Turkish Journal of Electrical Engineering & Computer Sciences

http://journals.tubitak.gov.tr/elektrik/

Research Article

Turk J Elec Eng & Comp Sci
(2016) 24: 1826 – 1837
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doi:10.3906/elk-1311-150

An intelligent design optimization of a permanent magnet synchronous motor by artificial bee colony algorithm

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Received: 18.11.2013 • **Accepted/Published Online:** 01.07.2014 • **Final Version:** 23.03.2016

Abstract: The artificial bee colony algorithm is one of the latest stochastic methods based on swarm intelligence. The algorithm simulates the foraging behavior of honeybees. The structure of the algorithm is quite simple and its coding is very easy. This paper proposes a design optimization based on geometrical variables to obtain a highly efficient surface-mounted permanent magnet synchronous motor with concentrated winding by use of the artificial bee colony algorithm. Input parameters for the algorithm are the geometrical variables of the motor. This approach is more advantageous than finite element analysis requiring a long period of time. Results of the artificial bee colony algorithm are compared with results of a genetic algorithm and checked with a commercial design program. The results emphasize the effectiveness of the algorithm on the design optimization of the permanent magnet synchronous motor.

Key words: Artificial bee colony algorithm, design optimization, genetic algorithm, permanent magnet synchronous motor

1. Introduction

Permanent magnet synchronous motors (PMSMs) have high efficiency and high torque/volume ratio and so the use of them has increased in industrial fields. Surface-mounted PMSMs with concentrated windings have often been chosen for low-speed applications such as elevator traction machines.

Design optimization studies of PMSMs have been done on the determination of geometrical variables such as air gap length, on the selection of structures such as slot/pole ratio or type of windings, on placement of permanent magnets, and so on [1–3]. The aims of these mentioned studies are high efficiency, low cost, low cogging torque and torque ripple, or several of these, e.g., the size of the permanent magnet is more important for low cost and high efficiency. However, due to design constraints and nonlinear/complex structures of PMSMs, effects of each variable on the performance of the motors should be investigated during the design optimization for an industrial production.

Artificial intelligence techniques have been used in the design optimization of PMSMs [4,5]. Because of the nonlinear/complex structures of PMSMs, stochastic methods are most suitable for design optimization studies and consequently the number of studies of artificial intelligence techniques in engineering optimization has also increased depending on the new algorithms. One of these novel algorithms is the artificial bee colony (ABC) algorithm that is currently under development.

According to previous studies, to obtain a highly efficient surface-mounted PMSM with concentrated winding for low-speed applications, this study aims to find optimal geometrical variables by use of the ABC algorithm.

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2. An overview of the algorithms

2.1. Genetic algorithm

The basic principle of the genetic algorithm (GA), developed by John Holland of the University of Michigan, is the struggle of individuals to survive. This algorithm is a well-established one and the most common of the population-based implementations. It does not produce only one solution to solve optimization problems. Instead, the GA tries to make the optimal solution in a population-based solution space of the problem. Here, the populations are composed of individuals independently of each other; individuals are composed of genes containing the solutions. The GA does not require the initial solution and does not guarantee to find the optimal solution to the global optimization problems. However, it can converge to a local solution.

The GA has three operators: the first is reproduction, that is, for selection of the parents to reproduce; the second is crossover to cross the genes of the individuals; and the third is mutation, to ensure genetic diversity [6,7]. Figure 1 shows the flowchart of the GA.

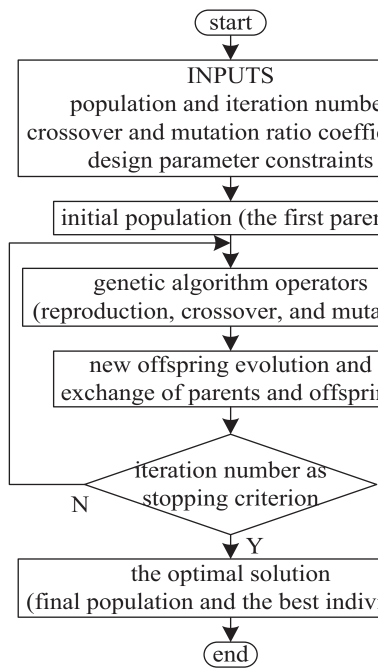

Figure 1. Flowchart of the genetic algorithm.

2.2. ABC algorithm

Swarm intelligence is the basis of both self-organization and division of labor [8]. Division of labor is the ability of a swarm of individuals to perform distinct tasks simultaneously. Self-organization is the interaction between the individuals in the swarm for vital behaviors and is composed of four features: positive feedback, negative feedback, fluctuations, and multiple interactions. Honeybees exhibit the specifications of swarm intelligence as follows [7,8]:

- Positive feedback is the motivation of honeybee individuals for foraging for rich food sources.

- Negative feedback provides controlled behavior; for example, employed bees abandon poor-quality food sources.

- Fluctuations are randomness as a product of new honeybee individuals.
- Multiple interactions are behaviors such as the sharing of information on food sources to perform the division of labor among honeybees with the waggle dance.

Artificial bee algorithms have been investigated in the last decade. As other swarm algorithms simulate the vital behaviors of living creatures, artificial bee algorithms simulate the vital behavior of bees, such as the behavior of the queen bee, or dances and reproduction of bees. The ABC algorithm was developed based on one of the important vital behaviors of honeybees: foraging [7]. Due to the foraging behavior of honeybees, the algorithm is based on three components: food sources, employed bees (foragers), and unemployed bees (onlooker and scout bees). Karaboğa first proposed the algorithm that includes some assumptions. Depending on the assumptions, the algorithm converges to the minimum or maximum optimal solution [7,8].

- Each nectar source belongs to only one honeybee; namely, the number of employed bees equals the number of food sources.
- The number of the employed bees equals the number of onlooker bees.
- The employed bee that has a nectar source is turned into a scout bee.
- Locations of food sources symbolize possible solutions of the algorithm and quantities of nectar sources represent fitness values (quality of solutions) of the algorithm.

In comparison with other conventional stochastic algorithms, the ABC algorithm makes an effort for both a global solution by scout bees and a local solution by employed and onlooker bees in less time. This algorithm obtains optimal solutions with great accuracy. Moreover, the algorithm based on a population has fewer operators and simple coding, and thus it has been used in engineering optimization problems in the last few years [9–12]. The pseudocode of the algorithm by Karaboğa with main equations is as follows [7,8]:

START

i. Produce food sources (initial population) by use of Eq. (1) and reset solution counters of the population ($failure_i = 0$)

$$x_{ij} = x_j^{\min} + rand\,(0,1)\left(x_j^{\max} - x_j^{\min}\right) \begin{cases} i = 1, ..., SN \\ j = 1, ..., D \\ \text{SN is number of food sources} \\ \text{D is number of parameter} \\ x_j^{\max} \text{ is maximum value of j. parameter} \\ x_j^{\min} \text{ is minimum value of j. parameter} \end{cases} \tag{1}$$

ii. Determine **“*limit*”** value

$$limit = (SN \times D)\,/\,2 \tag{2}$$

iii. Calculate fitness values of population ($fitness_i$) by use of the objective function and Eq. (3); namely, calculate quality of food sources

$$fitness_i = \begin{cases} 1/(1 + f_i), & f_i \geq 0 \\ 1/abs(f_i), & f_i < 0 \end{cases} \tag{3}$$

REPEAT

FOR $i = 1$ **to** SN **DO**

iv. Produce new food source for employed bee of x_i source by use of Eq. (4) and calculate fitness value (send employed bees to food sources)

$$\upsilon_{ij} = x_{ij} + \varphi_{ij}(x_{ij} - x_{kj}) \begin{cases} i, k = 1, ..., SN \\ j = 1, ...D \\ \text{SN is number of food sources} \\ \text{D is number of parameter} \\ \varphi_{ij} = [-1, 1] \\ \upsilon_{ij} = \begin{cases} x_j^{\min} & , \ \upsilon_{ij} < x_j^{\min} \\ \upsilon_{ij} & , \ x_j^{\min} < \upsilon_{ij} < x_j^{\max} \\ x_j^{\max} & , \ x_j^{\max} < \upsilon_{ij} \end{cases} \end{cases} \tag{4}$$

v. Implementation of greedy selection between υ_i and x_i

vi. If $fitness_{\upsilon_i} < fitness_{x_i}$, $failure_i = 0$; if not $failure_i = failure_i + 1$

END

vii. For onlooker bees, depending on the fitness values, calculate probability values by use of Eq. (5) and $t = 0$, $i = 1$

$$p_i = \frac{fitness_i}{\sum_{j=1}^{SN} fitness_j} \tag{5}$$

REPEAT

IF $random < p_i$ **THEN**

viii. Repeat steps iii, iv, and v and then $t = t + 1$

END IF

UNTIL $t = SN$

IF $\max\{failure_i\} >$ **limit THEN**

ix. Change x_i with a random solution (scout bee) produced by Eq. (1)

END IF

x. Keep optimal solution in mind

UNTIL *stopping criterion as iteration number*

3. Design equations and the objective function

In this study, the surface-mounted PMSM with concentrated winding has 16 poles and 18 slots. Seven independent geometrical variables that are magnet thickness l_m, air gap length δ, slot wedge height h_{sw}, stator tooth width b_{ts}, outer stator diameter D_o, stator slot height h_{ss}, and ratio of the slot opening over the slot width k_{open} were chosen. Some geometrical parameters, such as inner stator diameter $D = 209$ mm, half pole angle $\alpha = 63°$, and stator active length $L = 120$ mm, are not changeable. In addition, 7.2 kW of output power, 255 rpm of rated speed, and 360 V of supply voltage are invariable. ...| CA |AA | AA | AB | BB | BB | BC | CC | CC | C... where A represents return of the A coil is the winding layout of the motor. Figure 2 illustrates the winding layout for only one phase and Figure 3 shows the two-dimensional geometry of the surface-mounted PMSM.

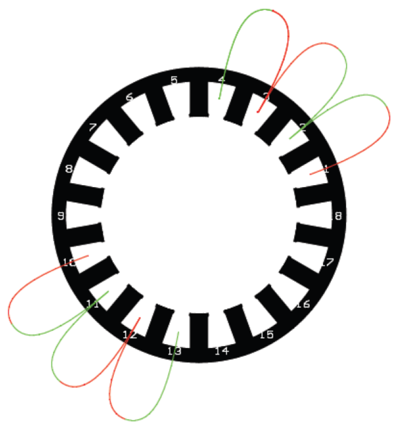

Figure 2. Winding layout of the PMSM for only one phase.

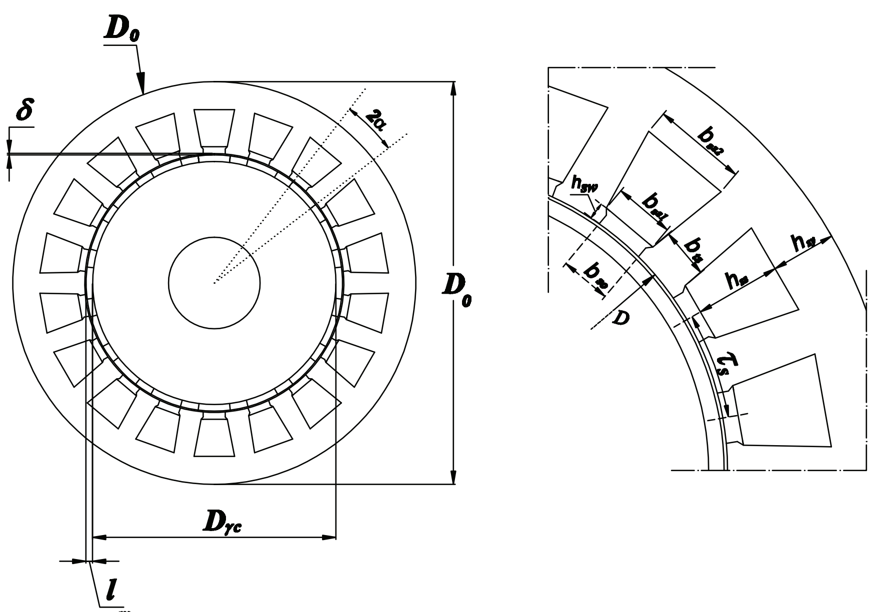

Figure 3. Two-dimensional geometry of the PMSM.

By use of the selected design parameters that definitely reflect the motor geometry, motor design equations can be categorized as follows [13–15].

3.1. Geometrical equations

$$D_{rc} = D - 2l_m - 2\delta \tag{6}$$

$$\tau_s = \pi D / Q_s \tag{7}$$

$$b_{ss1} = \pi \frac{D + 2h_{sw}}{Q_s} - b_{ts} \tag{8}$$

$$b_{ss2} = \pi \frac{D + 2h_{ss}}{Q_s} - b_{ts} \tag{9}$$

$$h_{sy} = (D_o - D - 2h_{ss}) / 2 \tag{10}$$

$$k_{open} = b_{so} / b_{ss1} \tag{11}$$

$$A_{sl} = 0.5 \times (b_{ss1} + b_{ss2}) \times (h_{ss} - h_{sw}) \tag{12}$$

Here, τ_s is the factor of the slot pitch, Q_s is the number of slots, b_{ss1} is the width of the inner stator slot, b_{ss2} is the width of the outer stator slot, h_{sy} is the height of the stator yoke, and A_{sl} is the area of slots.

3.2. Magnetic equations

The following equations are used to calculate the fundamental of air-gap flux density of surface-mounted PMSMs.

$$k_C = \frac{\tau_s}{\tau_s - \frac{(k_{open} b_{ss1})^2}{k_{open} b_{ss1} + 5\delta}} \tag{13}$$

$$k_{leak} = 1 - \frac{(7p / 60 - 0.5)}{100} \tag{14}$$

$$B_m = \frac{B_r k_{leak}}{1 + \frac{\mu_r \delta k_C}{l_m}} \tag{15}$$

$$\hat{B}_\delta = (4 / \pi) \times B_m \times \sin\alpha \tag{16}$$

Here, k_C is the Carter factor, k_{leak} is the leakage factor, B_r is the remanence flux density of permanent magnets and their value is 1.2 T, the relative permeability μ_r is 1.03, B_m is the maximum air-gap flux density, and $\hat{B}_\delta$ is the fundamental air-gap flux density.

3.3. Electrical equations

Current loading is an important factor for electric motors [15]. Each electric motor has different current loading ranges because of the distinct design architectures.

$$\hat{S}_1 = \frac{4T}{\pi D^2 L \hat{B}_\delta k_{\omega 1} k_{cor} \sin\beta} \tag{17}$$

$$n_s\hat{I} = \hat{S}_1\tau_s \text{ and } \hat{I} = \hat{S}_1\tau_s \Big/ n_s \tag{18}$$

$$E(t) = \frac{d\psi_m}{dt} = \frac{1}{\sqrt{2}}\omega k_{\omega 1} q n_s \hat{B}_\delta L (D - \delta) \tag{19}$$

$$R = \rho_{Cu}\frac{(pL + (D + h_{ss})\pi k_{coil})\, n_s^2 q}{f_s A_{sl}} \tag{20}$$

$$L_d = L_q = \left(pq\lambda_1 + \frac{3}{\pi}(qk_{\omega 1})^2 \frac{(D - \delta)}{\delta k_C + l_m / \mu_r}\right)\mu_o n_s^2 L \tag{21}$$

Here, S_1 is the current loading, the correction factor k_{cor} is 0.95, T is the rated torque, the angle between the d-axis and the current vector β is $\pi/2$ radian for nonsalient PMSMs, the fundamental winding factor $k_{\omega 1}$ is 0.945 for double-layer concentrated winding, ψ_m is the magnet flux linkage, p is the number of poles, m is the number of phases and the number of slots per pole per phase $q = Q_s/pm$ is 0.375 for the present motor, the copper resistivity ρ_{Cu} is 1.72e^{-8} Ω/m at 20 °C, the end winding coefficient k_{coil} is 0.93, and λ_1 is the specific permeance coefficient of the slot opening.

The q-axis and d-axis equivalent circuits and vector diagram in Figures 4 and 5 are used to obtain the number of conductors per slot for a nonsalient surface-mounted PMSM at nominal speed $(I_d = 0$ and $I = I_q)$.

$$\begin{aligned} U_q &= E + R \times I \\ U_d &= -\omega L_q \times I \\ U &= \sqrt{U_q^2 + U_d^2} = \sqrt{(E + R \times I)^2 + \omega^2 L_q^2 I^2} \end{aligned} \tag{22}$$

$$n_s = \frac{\hat{U}}{\sqrt{\left(\hat{E}' + R' n_s \hat{I}\right)^2 \left(L'_d \omega n_s \hat{I}\right)}} \tag{23}$$

Here, n_s is the number of conductors per slot.

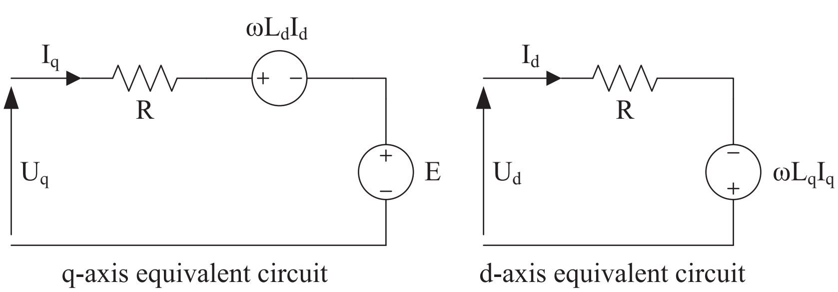

Figure 4. d-q equivalent circuits for a nonsalient PMSM.

After obtaining the design equations, copper and iron losses are calculated. The efficiency equation as the objective function is acquired as follows.

$$P_{Cu} = 3R_{Cu} \times I_{eff}^2 \tag{24}$$

$$P_{Fe} = P_h + P_e = k_h \hat{B}^{\beta_{ts}} \omega_e + k_e \hat{B}^2 \omega_e^2 \tag{25}$$

$$\eta = P_{out}/(P_{out} + P_{Cu} + P_{Fe}) \tag{26}$$

Here, β_{ts} is the Steinmetz constant, ω_e is the electrical angular velocity, k_h is the hysteresis loss coefficient, k_e is the eddy current loss coefficient, P_{out} is the output power, P_{Cu} is the copper loss, P_{Fe} is the iron loss, and η is the efficiency, namely the objective function.

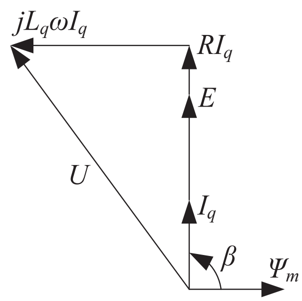

Figure 5. Phasor diagram for a nonsalient PMSM.

4. Design optimization steps

A preliminary analytical design was performed by use of a unique computer program. For the design optimization of the motor, honeybee populations of the algorithm are 20, 50, and 100 individuals. The iteration numbers as the stopping criterion of the algorithms are 20, 50, and 100, respectively. Each run of the algorithm is repeated three times. The crossover ratio and mutation ratio of the GA are 0.8 and 0.01, respectively.

In order to test the performance of the algorithms, no attention is given to industrial mechanical limits such as material size obtained that may be one-hundredth of a millimeter; namely, reproducibility has been briefly neglected and so limit values of the parameters that have been selected are in a wide range. Attention has been paid only to magnetic limits: for example, the stator tooth flux of 1.8 T, the rotor, and the stator yoke flux of 1.4 T.

Figure 6 shows the optimal efficiency results of the algorithms and Figure 7 shows the convergence times of each algorithm. The geometrical motor values obtained for better efficiency results were checked by use of a commercial design program (SPEED) [16].

The Table gives the optimal design parameters and efficiency results and Figures 8 and 9 show the graphics of the simulations for population and iteration numbers in which the optimal efficiencies are obtained.

5. Results and discussion

In this study, for the design optimization of the PMSM, geometrical parameters are only used to highlight the skills of the algorithms. Nevertheless, other motor parameters are important for the design and the performances of the motors, i.e. pole number, slot number, and features of winding and permanent magnets are invariable. Selection of the invariable parameters was based on former design experiences and studies for low-speed applications.

The previous and following figures and the Table provide comparisons of efficiency results and performance features of the algorithms for the design optimization. The preliminary analytical design of the PMSM was

Table. Values of optimal design parameters and efficiency results.

		Predesign	GA	ABC
esign parameters	l_m (mm)	4.7	5.5	6
	δ (mm)	1.25	0.78	0.79
	h_{sw} (mm)	3.31	2.59	2
	b_{ts} (mm)	18.2	20.45	20.93
	D_o (mm)	311.96	351.64	355
	h_{ss} (mm)	37.44	39.9	40.5
	k_{open}	0.94428	0.8788	0.75802
	η (%)	92.53	94.46	94.70
	η (%) (SPEED)	94.32	95.91	96.22
	Abs. error (%)	1.90	1.51	1.58

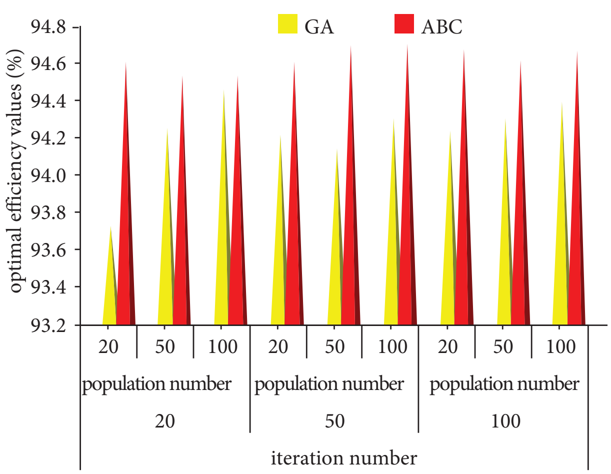

Figure 6. Optimal efficiency values by the GA and the ABC algorithm.

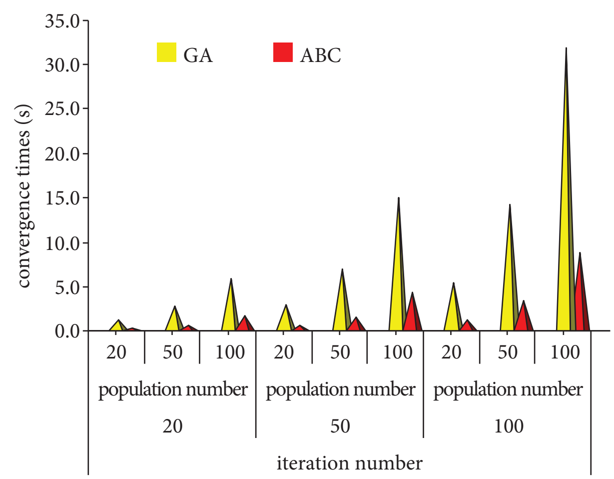

Figure 7. Convergence times of the GA and the ABC algorithm.

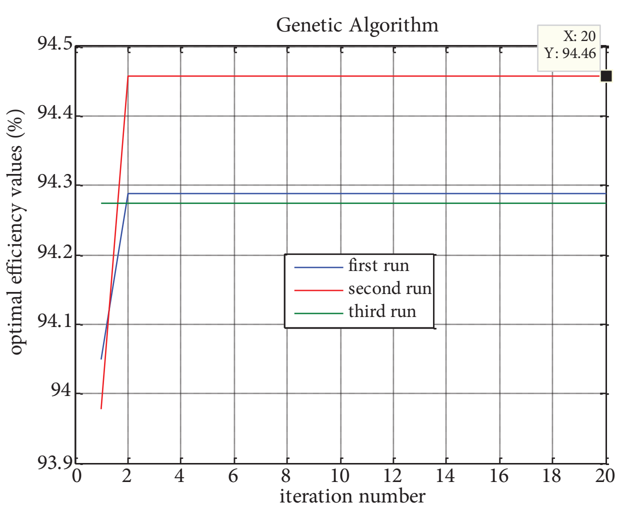

Figure 8. Graphics of the GA in each run.

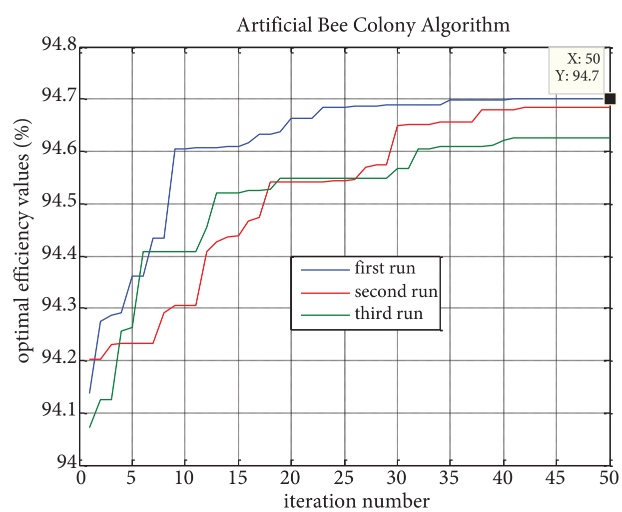

Figure 9. Graphics of the ABC algorithm in each run.

first performed by use of a unique computer program and then the results were tested by the SPEED software. Consequently, the efficient results were 92.53% for the preliminary analytical design and 94.32% by SPEED software, and so the absolute error was 1.90% by use of Eq. (27). The Table also shows that the best optimal efficiency results obtained by the GA for population number to 100 and iteration number to 20 and by the ABC algorithm for population number to 100 and iteration number to 50 are 94.46% and 94.70%, respectively (Figure 6). The convergence times for optimal efficiency results are 5.95 s and 4.33 s, respectively (Figure 7).

$$error\,(\%) = 100 \times \frac{\eta_{pre} - \eta_{SPEED}}{\eta_{SPEED}} \tag{27}$$

Efficiency results obtained by SPEED software for checking previous efficiency results are 94.32%, 95.91%, and 96.22%; the absolute errors are 1.90%, 1.51%, and 1.58%, respectively. The design parameters obtained in the Table emphasize that some geometrical parameters increased and others decreased, with correlation between geometric parameters and efficiency as the objective function. While magnet thickness, stator tooth width, outer stator diameter, and stator slot height increased, the ratio of the slot opening over the slot width, air gap length, and slot wedge height decreased.

Considering optimal efficiency results and convergence times of the GA in Figures 6 and 7, it is clear that the GA can obtain good results, but lower than those of the ABC algorithm. The GA may also fall in a trap at a local point. This situation prevents the obtaining of better efficiency results. However, the ABC algorithm is capable of simultaneously searching both global and local solution spaces. In Figures 8 and 9 the best runs show improvements of the optimal efficiency results during iterations of each run of the algorithms.

According to all results, the ABC algorithm provided collectively better optimal efficiency results than the GA in shorter times. The ABC algorithm reached more reliable results eventually. SPEED simulations verify this inference in the rated speed (Figures 10–12).

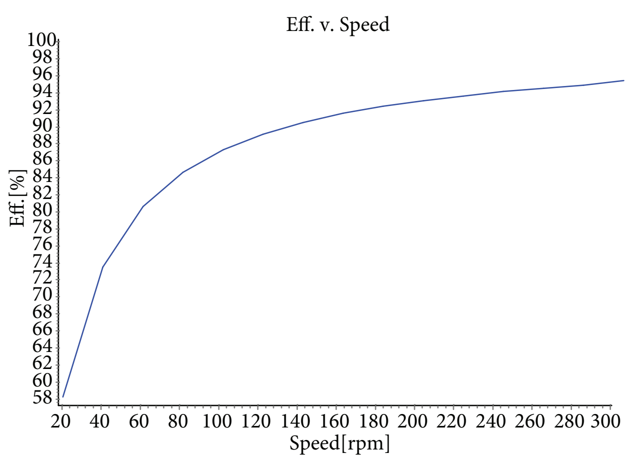

Figure 10. Graphics of the efficiency/speed by SPEED software for preanalytical results.

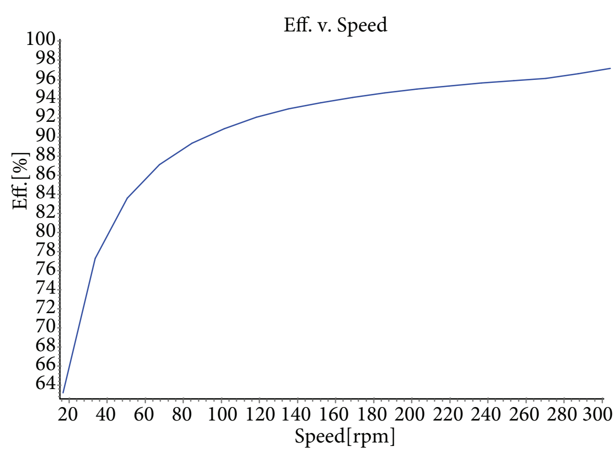

Figure 11. Graphics of the efficiency/speed by SPEED software for the GA results.

As a general assessment, because the ABC algorithm features a small number of operators, a simple coding structure, and superior convergence to optimal results, it is better than many conventional optimization algorithms, including the GA. Moreover, the ABC algorithm is more robust and satisfactory for complex and nonlinear problems such as the design optimization of electric motors.

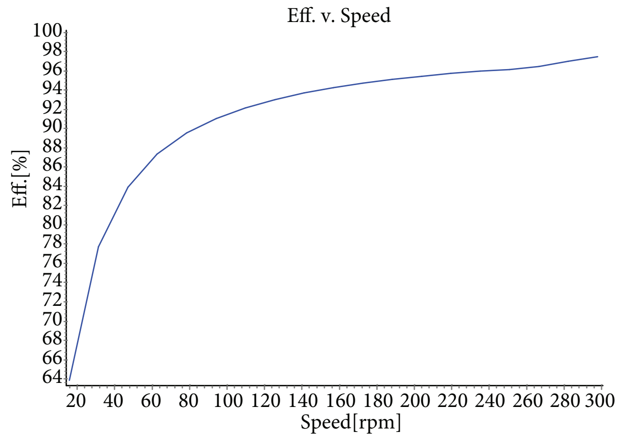

Figure 12. Graphics of the efficiency/speed by SPEED software for the ABC algorithm results.

6. Conclusion

In this study, design optimization of a surface-mounted PMSM with concentrated winding was proposed by use of the GA and ABC algorithm. Efficiency of the motor was first calculated by use of a unique analytical design program and then the better efficiencies were estimated by the GA and the ABC algorithm. The results were finally compared with the results of a commercial design program. Convergence times of the algorithms, the more optimal efficiency results, and the associated design parameters are different depending on the nature of the algorithms. According to efficiency results and convergence times, the ABC algorithm is more satisfactory for design optimization of the PMSM than the GA.

Acknowledgment

This study was supported by the Scientific Research Projects Unit of Selçuk University.

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