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Applying the Sine-Cosine Optimization Algorithm to the Parametric Estimation Problem in Three-Phase Induction Motors

Aplicación del algoritmo de optimización por senos y cosenos al problema de estimación paramétrica en motores de inducción trifásicos

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ABSTRACT

The steady-state analysis of electrical machines requires a detailed characterization of their equivalent electrical circuit, which adequately represents the transformation and interaction between electrical and mechanical energy. This research aims to characterize the equivalent circuit of three-phase induction motors by minimizing the mean square error between the measured and calculated torque variables. These torques are obtained from data provided by the manufacturer, including starting, peak, and full-load torques. A metaheuristic optimization technique is applied to solve the resulting nonlinear programming model based on the interactions between the sine and cosine functions. The numerical results obtained with this algorithm demonstrate its efficiency in terms of response quality, reaching objective function values of less than 1×10^{-8} with regard to the measured and calculated variables. Simulation results in two test systems allow concluding that the parametric estimation problem in three-phase induction motors is a multimodal optimization problem. This implies a potentially infinite set of solutions that minimize the root mean square error and adequately represent the behavior of the motor's output torque under various probable operating conditions.

Keywords: metaheuristic optimization, electrical circuit characterization, multimodal optimization problem, manufacturer data

RESUMEN

El análisis del estado estacionario de las máquinas eléctricas requiere una caracterización detallada de su circuito eléctrico equivalente que represente adecuadamente la transformación y la interacción entre energía eléctrica y mecánica. El objetivo de esta investigación es caracterizar el circuito equivalente de motores de inducción trifásicos mediante la minimización del error cuadrático medio entre variables de torque medidas y calculadas. Estos torques se obtienen de datos suministrados por el fabricante, incluyendo los torques inicial, máximo y de carga plena. Se aplica una técnica de optimización metaheurística para resolver el modelo de programación no linear resultante, que se basa en las interacciones entre las funciones de seno y coseno. Los resultados numéricos obtenidos con este algoritmo demuestran su eficiencia en términos de calidad de la respuesta, alcanzando valores de función objetivo de menos de 1×10^{-8} respecto a las variables medidas y calculadas. Los resultados de simulaciones realizadas en dos sistemas de prueba permiten concluir que el problema de estimación paramétrica en motores de inducción trifásicos es un problema de optimización multimodal. Esto implica un conjunto de soluciones potencialmente infinitas que minimizan el eror cuadrático medio y representan adecuadamente el torque de salida del motor en varias condiciones probables de operación.

Palabras clave: optimización metaheurística, caracterización de circuitos eléctricos, problema de optimización multimodal, datos del fabricante

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Nomenclature

Acronyms

GA Genetic algorithm

HGAPSO Hybrid between the GA and the PSO

PSO Particle swarm optimizer

SCA Sine-cosine algorithm

Functions

$\tau_{\max}$ **Maximum torque (N.m)**

τ_{fl} **full-load torque (N.m)**

τ_{ind} **Induced torque (N.m)**

τ_{st} **Starting torque (N.m)**

E_f **Objective function aimed at minimizing the mean square error**

R_{th} **Thevenin resistance (Ω)**

V_{th} **Thevenin voltage (V)**

X_{th} **Thevenin inductance (Ω)**

Parameters

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ω_{sinc}	**Synchronous speed (rad/s)**
$\tau^{m}_{\max}$	**Manufacturer data: maximum torque (N.m)**
τ^{m}_{fl}	**Manufacturer data: full-load torque (N.m)**
τ_{ind}	**Induced torque (N.m)**
τ^{m}_{st}	**Manufacturer data: starting torque (N.m)**
j	**Complex unit, *i.e.*, $j = \sqrt{-1}$**
$k_{\max}$	**Parameter that stops the search if the objective function does not consecutively improve during 20% of the iterations**
N_s	**Population size for the SCA**
$R_1^{\max}$	**Maximum value for the stator resistance (Ω)**
$R_1^{\min}$	**Minimum value for the stator resistance (Ω)**
r_2	**Decreasing coefficient associated with the importance of the sine and cosine functions during the exploration and exploitation stages**
$R_2^{\max}$	**Maximum value for the rotor resistance (Ω)**
$R_2^{\min}$	**Minimum value for the rotor resistance (Ω)**
r_3	**Random number between 0 and 2π with a uniform distribution**
r_4	**Random number between 0 and 1 with a uniform distribution**
s	**Sliding coefficient (%)**
t	**Iterative counter**
$t_{\max}$	**Maximum number of iterations**
V_{ph}	**Single-phase voltage applied to the induction motor (V)**
$X_1^{\max}$	**Maximum value for the stator reactance (Ω)**
$X_1^{\min}$	**Minimum value for the stator reactance (Ω)**
$X_2^{\max}$	**Maximum value for the rotor reactance (Ω)**
$X_2^{\min}$	**Minimum value for the rotor reactance (Ω)**
$X_M^{\max}$	**Maximum value for the magnetizing reactance (Ω)**
$X_M^{\min}$	**Minimum value for the magnetizing reactance (Ω)**

Sets and indices

i	**Position of the solution in the matrix of potential solutions**

Variables

R_1	**Resistive effect assigned to the windings of the stator in the induction motor (V)**
R_2	**Resistive effect assigned to the windings of the rotor in the induction motor (Ω)**
$s_{i,1}^{t+1}$	**Potential solution for the next iteration (*i.e.*, $t+1$), using the sine rule**
$s_{i,2}^{t+1}$	**Potential solution for the next iteration (*i.e.*, $t+1$), using the cosine rule**
s_i^t	**Vector containing the i^{th} potential solution at iteration t**
X_1	**Reactance effect assigned to the windings of the stator in the induction motor (Ω)**
X_2	**Reactance effect assigned to the windings of the rotor in the induction motor (Ω)**
X_M	**Equivalent magnetizing reactance (Ω)**

Introduction

General context

The processes related to the final use of electrical energy have gained significant relevance in terms of both operation and costs (Chauhan, Chauhan, and Badar, 2022). Therefore, energy efficiency plays a fundamental role in new industrial developments (Bouakkaz, Mena, Haddad, and Ferrari, 2021). This has been demonstrated multiple times through the increasing rate of vehicles that require less fuel and the growing efficiency of appliances (lower electricity consumption), *e.g.*, lamps that consume a quarter of the energy compared to classic lighting with incandescent bulbs (Nota, Nota, Peluso, and Lazo, 2020; Abo-Khalil *et al.*, 2022).

At the industrial level, one of the most common elements corresponds to induction motors, which are present in all economic sectors and are considered to be the cornerstone of the modern industry (Sengamalai *et al.*, 2022). It is estimated that engines use 65% of the electricity generated in the world, so they can contribute greatly to reducing energy consumption and CO_2 emissions (Payán, Fernandez, Ortega, and Santos, 2019). On the other hand, environmental policies based on energy efficiency, together with those related to the energy transition, comprise a large number of actions aimed at reducing global warming; the less energy is used, the fewer pollutants associated with the energy sector will be produced (Friederici, 2021).

Motivation

In order to contribute to the study of induction motors, large-scale industries with hundreds of engines must be analyzed. Here, due to intensive use, multiple internal parameters related to efficiency calculations can change over time (Trisha, Gupta, and Kumar, 2021). To update the internal parameters of induction motors (*i.e.*, series and parallel reactances), the specialized literature has proposed multiple optimization approaches that avoid physical interventions and favor classical laboratory tests (Véliz-Tejo, Travieso-Torres, Peters, Mora, and Leiva-Silva, 2022). These optimization algorithms focus on torque measurements at the terminals of the induction motor for different load conditions. With these measurements, a nonlinear non-convex optimization model has been proposed which minimizes the expected error between the calculated and the measured torques (Mohammadi and Akhavan, 2014).

This research proposes the application of the sine-cosine algorithm (SCA) to obtain the internal parameters of induction motors by solving the equivalent optimization model, since metaheuristic optimizers have demonstrated to be efficient and robust in solving parametric estimation problems associated with electrical devices, *i.e.*, induction machines, distribution transformers, and photovoltaic (PV) modules, among others.

Literature review

Although there are many methods to estimate the parameters of induction motors, iterative methods based on least squares are the most widespread, given their simplicity and reasonable convergence times (Lindenmeyer, Dommel, Moshref, and Kundur, 2001; Toliyat, Levi, and Raina, 2003; Pedra and Corcoles, 2004; Gupta, Wadhwani, and Kapoor, 2011). In addition, multiple metaheuristic optimization algorithms have been applied to solve the nonlinear non-convex optimization problem regarding parametric estimation in electrical machines, as they are easily programmable and require low computational efforts. These algorithms include bee colony optimization (Aminu, 2019), particle swarm optimization (Huynh and Dunnigan, 2010), the gravitational search algorithm (Avalos, Cuevas, and Gálvez, 2016), and the water cycle algorithm (Ćalasan, Micev, Ali, Zobaa, and Aleem, 2020), among others. Some of the most recent applications belonging to the family of metaheuristic optimization algorithms for parametric estimation in induction motors are discussed below.

(Mohammadi and Akhavan, 2014) combined the classical genetic algorithm and the particle swarm optimizer to obtain a hybrid optimization approach aimed at determining the electrical parameters of three-phase induction machines. The optimization problem was formulated as a nonlinear programming model, where the mean square error between manufacturer data and the calculated starting, maximum, and full-load torques was considered as the objective function. Numerical results confirmed that this hybrid approach provides better numerical results regarding the objective function value when compared to the genetic algorithm and particle swarm optimization.

The work by (Wu, Tseng, and Chen, 2018) employed the polynomial regression approach to determine the electrical parameters of induction machines. Numerical results provided accurate estimations when compared to the experimental motor curve and the procedure established by the IEEE Standard 112 Test.

In (Guedes, Castoldi, Goedtel, Agulhari, and Sanches, 2018), the authors applied the differential evolution algorithm to estimate the electrical parameters of three-phase induction motors via dynamic simulation. Theoretical results with the proposed optimization algorithm and experimental validations confirmed the accuracy of this approach. However, the authors provided no comparative analysis with additional optimization algorithms.

The study by (Rezk, Elghany, Al-Dhaifallah, Sayed, and Ibrahim, 2019) presented an effective optimization method to estimate parameters in three-phase induction motors. The particle swarm optimization algorithm was used in combination with experimental validations, with the purpose of reducing the error between the theoretical model and the experimental setup. Numerical results confirmed that the particle swarm optimizer yields acceptable results. However, comparative analyses with other metaheuristic optimizers were not presented to demonstrate the effectiveness of the proposed approach.

(Joodaki, Shojaei, and Lotfi, 2020) applied the cuckoo search algorithm to estimate parameters in three-phase induction motors while considering manufacturer torque data. Numerical comparisons in two machines with a genetic algorithm, the water cycle algorithm, and the bacterial proliferation approach, among others, confirmed the effectiveness of the cuckoo search algorithm in minimizing the error between the measured and the calculated torques.

The main characteristics of the approaches mentioned above are the following: (i) the manufacturer data regarding the starting, maximum, and full-load torques are typically used to formulate a minimization problem aimed at finding the electrical parameters of the motor, which makes the theoretical and the calculated torques equal; and (ii), given the complexity of the optimization model, most studies focus on the application of metaheuristic optimization algorithms to obtain an efficient solution.

Contributions and scope

In light of the above, this research presents the application of the sine-cosine algorithm (SCA) as an efficient optimization technique to estimate the parameters of the electrical circuits in induction motors. The SCA is implemented to solve the exact nonlinear non-convex optimization model for minimizing the error between measured and calculated torques under different load conditions (*i.e.*, starting, full, and maximum load torques). This algorithm was identified as a potential solution methodology because it has already demonstrated its effectiveness and robustness in solving similar problems, as is the case of parametric estimation in single-phase transformers and PV modules (Bocanegra, Montoya, and Molina, 2021; Montoya, Gil-González, and Grisales-Noreña, 2020).

Regarding the scope of this research, note that all measurements of the induction machine have been taken with specialized torque measurement systems, which have been reviewed and conditioned (filtered) prior to their evaluation in the proposed SCA. These data have also been provided by the manufacturer of the induction machine. In addition, a comparison between different metaheuristic optimizers (the genetic algorithm, the particle swarm optimizer, and a combination of the two) has been performed to validate our proposal.

Document structure

The remainder of this document is structured as follows. Section Mathematical formulation presents the general mathematical formulation associated with parametric estimation in three-phase induction motors while considering torque measurements. Section Solution methodology describes the general characteristics of the SCA and its application to the analyzed problem. Section Test systems outlines the main characteristics of the two induction machines examined with regard to their manufacturer data and the upper and lower bounds imposed on the decision variables. Section Numerical results and discussion shows the numerical validations and a comparison between the SCA, the genetic algorithm (GA), the particle swarm optimizer (PSO), and a GA-PSO hybrid in the first test system. In addition, the multimodal nature of the optimization model is shown via three solutions provided by the SCA in the second test system. Finally, Section Conclusions and future work lists the main concluding remarks of this research and possible future studies using metaheuristic optimization methods.

Mathematical formulation

The parametric estimation problem in three-phase induction motors is formulated as a nonlinear non-convex optimization problem using the Thevenin equivalent of these machines under steady-state conditions. Figure 1 presents the equivalent circuit representation of the induction motor.

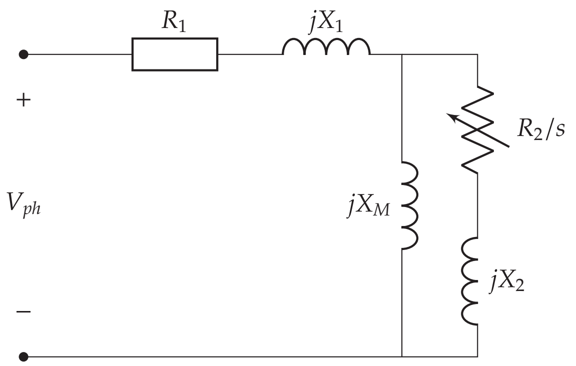

Figure 1. Single-phase equivalent of the induction motor
Source: Authors

In Figure 1, R_1 and R_2 denote the resistive effects on the stator and rotor elements, X_1 and X_2 correspond to the reactance equivalent values of the stator and rotor windings, X_M is the equivalent magnetization reactance, V_{ph} means the single-phase voltage applied to the induction motor, and s is the sliding under normal operating conditions. Note that j is the imaginary unit.

To obtain the equivalent Thevenin representation of the induction motor in Figure 1, consider that the motor load (*i.e.*, R_2/s) is removed. Under this condition, the equivalent V_{th}, R_{th}, and X_{th} are obtained.

$$V_{th} = \frac{X_M}{X_1 + X_M} V_{ph}, \tag{1}$$

$$R_{th} = \frac{X_M R_1}{X_1 + X_M}, \tag{2}$$

$$X_{th} = \frac{X_M X_1}{X_1 + X_M}, \tag{3}$$

Remark 1. *Note that, in order to obtain (1), it was assumed that $X_M >> R_1$, which implies that the effect of R_1 can be neglected in the Thevenin voltage calculation and equivalent impedance (Mohammadi and Akhavan, 2014).*

Figure 2 depicts the equivalent Thevenin circuit representing the induction motor per phase shown in Figure 1.

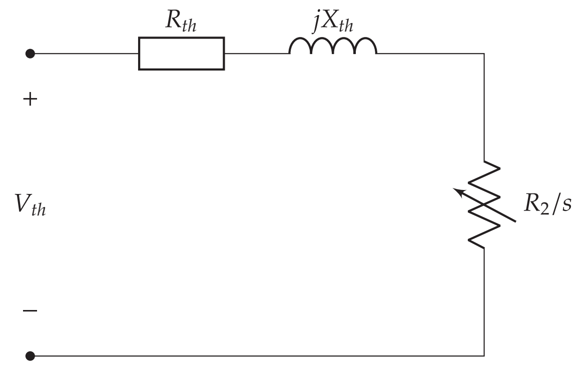

Figure 2. Thevenin equivalent of the single-phase circuit of the induction motor
Source: Authors

In Equation (4), the general induced torque is defined.

$$\tau_{ind} = \frac{3V_{th}^2 R_2}{s\omega_{\text{sinc}}\left[\left(R_{th} + \frac{R_2}{s}\right)^2 + (X_{th} + X_2)^2\right]}, \tag{4}$$

where ω_{sinc} is the synchronous speed.

In addition, the starting torque (τ_{st}) occurs when $s = 1$, which implies that it can be defined from (4) as follows:

$$\tau_{st} = \frac{3V_{th}^2 R_2}{\omega_{\text{sinc}}\left[(R_{th} + R_2)^2 + (X_{th} + X_2)^2\right]}, \tag{5}$$

The maximum torque ($\tau_{\max}$) is reached at maximum converted power, which occurs when $\frac{R_2}{s} = \sqrt{R_{th}^2 + (X_{th} + X_2)^2}$. This maximum torque is defined in (6).

$$\tau_{\max} = \frac{3V_{th}^2}{2\omega_{\text{sinc}}\left[R_{th} + \sqrt{R_{th}^2 + (X_{th} + X_2)^2}\right]}, \tag{6}$$

Finally, the full-load torque (τ_{fl}) is reached when $s = s_{fl}$ in (4), which yields

$$\tau_{fl} = \frac{3V_{th}^2 R_2}{s_{fl}\omega_{\text{sinc}}\left[\left(R_{th} + \frac{R_2}{s_{fl}}\right)^2 + (X_{th} + X_2)^2\right]}. \tag{7}$$

Considering the starting, maximum, and full-load torques defined from (5) to (7), the optimization model that includes the calculated and measured torques of an induction motor is formulated, using the sum of the errors as the objective function, which is defined in (8).

$$\min E_f = \left(\frac{\tau_{st} - \tau_{st}^m}{\tau_{st}^m}\right)^2 + \left(\frac{\tau_{\max} - \tau_{\max}^m}{\tau_{\max}^m}\right)^2 + \left(\frac{\tau_{fl} - \tau_{fl}^m}{\tau_{fl}^m}\right)^2, \tag{8}$$

where E_f is the objective function, and τ_{st}^m, $\tau_{\max}^m$, and τ_{fl}^m represent the measured values associated with the starting, maximum, and full-load torques, respectively.

Note that, in order to ensure that the solution to the objective function in (8) is subject to the torque equality constraints (5)–(7), some typical bounds are imposed. These are associated with the stator and rotor resistances and reactances, including the magnetization reactance. These box-type constraints are listed below.

$$R_1^{\min} \leq R_1 \leq R_1^{\max}, \tag{9}$$

$$X_1^{\min} \leq X_1 \leq X_1^{\max}, \tag{10}$$

$$R_2^{\min} \leq R_2 \leq R_2^{\max}, \tag{11}$$

$$X_2^{\min} \leq X_2 \leq X_2^{\max}, \tag{12}$$

$$X_M^{\min} \leq X_M \leq X_M^{\max}, \tag{13}$$

where $Y^{\min}$ and $Y^{\max}$ represent the lower and upper bounds assigned to the decision variables.

Remark 2. *The problem regarding parametric estimation in three-phase induction motors corresponds to a nonlinear programming model aimed at minimizing the average square error defined in* (8) *and constrained by equalities* (5)–(7)*, which are related to the starting, maximum, and full-load torques* (*calculated*)*, as well as by the box-type constraints* (9)–(13)*, which define the solution space where the decision variables exist* (*i.e., reactances and resistances*).

Solution methodology

This study applies the SCA to solve the optimization problem expressed in (5)–(13). The SCA is a metaheuristic optimization algorithm that belongs to the family of mathematics-inspired metaheuristics. It works from an initial (feasible) population that evolves during the iteration process while following trigonometric rules based on the sine and cosine functions (Attia, Sehiemy, and Hasanien, 2018). The main characteristics of the SCA approach are presented below.

Initial population

The SCA is a population-based optimizer that explores and exploits the solution space from an initial population generated upon the basis of the upper and lower bounds of the decision variables in order to make it 100% feasible. The structure of the solution individual *i* at iteration *t* (with $t = 0$) that conforms to the initial population is presented below.

$$s_i^t = [\overbrace{0.1242}^{R_1}\ \overbrace{0.3589}^{R_2}\ \overbrace{1.1614}^{X_1}\ \overbrace{1.3221}^{X_2}\ \overbrace{39.4618}^{X_M}]$$

where each vector component is obtained as a random value between the lower and upper bounds defined in (9)–(13), following a uniform distribution.

Evolution of the population

The SCA applies evolution rules based on the trigonometric sine and cosine functions in order to explore the solution space. To determine whether an individual s_i^{t+1} will be part of the population, the following evolution rule is applied:

$$s_{i,1}^{t+1} = s_i^t + r_2 \sin(r_3)\,|r_4 s_{\text{best}}^t - s_i^t|,\ i = 1, 2, ..., N_s \tag{14}$$

$$s_{i,2}^{t+1} = s_i^t + r_2 \cos(r_3)\,|r_4 s_{\text{best}}^t - s_i^t|,\ i = 1, 2, ..., N_s \tag{15}$$

where $s_{i,1}^{t+1}$ and $s_{i,2}^{t+1}$ are two potential candidate solutions derived from the sine and cosine rules in (14) and (15), r_3 is a random number with a uniform distribution between 0 and 2π, r_4 is a random number between 0 and 1 with a uniform distribution, and N_s is the number of potential individuals that make up the population. Note that s_{best}^t represents the best current solution in the population. In addition, r_1 controls the exploration and exploitation stages of the optimization algorithm by following a linear rule defined below.

$$r_2 = 2\left(1 - \frac{t}{t_{\max}}\right). \tag{16}$$

To determine whether one of the individuals $s_{i,1}^{t+1}$ or $s_{i,2}^{t+1}$ will be part of the next population, the following criteria are applied:

i. If $E_f\left(s_{i,1}^{t+1}\right) < E_f\left(s_{i,2}^{t+1}\right)$ and $E_f\left(s_{i,1}^{t+1}\right) < E_f\left(s_i^t\right)$, then $s_i^{t+1} = s_{i,1}^{t+1}$.

ii. If $E_f\left(s_{i,2}^{t+1}\right) \leq E_f\left(s_{i,1}^{t+1}\right)$ and $E_f\left(s_{i,2}^{t+1}\right) < E_f\left(s_i^t\right)$, then $s_i^{t+1} = s_{i,2}^{t+1}$.

iii. Otherwise, $s_i^{t+1} = s_i^t$.

Remark 3. *To ensure that each potential solution* ($s_{i,1}^{t+1}$ *and* $s_{i,2}^{t+1}$) *is feasible, each of its components is reviewed/corrected, with the purpose of maintaining their values between the lower and upper bounds* (*see box-type constraints* (9)–(13)).

Stopping criteria

One of these stopping criteria must be met to determine whether the SCA has finished exploring and exploiting the solution space.

i. If the number of iterations $t_{\max}$ has been reached, or

ii. if, during $k_{\max}$ iterations, the value of the objective function (*i.e.*, $E_f\left(s_{\text{best}}^t\right)$) has not improved.

Note that $k_{\max}$ is set as 20% of the total number of iterations.

Summary of the SCA

The application of the SCA to the parametric estimation problem in three-phase induction motors while considering torque measurements is summarized in Algorithm 1.

Test systems

Two induction machines were considered to validate the proposed SCA with regard to the studied problem. The first system corresponds to a three-phase induction motor with 5 hp, 460 V, and 60 Hz. Its main characteristics are reported in Table 1, which have been adapted from (Mohammadi and Akhavan, 2014). The second machine is a three-phase induction motor with 25 hp, 460 V, and 60 Hz, whose main characteristics are reported in Table 2.

Algorithm 1: Application of the SCA to estimate parameters in three-phase induction motors

Data: Read data of the three-phase induction motor under analysis
Define the lower and upper bounds of the decision variables;
Define N_s, $t_{\max}$, and $k_{\max}$;
Generate the initial population while observing the lower and upper bounds in (9)–(13);
Evaluate the starting, maximum, and full-load torques in (5), (6), and (7);
Evaluate the objective function in (8);
Find the best current solution s^t_{best};
Make $k = 0$;
for $t = 1 : t_{\max}$ **do**
  Obtain the value of r_1 using (16);
  for $i = 1 : N_s$ **do**
    Obtain the random numbers for r_3 and r_4;
    Generate the potential solutions $s^{t+1}_{i,1}$ and $s^{t+1}_{i,2}$ using Equations (14) and (15);
    Check the feasibility of $s^{t+1}_{i,1}$ and $s^{t+1}_{i,2}$ and correct if necessary;
    Evaluate the starting, maximum, and full-load torques for $s^{t+1}_{i,1}$ and $s^{t+1}_{i,2}$ in (5), (6), and (7);
    Evaluate the objective functions $E_f\left(s^{t+1}_{i,1}\right)$ and $E_f\left(s^{t+1}_{i,2}\right)$;
    if $E_f\left(s^{t+1}_{i,1}\right) \leq E_f\left(s^{t+1}_{i,2}\right)$ & $E_f\left(s^{t+1}_{i,1}\right) \leq E_f\left(s^{t}_{i}\right)$ **then**
      Make $s^{t+1}_i = s^{t+1}_{i,1}$;
    else
      if $E_f\left(s^{t+1}_{i,2}\right) \leq E_f\left(s^{t+1}_{i,1}\right)$ & $E_f\left(s^{t+1}_{i,2}\right) \leq E_f\left(s^{t}_{i}\right)$ **then**
        Make $s^{t+1}_i = s^{t+1}_{i,2}$;
      else
        Make $s^{t+1}_i = s^{t}_{i}$;
      end
    end
  end
  Update the value of the best current solution s^{t+1}_{best};
  if $E_f\left(s^{t+1}_{best}\right) < E_f\left(s^{t}_{best}\right)$ **then**
    Make $k = k + 1$;
  end
  Make $k = 0$;
  if $k \geq k_{\max}$ **then**
    Report the best current solution in s^{t+1}_{best};
    break;
  end
end
Result: Return the best solution found

Table 1. First test system (5 hp, 460 V, and 60 Hz)

Characteristic	Value	Unit
Capacity	5	HP
Rate power	3.7285	kW
Nominal voltage	460	V
Frequency	60	Hz
Number of poles	4	–
Full-load sliding (s_{fl})	0.0210	–
Starting torque (τ_{st})	119.2629	Nm
Maximum torque ($\tau_{\max}$)	149.0820	Nm
Full-load torque (τ_{fl})	19.6730	Nm

Source: Authors

Table 2. Second test system (25 hp, 460 V, and 60 Hz)

Characteristic	Value	Unit
Capacity	25	HP
Rate power	15.54	kW
Nominal voltage	460	V
Frequency	60	Hz
Number of poles	4	–
Full-load sliding (s_{fl})	0.030	–
Starting torque (τ_{st})	106.46	Nm
Maximum torque ($\tau_{\max}$)	82.43	Nm
Full-load torque (τ_{fl})	228.73	Nm

Source: Authors

The lower and upper limits of the decision variables for both test systems are listed in Table 3.

Table 3. Upper and lower bounds of the decision variables in both test systems

	First test system		Second test system	
Par.	**Min.** (Ω)	**Max.** (Ω)	**Min.** (Ω)	**Max.** (Ω)
R_1	1.0	1.20	0.40	0.80
R_2	1.0	1.20	0.20	0.50
X_1	1.0	1.20	0.80	1.40
X_1	1.0	1.20	0.20	0.60
X_M	30	50	20	40

Source: Authors

Numerical results and discussion

For the computational implementation of the proposed SCA, the MATLAB software (version 2021*b*) was employed on a PC with an AMD Ryzen 7 3700 2.3 GHz processor and 16.0 GB RAM, running a 64-bit version of Microsoft Windows 10 Single Language. To implement the SCA, a population size (*i.e.*, N_s) of 100, 1000 iterations, and 100 repetitions were employed.

Results obtained for the first test system

The first test system was taken from (Mohammadi and Akhavan, 2014), where three metaheuristic optimizers were applied: the PSO (Gulbahçe and Karaaslan, 2021), the classical GA (Fortes, Ferreira, and Coelho, 2013), and a hybrid between the two (HGAPSO) (Mohammadi and Akhavan, 2014). The numerical results obtained with each comparison method were contrasted with those of the proposed SCA.

Table 4 presents a comparative analysis between the measured torques (provided by the manufacturer) and the values calculated via the optimal solution reported by the methods used for comparison (Rengifo-Santana, Benzaquen-Suñe, Aller-Castro, Bueno-Montilla, and Restrepo-Zambrano, 2015). Note that the errors in Table 4 correspond to the absolute error, which was calculated as presented below:

$$\text{Error} = 100\% \left| \frac{z_m - z_c}{z_m} \right|, \tag{17}$$

where z_m corresponds to the measured data and z_c to the calculated value for each variable.

Table 4. Comparative torque analysis for the first test system

Method	τ_{st} (Nm)		$\tau_{\max}$ (Nm)		τ_{fl} (Nm)	
	Calculated	**Error** (%)	**Calculated**	**Error** (%)	**Calculated**	**Error** (%)
Manuf.	119.2629	–	149.0820	–	19.6730	–
GA	124.0018	3.97	154.0410	3.33	19.8227	0.76
PSO	121.0186	1.47	151.1170	1.37	19.8136	0.71
HGAPSO	119.2300	0.03	149.1226	0.03	19.7877	0.58
SCA	119.2639	8.38×10^{-4}	149.0827	4.58×10^{-4}	19.6734	1.90×10^{-3}

Source: Authors

In comparison with those reported in the literature (Mohammadi and Akhavan, 2014), the results in Table 4 show that:

i. The SCA provides the best estimates for the starting, maximum, and full-load torques. Regarding the starting torque, the estimation error was about 8.38×10^{-4}%, while the HGAPSO approach reported about 3×10^{-2}%, *i.e.*, about 35 times higher than the SCA. As for the maximum torque, the SCA reached an estimation error of about 4.58×10^{-4}%, which is 65 times lower than the result reported for the HGAPSO approach. In the case of the full-load torque, the SCA reported an estimation error of about 1.90×10^{-3}, followed by the HGAPSO with a value of 0.58%, *i.e.*, the precision of the SCA is about 305 times better than that of the HGAPSO for this torque estimation.

ii. The GA and the PSO, when implemented independently, exhibit higher estimation errors in comparison with the HGAPSO approach, which is evident in the case of the starting and maximum torques. However, in the case of the full-load torque, these three methods have a similar behavior, with values between 0.58 and 0.76%.

iii. As for the objective function value, it is worth mentioning that the GA showed a value of about 2.75×10^{-4}, the PSO reported about $3{,}48 \times 10^{-5}$, the HGAPSO found about 3.41×10^{-5}, and the SCA reached about 4.63×10^{-10}. These results confirm that the proposed SCA is the best optimization method to estimate parameters in three-phase induction machines while considering manufacturer data, as the objective function value is more than 70 000 times lower than that of the HGAPSO as reported by (Mohammadi and Akhavan, 2014).

Table 5 compares the estimated parameters with respect to the manufacturer data and the results obtained with the metaheuristic optimizers.

In comparison with the specialized literature (Mohammadi and Akhavan, 2014), these numerical results show the following:

i. Regarding the resistive and reactance parameters in the stator and rotor (*i.e.*, R_1, R_2, X_1, and X_2), the SCA exhibited the best numerical estimations, with errors lower than 0.30%. Meanwhile, the HGAPSO approach reported errors higher than 0.70% for the same parameters, which confirms the effectiveness of the SCA in dealing with the analyzed optimization problem.

ii. The magnetization reactance, as estimated by the SCA, was 36.5475 Ω, with an error of about 4.82% compared to the manufacturer data. The HGAPSO approach reported 36.8888 Ω, with an estimation error of about 3.94%. However, even though the SCA showed a higher estimation error in this parameter, given its magnitude in comparison with the stator and rotor resistances and reactances, this has no significant effects on the final objective function value, which is much better for the SCA when compared to the HGAPSO approach. Furthermore, these results confirm that the problem under study is in fact a multimodal optimization problem, *i.e.*, it involves multiple combinations of variables to minimize the objective function (Bocanegra *et al.*, 2021).

Results obtained for the second test system

The second test system is a three-phase induction motor that has not previously been reported in the specialized literature on parameter estimation via metaheuristic optimization. Therefore, considering the effective, efficient, and robust performance of the proposed SCA in the first test system, its best three results for this system are presented. Table 6 presents a comparison between the manufacturer torque data and the calculated values for each of these solutions (Pedra and Corcoles, 2004). In contrast, Table 7 presents the estimated resistances and reactances, as well as their comparison against manufacturer data.

These results confirm that the best three solutions reached with the SCA report objective function values lower than 2.17×10^{-8}, with excellent performance regarding maximum torque, and slight deviations for the starting and full-load torques.

The numerical results in Table 7 show that:

i. The parameter with the lowest estimation error regarding the manufacturer data is the stator resistance (R_1).

ii. Solution 1 is the best one regarding the objective function value and the estimation errors in each parameter, with values lower than 2% in the case of stator and rotor resistances and reactances and about 15.43% in the case of the magnetization reactance.

iii The parameter with the highest estimation error is the magnetization reactance, which varies from 15 to

Table 5. Comparative analysis for the first test system

Method	R_1 (Ω)		R_2 (Ω)		X_1, X_2 (Ω)		X_M (Ω)	
	Calculated	**Error** (%)	**Calculated**	**Error** (%)	**Calculated**	**Error** (%)	**Calculated**	**Error** (%)
Manuf.	1.1150	–	1.0830	–	1.1260	–	38.4000	–
GA	1.0291	7.70	1.0304	4.86	1.0739	4.63	20.4139	46.84
PSO	1.1029	1.09	1.0351	4.42	1.0858	3.57	21.9514	42.80
HGAPSO	1.1229	0.71	1.0741	0.82	1.1169	0.81	36.8888	3.94
SCA	1.1135	0.13	1.0800	0.28	1.1237	0.20	36.5475	4.82

Source: Authors

Table 6. Comparative torque analysis for the second test system

Sol.	τ_{st} (Nm)		$\tau_{\max}$ (Nm)		τ_{fl} (Nm)		
	Calculated	**Error** (%)	**Calculated**	**Error** (%)	**Calculated**	**Error** (%)	E_f
Manuf.	106.46	–	228.73	–	82.43	–	–
Sol. 1	106.46	0	228.73	0	82.43	0	2.84×10^{-9}
Sol. 2	106.47	9.39×10^{-3}	228.73	0	82.42	1.21×10^{-2}	1.84×10^{-8}
Sol. 3	106.45	9.39×10^{-3}	228.73	0	82.44	1.21×10^{-2}	2.17×10^{-8}

Source: Authors

47% in all solutions. However, these variations did not affect the torque calculations reported in Table 6.

To demonstrate that the best solutions reached with the SCA (Tables 6 and 7) adequately model the torque curve in the analyzed three-phase induction machine, the torque behavior for all solutions, including the benchmark case, is depicted in Figure 3.

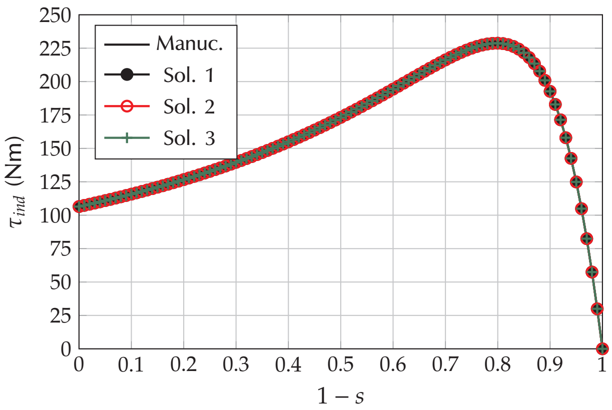

Figure 3. Torque behavior in the second test system for the best three solutions reached with the SCA
Source: Authors

Note that, regardless of the estimation difference exhibited by this particular parameter in Table 7 with respect to the manufacturer data, the best three solutions reached with the SCA allow adequately reproducing the induced torque defined in Equation (4), which confirms the results regarding the starting, maximum, and full-load torques in Table 6. These results confirm the multimodal nature of the parametric estimation problem in three-phase induction motors.

It is worth mentioning that an optimization problem is considered to be multimodal when multiple combinations of variables provide the same numerical objective function value, *i.e.*, the solution is not unique. However, in the case of parametric estimation in electrical machines, this behavior is typical, given the nonlinearities between parameters and electrical variables. Notwithstanding, if one solution is selected for numerical simulations and physical implementations, the motor's expected dynamic and static behavior will exhibit slight variations with respect to other potential solutions.

Conclusions and future work

This paper proposed an efficient solution methodology to determine electrical parameters in three-phase induction machines while considering measurement data provided by the manufacturer regarding starting, maximum, and full-load torques. This problem was formulated as a nonlinear programming model, with the aim of minimizing the sum of the errors between the measured and the calculated torques.

According to a comparative analysis with three metaheuristic optimization algorithms (*i.e.*, GA, PSO, and HGAPSO) in the first test system analyzed, the proposed SCA was the most effective optimization algorithm for the studied objective function, with a final value of about 4.63×10^{-10}, while the best literature report (the HGAPSO) found an objective function value of 3.41×10^{-5}. In addition, regarding each particular parameter (*i.e.*, stator and rotor resistances and reactances), the SCA exhibited the best numerical performance, with the lowest estimation errors. However, in the case of the magnetization reactance, the HGAPSO approach reported a better estimation, which could be attributed to the multimodal nature of the optimization problem under study.

Numerical results in the second test system confirmed that there are multiple combinations of resistances and reactances that allow for an adequate reproduction of the induced torque in the entirety of the operating range. In addition, the parameter with the highest deviation with respect to the manufacturer data was the magnetization reactance, which can also be attributed to the multimodal nature of the optimization model and the lack of information regarding the active power behavior of the induction motor.

Table 7. Comparative analysis for the second test system

Solution	R_1 (Ω)		R_2 (Ω)		X_1 (Ω)		X_2 (Ω)		X_M (Ω)	
	Calc.	**Error** (%)	**Calc.**	**Error** (%)	**Calc.**	**Error** (%)	**Calc.**	**Error** (%)	**Calc.**	**Error** (%)
Manuf.	0.6410	–	0.3320	–	1.1060	–	0.4640	–	26.3000	–
Sol. 1	0.6444	0.53	0.3356	1.08	1.1076	0.14	0.4733	2.00	30.3571	15.43
Sol. 2	0.6507	1.51	0.3422	3.07	1.0235	7.46	0.5750	23.92	38.6619	47.00
Sol. 3	0.6455	0.70	0.3367	1.42	1.2458	12.64	0.3432	26.03	35.8999	36.50

Source: Authors

In this study on parametric estimation, the highest errors were reported for the magnetizing reactance (*i.e.*, X_M). However, these errors can be explained by the fact that this is the largest parameter in the induction motor, with a parallel connection to the equivalent circuit motor. According to circuit theory, the sum of two or more parallel elements is always lower than the small parameter, which confirms that, for variations in the largest parameter, this effect is minimal or negligible in the final solution.

As future work, the following studies could be conducted: (i) the application of new metaheuristic optimization algorithms to solve the nonlinear programming model that represents the studied problem; (ii) the use of the exact model of the induction machine without simplifications in the Thevenin equivalent impedance; and (iii) the development of a formulation that includes efficiency, reactive power, and the power factor, among other parameters.

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CRedit author statement

ODM conceived the idea, conducted the background research, supervised the study, and provided critical feedback. *SDN-C.* and *JCP-G.* collected the data, developed the workflow, and performed assessments. *SDN-C* and *JCP-G* wrote the main part of the manuscript, to which all authors contributed.

Conflicts of interest

The authors declare no conflict of interest.

Implementation of the first motor in MATLAB using the SCA

This appendix presents the commands used to implement the proposed optimization method. In the following MATLAB code, three essential things should be noted.

1. The first part of the algorithm focuses on parameterizing the test motor under analysis.
2. The main characteristics of the SCA are defined in order to carry out the optimization process.
3. A function named `[···] = PCM(···)` is recursively called to determine all the electromagnetic torques required in evaluating the objective function. This function is defined in the final part of the MATLAB code.

```
clc;clear;close;
tStart = tic;
Neval = 1;
ResultadosF = zeros(Neval,5);
for cant = 1:Neval
    Vph = 460*sqrt(2)/sqrt(3);
    f = 60;
    Xm = 38.4000; Xs = 1.1260; Xr = 1.1260;
    Rr = 1.0830; Rs = 1.1150;Tst = 119.2629;
    Tfl = 19.6730;Tmx = 149.0820;Sfl = 0.0210;
    [Tflo,f1,Tsta,f2,Tmax,f3,FF] = ...
    PCM(Vph,f,Xm,Xs,Rr,Rs,Tst,Tfl,Tmx,Sfl);
    tmax = 1000;
    xmin = [30.0000 1.0000 1.0000 1.0000];
    xmax = [46.0000 1.2000 1.2000 1.2000];
    NV = size(xmin,2);
    Ns = 100;
    x = (xmin) + rand(Ns,1).*(xmax - xmin);
    for i = 1:Ns
        Xm = x(i,1); Xs = x(i,2);
        Rs = x(i,3); Rr = x(i,4);
        [Tflo,f1,Tsta,f2,Tmax,f3,FF] = ...
        PCM(Vph,f,Xm,Xs,Rr,Rs,Tst,Tfl,Tmx,Sfl);
        x(i,NV+1) = f1^2 + f2^2 + f3^2;
    end
    x = sortrows(x,NV+1);
    for t = 0:tmax
        r1 = 1 - t/tmax; r2 = -pi + rand()*(2*pi);
        r3 = rand(); xbest = x(1,:);
        for i = 1:Ns
            if rand(1) >= 1/2
                xd = x(i,:) + r1*sin(r2)*...
                    abs(r3*xbest - x(i,:));
            else
                xd = x(i,:) + r1*cos(r2)*...
                    abs(r3*xbest - x(i,:));
            end
            for j = 1:NV
                if  xd(1,j) < xmin(1,j) ||...
                        xd(1,j) > xmin(1,j)
                    xd(1,j)  = xmin(1,j) + ...
                        rand()*(xmax(1,j) - ...
                        xmin(1,j));
                end
            end
            Xm  = xd(1,1); Xs  = xd(1,2);
            Rs= xd(1,3); Rr  = xd(1,4);
            [Tflo,f1,Tsta,f2,Tmax,f3,FF] = ...
            PCM(Vph,f,Xm,Xs,Rr,Rs,Tst,Tfl,Tmx,Sfl);
            xd(1,NV+1) = f1^2 + f2^2 + f3^2;
            if xd(1,end) < x(i,end)
                x(i,:) = xd;
            end
        end
```

```
        x = sortrows(x,NV+1);
        fprintf('Iteration: %d\n',t);
    end
    disp(xbest)
    ResultadosF(cant,:) = xbest;
end
tEnd = toc(tStart);
function [Tflo,f1,Tsta,f2,Tmax,f3,FF] = ...
  PCM(Vpha,f,Xmd,Xse,Rrg,Rsh,Tsti,Tflj,Tmxk,Sflm)
  Vth = Vpha*Xmd/(Xmd + Xse);
  Rth = Rsh*Xmd/(Xmd + Xse);
  Xth = Xse*Xmd/(Xmd + Xse);
  Kt = 3*(Vth^2)/(2*pi*f );
  Tflo = (Kt*Rrg)/(Sflm*((Rth + Rrg/Sflm)^2 + ...
        (Xth + Xse)^2));
  f1 = (Tflj- Tflo)/(Tflj);
  Tsta = (Kt*Rrg)/((Rth + Rrg)^2 + ...
        (Xth + Xse)^2);
  f2 = (Tsti - Tsta)/(Tsti);
  Tmax = (Kt)/(2*(Rth + sqrt((Rth)^2 + ...
        (Xth + Xse)^2)));
  f3 = (Tmxk -  Tmax)/(Tmxk);
  FF = f1^2 + f2^2 + f3^2;
end
```

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