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Comparative Analysis of Metaheuristic Algorithms for Parameters Estimation of Single-Cage and Double-Cage Induction Machine Models

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Summary **— This paper deals with the estimation of parameters of single-cage and double-cage induction machine models using HBA (Honey Badger Algorithm) and EO (Equilbrium Optimizer) algorithms. The input data for the estimation procedure are the induction machine nameplate data – power factor, starting, rated, and maximum torque. Based on the nameplate data, the criterion function is defined. The applicability of both considered methods is proven by comparing the output characteristics of induction machine determined using parameters estimated with other literature known algorithm. The obtained results demonstrate that the applied algorithm is very efficient, accurate, and precise method for the parameters estimation of single-cage and double-cage induction machine models.**

Keywords **— induction machine, estimation, parameters, metaheuristic algorithms.**

I. Introduction

Induction machine (IM) is the most common type of alternating current (AC) electric machine. The main characteristic of this machine type is that the rotor speed and the speed of stator's rotating magnetic field are not equal. Due to the fact that IMs cannot produce reactive power, they are mainly used as a motor.

The proper functioning of an IM is very important for every electrical drive, device or application in which the IM is used. In order to provide reliable and efficient operating of an IM, it is very important to know the parameters of the machine, as well as the current, torque, and other electrical and mechanical characteristics. The operation of an IM is defined with its' equivalent circuit and the values of the parameters. According to that, it is obvious that the determination of IM's parameters provides insight into the condition of the machine and the expected level of its' performances [1]. Classic method for IM's parameters estimation is based on the short-circuit and open-circuit tests, as described in IEEE and IEC standards [2], [3]. However, since there is practical need to estimate the parameters of IM during the normal operation mode, it is evident that the standard short-circuit and open-circuit tests are not applicable. Therefore, the authors in the available literature tend to develop the methods for estimation of IM's parameters which do not require the disconnection of the machine from the load. Generally, the developed methods for the estimation of IM parameters can be divided into two main categories. The first category comprises methods that rely on the IM's nameplate data, such as rated torque and slip, as well as starting and maximum torque [4] – [6]. On the other side, the second category of estimation methods relies on measuring the data during the normal operation mode of the machine [7] – [12]. To be more precise, the methods based on the analysis of the machine's acceleration are presented in [7] and [8]. The direct start of the induction machine represents the basic for the test method proposed in [9], while the U/f regulation is considered in [10]. The parameters of the IM are determined while operating in generator mode in [11]. Also, the impulse response of an IM is used for the parameters estimation procedure in [12].

This paper presents the comparative analysis between HBA [13] and EO [14] algorithms for estimation of parameters of single cage induction machine (SCIM) and double cage induction machine (DCIM) models. The parameters are estimated using the nameplate data. Also, the comparison with SA-ERWCA algorithm, used in [6], is provided.

The paper is organized as follows. In Section 2, both single cage and double cage induction machine models are described in details, along with the presentation of corresponding equivalent circuits. Considered metaheuristic algorithms are described in Section 3. The results of the estimation procedure, along with the comparative analysis, are presented in Section 4.

II. Single Cage and Double Cage Induction Machine Models

In this section, two basic models of induction machine are presented – single cage and double cage models. Also, equivalent circuits and corresponding mathematical equations will be analyzed.

A. Single cage model (SCM) of induction machine

The equivalent circuit of the single cage induction machine model is depicted in Fig. 1. The resistances of stator and rotor are denoted with R_1 and R_2, X_1 and X_2 stand for reactances of stator and rotor, respectively, X_m is magnetization reactance, and s is slip.

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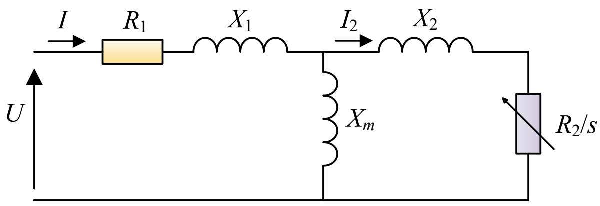

Fig. 1. Equivalent circuit of single cage induction machine model.

Based on the presented equivalent circuit, firstly the equivalent impedance of rotor circuit and magnetization branch $\underline{Z}_p$ is determined:

$$\underline{Z}_p = \frac{1}{\frac{1}{jX_m} + \frac{1}{\frac{R_2}{s} + jX_2}}. \tag{1}$$

Therefore, the stator current I can be determined as follows:

$$\underline{I} = \frac{\underline{U}}{R_1 + jX_1 + \underline{Z}_p}. \tag{2}$$

Knowing the stator current, the rotor's current I_2 can be easily determined:

$$\underline{I}_2 = \frac{\underline{Z}_p \cdot \underline{I}}{\frac{R_2}{s} + jX_2}. \tag{3}$$

Based on that, the electromagnetic torque of the motor can be calculated using the following equation:

$$T = \frac{3 \cdot p}{\omega_s} \cdot \left|\underline{I}_2\right|^2 \cdot \frac{R_2}{s}, \tag{4}$$

where p stands for the number of pole pairs of the machine, and ω_s is the synchronous speed. Starting torque, denoted as T_s, can be easily determined by including s=1 in (4). In order to determine the maximum value of torque T_{max}, the first step is to differentiate torque expression with respect to slip s, and to set the first derivative to be equal to 0:

$$\frac{dT}{ds} = 0. \tag{5}$$

The solution of (5) is the value of slip s_{max} that corresponds to maximum torque:

$$s_{max} = \frac{R_2}{\sqrt{R_{TH}^2 + \left(X_{TH} + X_2\right)^2}}, \tag{6}$$

where R_{TH} and X_{TH} correspond to resistance and reactance of the equivalent Thevenin circuit of single cage induction machine model:

$$\underline{Z}_{TH} = \frac{\underline{Z}_1 \cdot \underline{Z}_p}{\underline{Z}_1 + \underline{Z}_p}, \underline{Z}_1 = R_1 + jX_1, \\ R_{TH} = Re\left\{\underline{Z}_{TH}\right\}, X_{TH} = Im\left\{\underline{Z}_{TH}\right\}. \tag{7}$$

Thevenin voltage V_{TH} is calculated as follows:

$$\underline{V}_{TH} = \underline{U} \cdot \frac{\underline{Z}_p}{\underline{Z}_1 + \underline{Z}_p}. \tag{8}$$

Finally, expressions for torque and maximum torque are obtained as follows:

$$T = \frac{3 \cdot R_2 \cdot \left|\underline{V}_{TH}\right|^2}{s \cdot \omega_s \cdot \left(\left(R_{TH} + \frac{R_2}{s}\right)^2 + \left(X_{TH} + X_2\right)^2\right)}, \\ T_{max} = \frac{3 \cdot \left|\underline{V}_{TH}\right|^2}{2 \cdot \omega_s \cdot \left(R_{TH} + \sqrt{R_{TH}^2 + \left(X_{TH} + X_2\right)^2}\right)}. \tag{9}$$

B. Double Cage model (DCM) of Induction Machine

The equivalent circuit of the induction machine double cage model is given in Fig. 2.

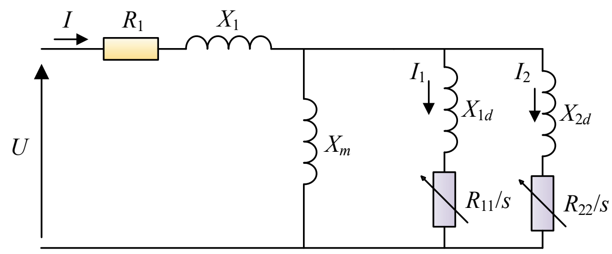

Fig. 2. Equivalent circuit of double cage induction machine model.

In the presented equivalent circuit, R_{11} and R_{22} represent the resistances of the first and second cage, while X_{1d} and X_{2d} stand for the reactances of the first and second rotor cage, respectively. Therefore, the stator current can be calculated as follows:

$$\underline{I} = \frac{\underline{U}}{R_1 + jX_1 + \underline{Z}_p}, \tag{10}$$

where the equivalent impedance of parallel branches Z_p is calculated using the following equation:

$$\underline{Z}_p = \frac{1}{\frac{1}{jX_m} + \frac{1}{\frac{R_{11}}{s} + jX_{1d}} + \frac{1}{\frac{R_{22}}{s} + jX_{2d}}}. \tag{11}$$

Based on the value of stator current, the currents I_1 and I_2 of the first and second rotor cages, respectively, are obtained:

$$\underline{I}_1 = \frac{\underline{Z}_p \cdot \underline{I}}{\frac{R_{11}}{s} + jX_{1d}}, \\ \underline{I}_2 = \frac{\underline{Z}_p \cdot \underline{I}}{\frac{R_{22}}{s} + jX_{2d}}. \tag{12}$$

Afterward, the machine torque can be easily calculated:

$$T = \frac{3 \cdot p}{\omega_s} \cdot \left(\left|\underline{I}_1\right|^2 \cdot \frac{R_{11}}{s} + \left|\underline{I}_2\right|^2 \cdot \frac{R_{22}}{s}\right). \tag{13}$$

Similar to the approach presented within SCM analysis, the starting torque can be obtained by substituting s=1 in (13). Also, the value of slip s_{max} that corresponds to maximum torque is obtai-

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ned by solving (5). After determining s_{max}, maximum torque T_{max} is obtained by substituting $s=s_{max}$ in (13).

III. Description of Applied Metaheuristic Algorithms

In this section, the description and basic mathematical equations for two metaheuristic algorithms – HBA and EO algorithms- are provided.

A. Honey Badger Algorithm (HBA)

The honey badger algorithm is based on the social behavior of honey badgers, precisely on the search and locating of the food. From mathematical aspect, each badger is represented with vector $\boldsymbol{x}_i=[x_{i1}, x_{i2},\ldots, x_{iD}]$, where $\boldsymbol{x}_i$ is position of i-th badger, and i counts from 1 to N (N-population size). Also, D denotes the dimension of the optimization problem, or the number of variables that are being optimized. First step in the algorithm is to randomly initialize the position of each honey badger between the lower and upper bounds of the optimization variable:

$$x_{i,j} = LB_j + rand \cdot \left(UB_j - LB_j\right); i=1,2,...,N; j=1,2,...,D, \quad (14)$$

where $rand$ stands for a random number between 0 and 1, while LB_j and UB_j are the lower and upper bound of j-th optimization variable, respectively. The main equations that iteratively repeat in the HBA algorithm are the digging phase and the honey phase. These equations are used to update the positions of the honey badgers.

The digging phase is expressed as follows:

$$\boldsymbol{x}_{new} = \boldsymbol{x}_{prey} + F \cdot \beta \cdot \boldsymbol{I} \cdot \boldsymbol{x}_{prey} + F \cdot r_3 \cdot \alpha \cdot \boldsymbol{d}_i \cdot |cos(2\pi r_4) \cdot [1 - cos(2\pi r_5)]|, \quad (15)$$

where $\boldsymbol{x}_{new}$ stands for the updated position of each honey badger, $\boldsymbol{x}_{prey}$ is the best badger so far (the one with the lowest criterion function value); r_3, r_4, and r_5 are random numbers in range from 0 to 1, and β is the ability of the badger to get food – according to [13], it is selected to be 6.

The other factors mentioned in (15), are defined as follows:

- $\boldsymbol{I}_i$ is smell intensity of the prey:

$$\boldsymbol{I}_i = r_2 \times \frac{\boldsymbol{S}}{4p\boldsymbol{d}_i^2}, \quad (16)$$

- $\boldsymbol{S}$ is strength source:

$$\boldsymbol{S} = \left(\boldsymbol{x}_i - \boldsymbol{x}_{i+1}\right)^2, \quad (17)$$

- $\boldsymbol{d}_i$ is distance between prey and i-th badger:

$$\boldsymbol{d}_i = \boldsymbol{x}_{prey} - \boldsymbol{x}_i, \quad (18)$$

- α is density factor:

$$a = e^{-\frac{t}{t_{\max}}}, \quad (19)$$

- F is flag, defined as follows:

$$F = \begin{cases} 1, \text{if } r_6 \leq 0.5 \\ 1, \text{else} \end{cases} \quad (20)$$

In previous equations, r_2 and r_6 are random numbers between 0 and 1, while t and $t_{\max}$ stand for current and maximum number of iterations, respectively.

After completing digging phase, the following step in HBA is honey phase. It is described using (21):

$$\mathbf{x}_{new} = \mathbf{x}_{prey} + F \cdot r_7 \cdot \alpha \cdot \mathbf{d}_i. \quad (21)$$

The described procedure is iteratively repeated until the algorithm reaches predefined maximum number of iterations t_{max}. After completing the last iterations, the solution of the optimization problem is the honey badger with the lowest criterion function value.

B. Equilibrium optimizer (EO) algorithm

The inspiration for equilibrium optimizer (EO) algorithm is found in the law related tothe mass balance, which is frequently mentioned in chemistry and physics. Similar to the previously described HBA, the population of EO algorithm is presented as the population of N particles. The concentration of i-th particle, denoted as $\boldsymbol{C}_i$, represents a potential solution of the optimization problem, and is presented as vector of D variables. The first step of the algorithm is to randomly initialize the population, which is carried out using (14). Afterward, the iteration procedure begins, and it is carried out until maximum number of iterations t_{max} is reached. In each iterations, the concentration of every particle is updated as

$$\boldsymbol{C}_i(t) = \boldsymbol{C}_{eq} + \left(\boldsymbol{C}_i(t-1) - \boldsymbol{C}_{eq}\right) \cdot \boldsymbol{F} + \frac{\boldsymbol{G}}{\boldsymbol{\lambda}}\left(1 - \boldsymbol{F}\right). \quad (22)$$

The explanation of each term from previous equation is given as follows:

- Randomly chosen particle from equilibrium pool is denoted as $\boldsymbol{C}_{eq}$. The equilibrium pool is formed once after each iteration – it consists of four best particles of the population, and of the their average value.
- The exponential term is denoted as $\boldsymbol{F}$. Taking into account that $\boldsymbol{\lambda}$ (turnover rate) represents vector of random numbers in the range from 0 to 1, the exponential term can be calculated as follows:

$$\begin{aligned} \boldsymbol{F} &= e^{-\boldsymbol{\lambda}(\boldsymbol{x}-\boldsymbol{x}_0)}, \\ \boldsymbol{x} &= \left(1 - \frac{t}{t_{\max}}\right)^{a_2 \frac{t}{t_{\max}}}, \\ \boldsymbol{x}_0 &= \frac{1}{\boldsymbol{\lambda}} ln\left[-a_1 \cdot (1 - e^{-\boldsymbol{\lambda} \boldsymbol{x}}) \cdot sign(\boldsymbol{r} - 0.5)\right] + \boldsymbol{x}, \end{aligned} \quad (23)$$

- The third term is called generation rate, and is denoted as the vector $\boldsymbol{G}$. It can be calculated as follows:

$$\begin{aligned} \boldsymbol{G} &= \boldsymbol{G}_{CP}\left(\boldsymbol{C}_{eq} - \boldsymbol{\lambda}\boldsymbol{C}(t-1)\right)\boldsymbol{F}, \\ \boldsymbol{G}_{CP} &= \begin{cases} 0.5\boldsymbol{r}_1, \ \boldsymbol{r}_2 \geq GP \\ 0, \ \boldsymbol{r}_2 < GP \end{cases}. \end{aligned} \quad (24)$$

In (23) and (24), a_1 and a_2 stand for random numbers between 0 and 1, while $\boldsymbol{r}$, $\boldsymbol{r}_1$ and $\boldsymbol{r}_2$ are vectors of random numbers also in ran-

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ge from 0 to 1. Also, *GP* stands for generation probability, whose value is set to 0.5, according to [14].

After reaching the maximum number of iterations t_{max}, the particle whose concentration has the lowest fitness function value is considered as the optimal solution.

IV. Results of the Optimization

In this section, the formulation of the optimization problem is firstly described. Afterward, the results of the parameters estimation procedure for SCM and DCM of two different induction machines are presented.

A. Formulation of the optimization problem

The most important step in application of metaheuristic algorithms is to define criterion function (*CF*). The goal of this paper is to estimate the parameters of the induction machine, so that the calculated values of torques, currents, and power factor match with the values from the nameplate of the machine. To be more precise, the criterion functions used in this work are given with the following equations:

$$CF_1 = F_1^2 + F_2^2 + F_3^2 + F_4^2, \\ CF_2 = F_1^2 + F_2^2 + F_3^2 + F_4^2 + F_5^2 + F_6^2, \tag{25}$$

where functions F_1-F_6 are defined as follows:

$$F_1 = \frac{T_{fl,c} - T_{fl,n}}{T_{fl,n}}; F_2 = \frac{T_{st,c} - T_{st,n}}{T_{st,n}}; F_3 = \frac{T_{\max,c} - T_{\max,n}}{T_{\max,n}}; \\ F_4 = \frac{\cos(\varphi)_{fl,c} - \cos(\varphi)_{fl,n}}{\cos(\varphi)_{fl,n}}; F_5 = \frac{I_{st,c} - I_{st,n}}{I_{st,n}}; F_6 = \frac{I_{fl,c} - I_{fl,n}}{I_{fl,n}}. \tag{26}$$

In the previously defined criterion function, index *fl* stands for full load, *st* denotes starting, max is maximum, and also *c* and *n* stand for calculated and nameplate value, respectively. Also, CF_1 is criterion function for single cage model, while CF_2 denotes criterion function for double cage model.

B. Case 1 – Estimation of Parameters of SCM of the Machine

Firstly, the parameters of the single cage model equivalent circuit of induction motor are estimated. The nameplate data of the considered motor are given in Table 1.

TABLE I.
Induction Motor 1 – Nameplate Data

Quantity	Description	Value
P_n	Nominal power	40 HP (horse power)
V_n	Nominal voltage	400 V
f	Frequency	50 Hz
p	Pole pairs	2
T_{st}	Starting torque	260 Nm
T_{fl}	Full-load torque	190 Nm
$T_{\max}$	Maximum torque	370 Nm
$\cos(\varphi)_{fl}$	Full-load power factor	0.8
s_{fl}	Full-load slip	0.09

The parameters of the SCM equivalent circuit of the presented induction motor (R_1, R_2, X_1, X_2, and X_m) are estimated using HBA and EO algorithms. The results are compared with the corresponding results obtained with SA-ERWCA algorithm [6]. The results of the estimation, along with the criterion function values, are given in Table 2.

TABLE II.
Induction Motor 1 – Results of the Estimation

Parameter	HBA	EO	SA-ERWCA
R_1	0.27821	0.27821	0.27821
X_1	0.68056	0.16343	0.20111
R_2	0.34216	0.39167	0.38795
X_2	0.25867	0.84936	0.80380
X_m	7.39873	7.91588	7.87820
CF	$3.88 \cdot 10^{-14}$	$1.993 \cdot 10^{-13}$	$1.6 \cdot 10^{-10}$

Furthermore, the graphical comparison of the obtained resultsis provided. Namely, the torque-slip and power factor-slip characteristics are calculated using the parameters from the previous table. The mutual comparison of the calculated characteristics is presented in Fig. 3 (torque-slip) and Fig. 4 (power factor-slip). Also, the nameplate values of torque and power factor are drawn on the corresponding figures.

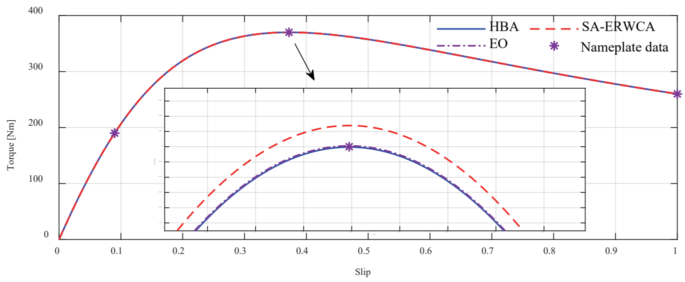

Fig. 3. Comparison of torque-slip characteristics for single cage model.

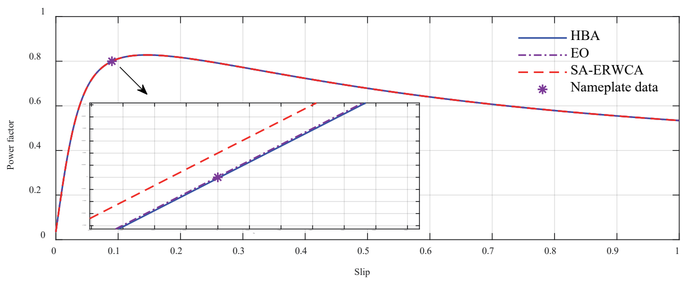

Fig. 4. Comparison of power factor-slip characteristics of single cage model.

Based on the results presented in Table 2, as well as the graphical comparison given in previous figures, it is evident that both HBA and EO algorithms can ensure better matching than the SA-ERWCA algorithm. Also, mutual comparison between HBA and EO algorithms shows that HBA algorithm provides slightly less criterion function value than EO algorithm.

C. Case 2 – Estimation of Parameters of DCM of the Machine

The parameters of the double cage equivalent circuit of the induction motor are estimated in the second case presented in this paper. The nameplate data of the considered motor are given in Table 3.

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TABLE III
INDUCTION MOTOR 2 – NAMEPLATE DATA

Quantity	Description	Value
P_n	Nominal power	148 HP (horse power)
V_n	Nominal voltage	400 V
f	Frequency	50 Hz
p	Pole pairs	2
T_{st}	Starting torque	847.2 Nm
T_{fl}	Full-load torque	353 Nm
T_{max}	Maximum torque	1094.3 Nm
$\cos(\varphi)_{fl}$	Full-load power factor	0.9
s_{fl}	Full-load slip	0.0077
I_{st}	Starting current	1527.2 A
I_{fl}	Full-load current	184 A

Considered EO and HBA algorithms are applied to estimate the parameters of the double cage model equivalent circuit – R_1, X_1, R_{11}, X_{1d}, R_{22}, X_{2d}, and X_m. Table 4 presents the comparison of obtained results with corresponding results from [6], where SA-ERWCA algorithm is applied.

TABLE IV.
INDUCTION MOTOR 2 – RESULTS OF THE ESTIMATION

Parameter	HBA	EO	SA-ERWCA
R_1	0.037748	0.0377021165	0.037614
X_1	0.03664	0.1113609818	0.050454
R_{11}	0.01077	0.01204092448	0.010833
X_{1d}	0.171758	0.1114089951	0.159068
R_{22}	0.162733	0.0500786904	0.135273
X_{2d}	0.150063	0.003877696845	0.112364
X_m	3.779905	3.705739386	3.767293
CF	$5.02\cdot10^{-11}$	$3.75\cdot10^{-10}$	$4.73\cdot10^{-9}$

Similar to the previously presented approach, the graphical comparison of the obtained results is also provided. To be precise, Fig. 5 presents the comparison of torque-slip characteristics, which are calculated using the parameters from the previous table. Also, the power factor-slip characteristics are presented in Fig. 6.

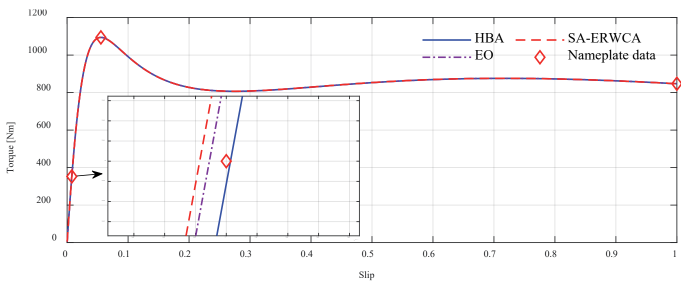

Fig. 5. Comparison of torque-slip characteristics for double cage model.

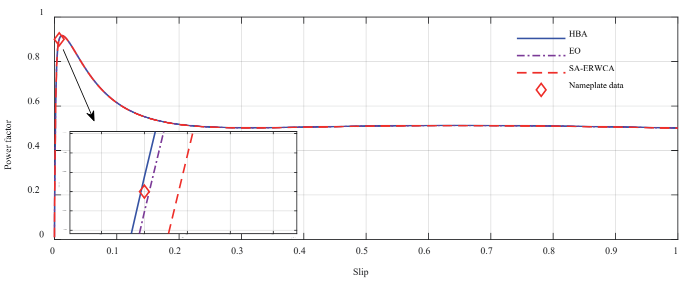

Fig. 6. Comparison of power factor-slip characteristics of double cage model.

As it can be seen from the previous figures, the characteristics calculated with parameters estimated with HBA have the best matching with the nameplate data. Very close matching is also provided with EO algorithm, while the application of SA-ERWCA algorithm leads to the results that are further from nameplata data compared with other two considered algorithms. The same conclusion can also be drawn observing the criterion function values from Table 4.

D. CONVERGENCE CURVES COMPARISON

One of the main characteristics of each metaheuristic algorithm is its' convergence curve, which denotes the criterion function value after each iteration. Therefore, the convergence curves for the algorithms applied in this paper are presented, in both considered cases.

In case 1, where the SCM equivalent circuit parameters are estimated, the parameters of both HBA and EO algorithm are selected to have equal values. Precisely, maximum number of iterations is 100, and the population size is also 100. The convergence curves comparison is depicted in Fig. 7.

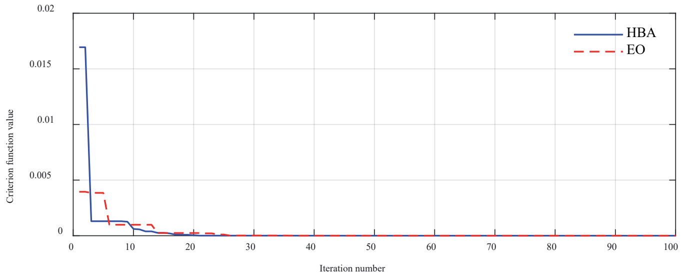

Fig. 7. Comparison of convergence curves – case 1.

In the second considered case, the parameters of DCM equivalent circuit are estimated. Population size and maximum number of iterations, for both HBA and EO algorithm, are selected to be 300 in this case. The graphical comparison of convergence curves is provided in case 2.

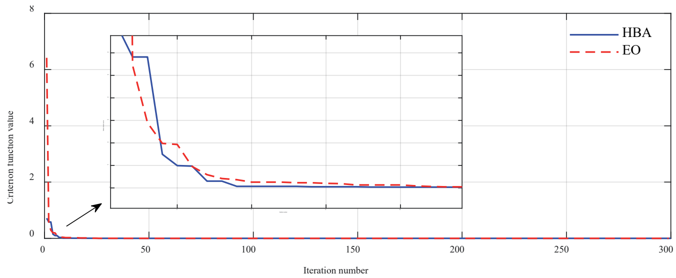

Fig. 8. Comparison of convergence curves – case 2.

The analysis of the presented convergence curves, in both of the considered cases, clearly proves the applicability of both HBA and EO algorithm for the estimation of IM equivalent circuits parameters. Both of the algorithms reach optimal solution really fast, after only a couple of iterations. Mutual comparison gives slight advantage to the HBA, because it reaches optimal solution before the EO algorithm.

V. CONCLUSION

This paper presented a comparative analysis of the Honey Badger Algorithm and Equilibrium Optimizer for the estimation of parameters of single-cage and double-cage induction machine models using nameplate data. The obtained results clearly demonstrate that both algorithms provide high accuracy and fast convergence, with HBA showing a slight advantage in terms of convergence speed and criterion function value in all considered cases. The comparison with a previously published SA-ERWCA-based approach further confirms the effectiveness and robustness of the proposed methods for practical parameter estimation of induction machines.

Future work will be focused on extending the proposed methodology to include parameter estimation based on measured operational data, as well as the application of hybrid and adaptive metaheuristic algorithms. Additionally, the integration of the proposed estimation framework into real-time monitoring and control systems, as well as its validation on a wider range of induction machine ratings and operating conditions, will be considered.

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