p_i^{iter}\right) \tag{22}$$

$$p_i^{iter+1} = p_i^{iter} + v_i^{iter+1} \tag{23}$$

where c_1, c_2 are weighting factors.

Identifying the Parameters

From the identification of the parameters using the hybrid particle swarm based gravitational search algorithm, the parameters are randomized to the initial parameter and then fed to the model of the induction mechanical machine. The conventional objective function is identified at present by the integral of the squared error (ISE) for the stator current and the rotor speed of the induction machine. In this paper we present a new objective function for the identification of the parameters by taking into account the electromagnetic torque. The two objective functions are shown as follows [2, 20].

$$f_{obj}^{old} = \sum_{k=1:3}\left(i_{sk} - i_{skm}\right)^2 + \left(\omega_r - \omega_{rm}\right)^2 \tag{24}$$

$$f_{obj}^{new} = \sum_{k=1:3}\left(i_{sk} - i_{skm}\right)^2 + \left(\omega_r - \omega_{rm}\right)^2 + \left(T_{em} - T_{emm}\right)^2 \tag{25}$$

where

i_{sk} : stator current of the induction machine model

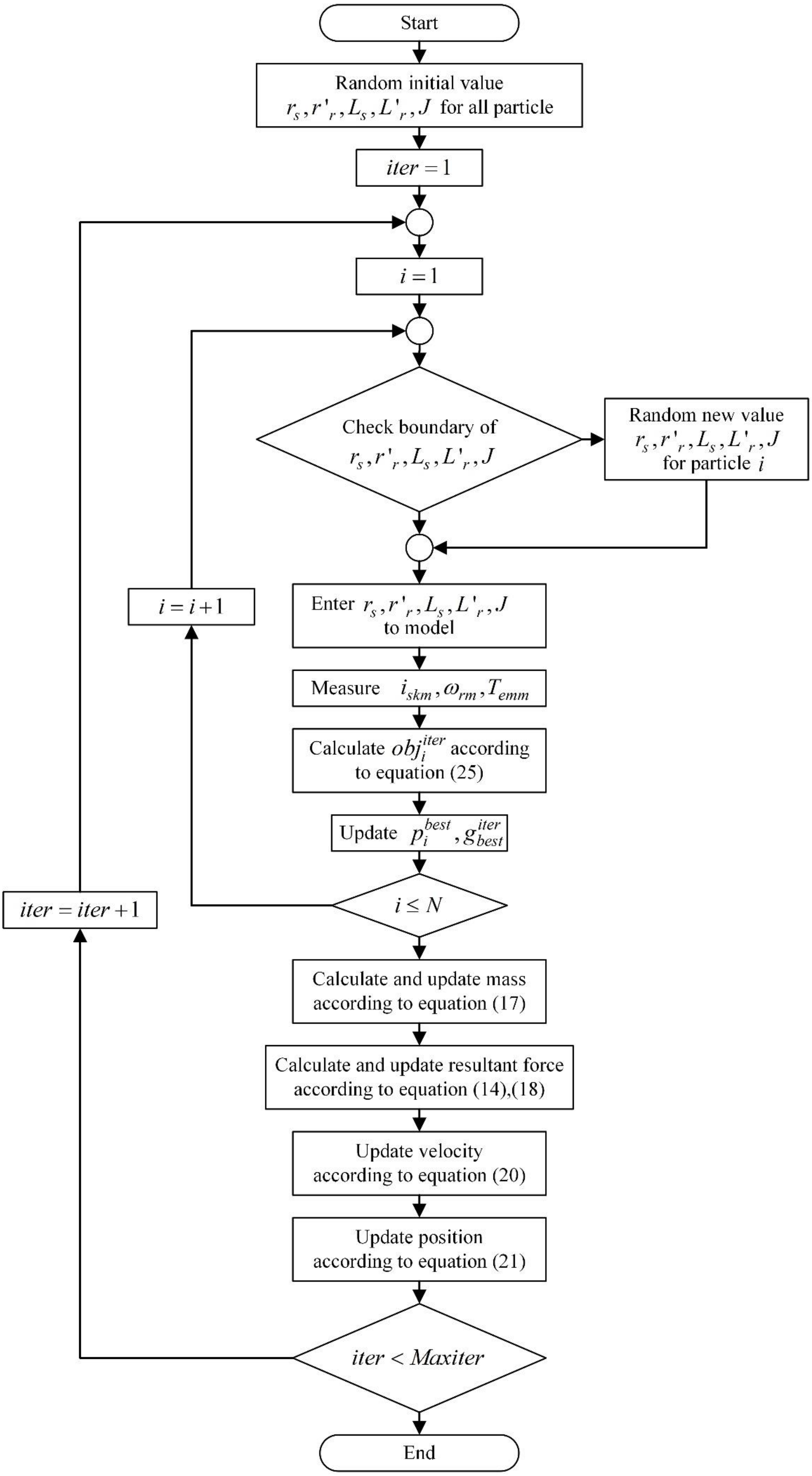


Fig.3. Identifying the Parameters using a Hybrid Particle Swarm based Gravitational Search Algorithm Char.

i_{skm} : measured stator current
ω_r : rotor speed of the inductor machine model
ω_{rm} : measured rotor speed
T_{em} : electromagnetic torque of the induction machine model
T_{emm} : measured electromagnetic torque
f_{obj}^{old} : old objective function
f_{obj}^{new} : new objective function

Identifying the parameters using the hybrid particle swarm based gravitational search algorithm procedure is shown in Fig. 3.

4. RESULTS OF IDENTIFYING THE PARAMETERS USING THE HYBRID PARTICLE SWARM BASED GRAVITATIONAL SEARCH ALGORITHM

Conventional methods used to identify the parameters of the induction machine consist of a No-load test, a DC test, a locked rotor test, and a retardation test. A three-phase induction motor 1.5 kW, 230/400 V, 50 Hz was used in the test. The induction machine is considered to be in a steady state and with reference mechanical torque as shown in Fig. 4

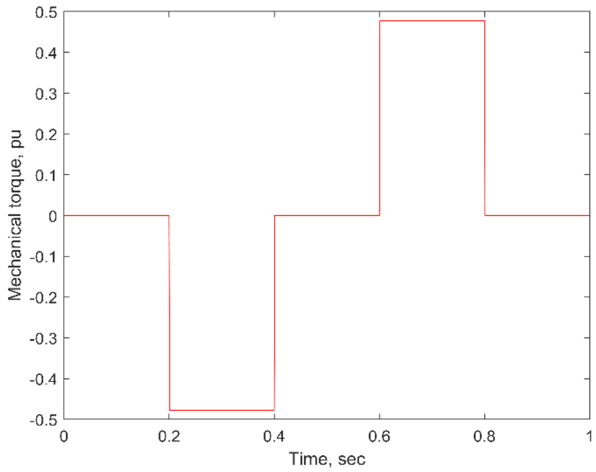
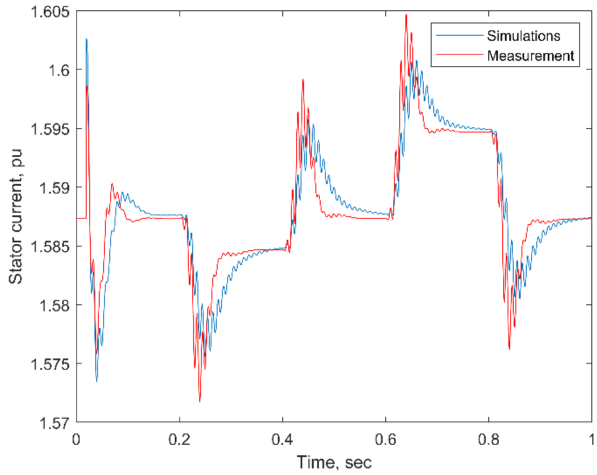


Fig. 4 Mechanical Torque in System

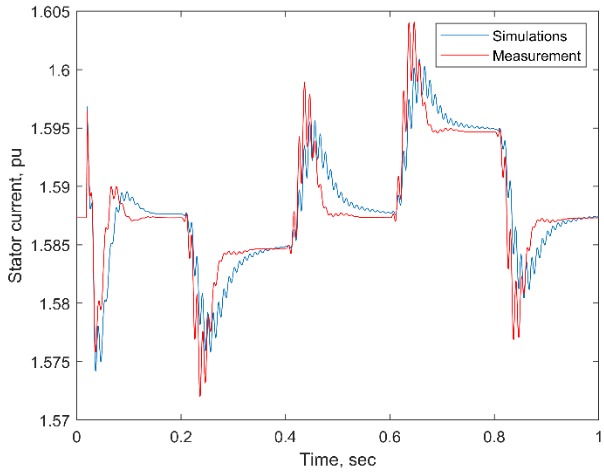
In Fig. 5 (a), (b), (c) the stator current without considering the electromagnetic torque in the objective function is made for a comparison between simulation and measurement. The integral of squared error (ISE) value for the three-phase stator current is equal to 0.0047, 0.0046, 0.0046, respectively.

In Fig. 6 (a), (b), (c) the stator current considers the electromagnetic torque in the objective function which is shown for a comparison between simulation and measurement. The integral of squared error (ISE) value for the three-phase stator current is equal to 5.9524e-05, 6.4315e-05, 6.0246e-05, respectively. Figs. 3 and 4 show that the new objective function has a lower ISE value than the old objective function.

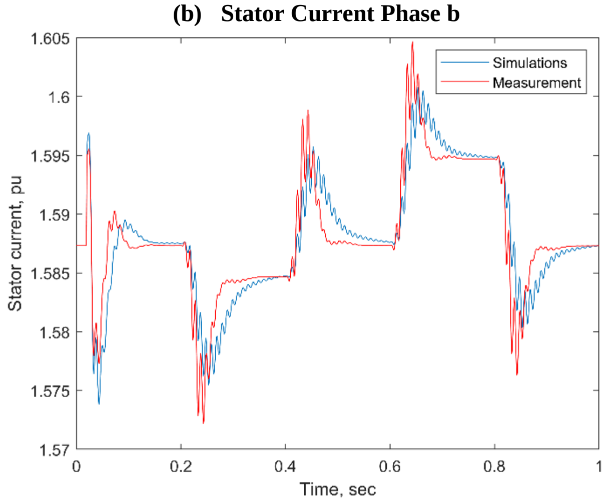
In Fig. 7 the rotor speed is shown without considering the electromagnetic torque in the objective function for a comparison between simulation and measurement. The integral of squared error (ISE) value for stator current is equal to 2.1316e-04.



(a) Stator Current Phase a

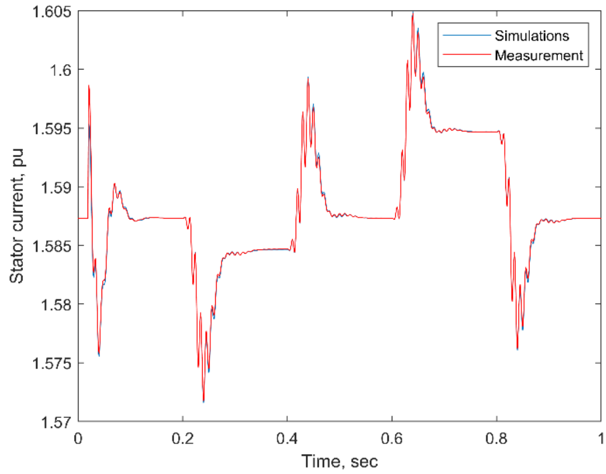


(b) Stator Current Phase b

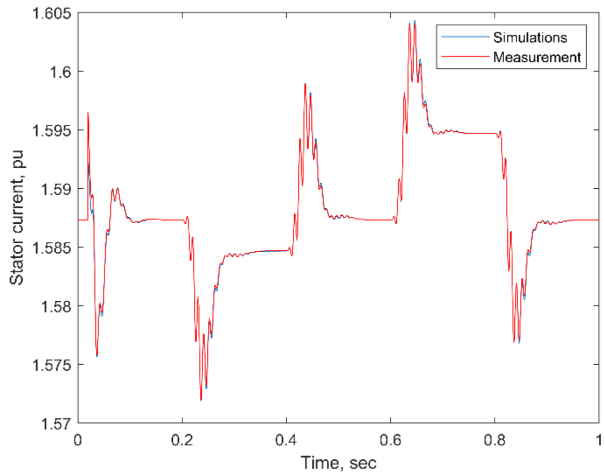


(c) Stator Current Phase c

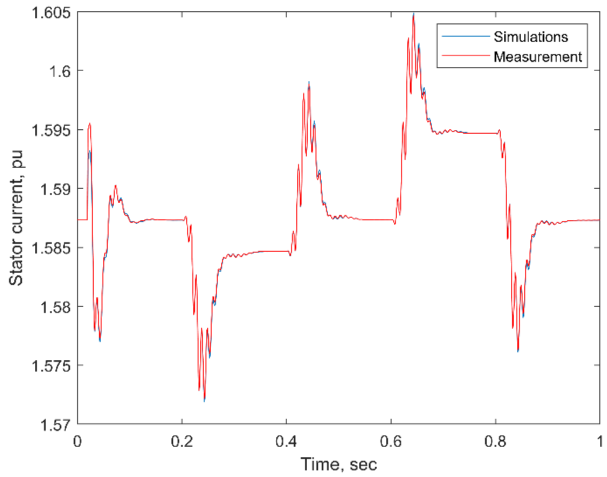
Fig. 5. Stator Current Measured and Simulation does not consider Electromagnetic Torque in the Objective Function, (a), (b), (c).



(a) Stator Current Phase a.



(b) Stator Current Phase b.



(c) Stator Current Phase c

Fig. 6. Stator Current measured and Electromagnetic Torque considered in a Simulation of the Objective Function, (a), (b), (c).

Fig. 8 shows the rotor speed and considers the electromagnetic torque in the objective function for a comparison between simulation and measurement. The integral of squared error (ISE) value for the stator current is equal to 2.2876e-07. Figs. 5 and 6 show that the new objective function has a lower ISE value than the old objective function.

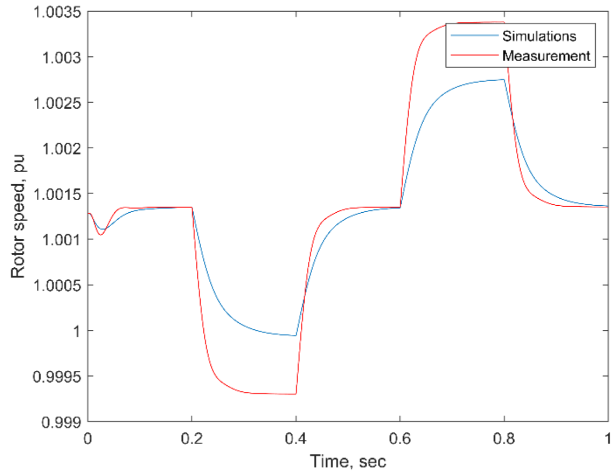


Fig. 7. Rotor Speed Measured and Simulation does not consider Electromagnetic Torque in the Objective Function.

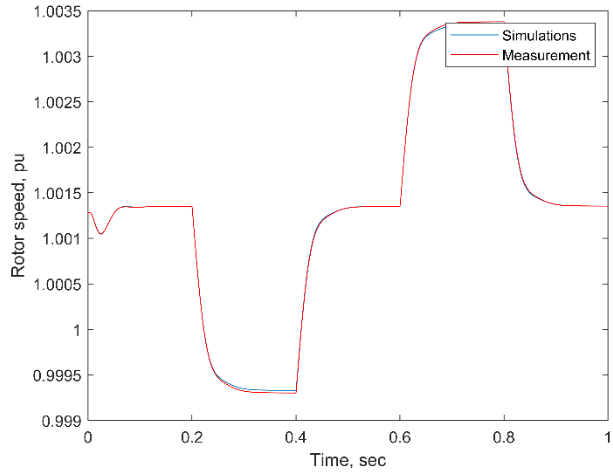


Fig. 8. Rotor Speed Measured and Simulation considers Electromagnetic Torque in the Objective Function.

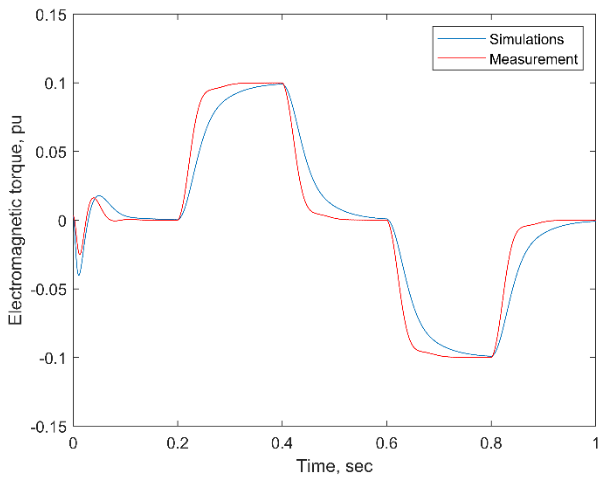


Fig. 9 Electromagnetic Torque Measured and Simulation does not consider Electromagnetic Torque in the Objective Function

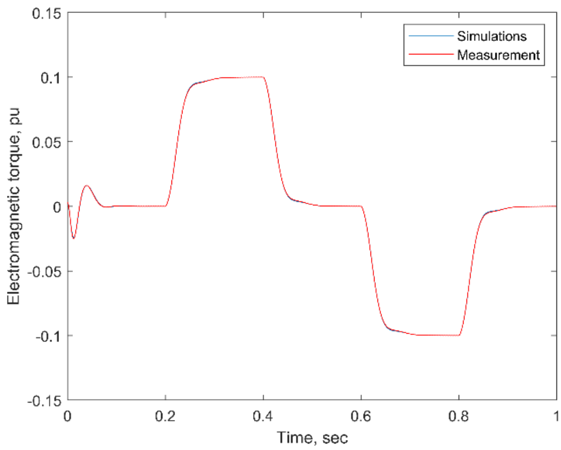


Fig. 10 Electromagnetic Torque Measured and Simulation considers Electromagnetic Torque in the Objective Function.

In Fig. 9 the electromagnetic torque is shown without considering the electromagnetic torque in the objective function for a comparison between simulation and measurement. The integral of squared error (ISE) value for stator current is equal to 0.1985.

In Fig. 10 the electromagnetic torque is measured and the simulation considers the electromagnetic torque in the objective function for a comparison between simulation and measurement. The integral of squared error (ISE) value for stator current is equal to 5.0218e-05. Figs. 7 and 8 show that the new objective function has a lower ISE value than the old objective function.

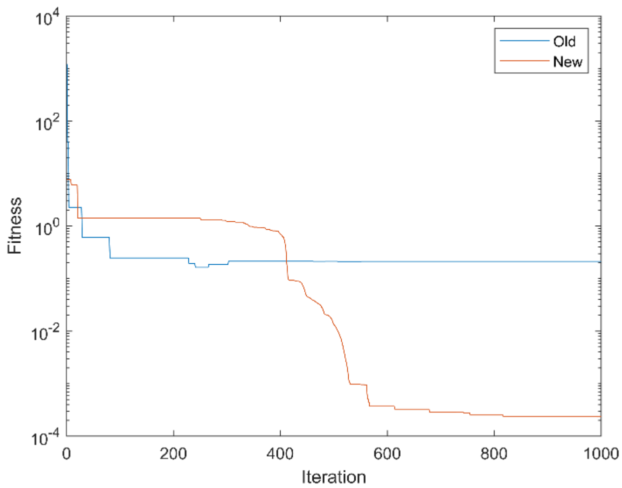


Fig. 11 Fitness Curve.

In Fig. 11 the fitness curve is an objective function of a hybrid particle swarm based gravitational search algorithm. The integral of squared error (ISE) value for the old objective function is 2.1257e-01 and the integral of squared error (ISE) value for the new objective function is 2.3453e-04. Overall, the new objective function has a higher ISE value than the old objective function.

Parameters and values obtained from identifying the parameters using a hybrid particle swarm based gravitational search algorithm are shown in Table 1.

Table 1. Parameters used in the Hybrid Particle Swarm based Gravitational Search Algorithm

Parameters	Signification	Value
$r_s\,(\Omega)$	Stator resistance	[3,4]
$r'_r\,(\Omega)$	Rotor resistance	[1,2]
$L_s\,(mH)$	Stator inductance	[1,10]
$L_m\,(mH)$	Mutual inductance	[1,1000]
$J\left(kg\cdot m^2\right)$	Machine inertia	[0.001,1]
N	Population size	10
G_0	Initial value respectively	100
c_1	Weighting factor for GSA	0.5
c_2	Weighting factor for PSO	1.5
Maxiter	Maximum number of iterations	1000

Table 2. A Comparison of the Real Parameters obtained from the Results of the Simulation

Parameters	Test	Old	New
$r_s\,(\Omega)$	3.35	3.29	3.37
$r'_r\,(\Omega)$	1.99	1.38	1.96
$L_s\,(mH)$	6.94	7.06	7.04
$L_m\,(mH)$	163.7	163.6	163.6
$J\left(kg\cdot m^2\right)$	0.100	0.262	0.101

Table 2 shows a comparison of the parameters of the old objective function and the new objective function. The new objective function values are closest to the test values when compared to the old objective function.

Table 3. A Comparison between the Old Objective Function and the New Objective Function

	Old	New
Calculation time (sec) at 1000 iteration	41372	40470
Fitness at 1000 iteration	0.21257	0.00023

Table 3 shows a comparison of the calculation time and fitness. The calculation time for the new objective function is close to that of the old objective function and the fitness of the new objective function has a lower value than that of the old objective function.

5. CONCLUSION

The performance of the parameters identified for an induction machine using a hybrid particle swarm based gravitational search algorithm is detailed in this article. Although the induction mechanical parameters could be obtained by conventional tests such as a no-load test, a DC test, a locked rotor test, and a retardation test, this procedure can result in errors because of the many measurement tools involved. Finally, the additional consideration of the electromagnetic torque in the objective function shows a better result. Therefore, the new objective function is better when compared with the old objective function and the additional consideration of electromagnetic torque in the objective function makes it more effective for this task.

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