BULLETIN OF THE POLISH ACADEMY OF SCIENCES
TECHNICAL SCIENCES, Vol. 71(1), 2023, Article number: e144586
DOI: 10.24425/bpasts.2023.144586

ARTIFICIAL AND COMPUTATIONAL INTELLIGENCE

A novel hybrid cuckoo search algorithm for optimization of a line-start PM synchronous motor

Łukasz KNYPIŃSKI *

Poznan University of Technology, Institute of Electrical Engineering and Electronics, Piotrowo 3a, 60-965 Poznań, Poland

Abstract. The paper presents a novel hybrid cuckoo search (CS) algorithm for the optimization of the line-start permanent magnet synchronous motor (LSPMSM). The hybrid optimization algorithm developed is a merger of the heuristic algorithm with the deterministic Hooke–Jeeves method. The hybrid optimization procedure developed was tested on analytical benchmark functions and the results were compared with the classical cuckoo search algorithm, genetic algorithm, particle swarm algorithm and bat algorithm. The optimization script containing a hybrid algorithm was developed in Delphi Tiburón. The results presented show that the modified method is characterized by better accuracy. The optimization procedure developed is related to a mathematical model of the LSPMSM. The multi-objective compromise function was applied as an optimality criterion. Selected results were presented and discussed.

Key words: hybrid cuckoo search algorithm; heuristic algorithms; multi-objective optimization; permanent magnet synchronous motor.

1. INTRODUCTION

Heuristic (probabilistic) optimization algorithms have been applied for several years now in order to solve different optimization problems [1–3]. Such algorithms are very often used to solve optimal design problems of electromagnetic devices, such as transformers, motors, generators and actuators [4–8]. The optimization procedure often cooperates with a mathematical model of the devices studied, elaborated by means of finite element analysis (FEA). Applying the algorithms, which require the determination of partial derivatives, is extremely difficult due to the necessity to determine the derivative.

In heuristic optimization algorithms, the optimal solution is sought within a group of individuals called, depending on the algorithm: a generation (genetic algorithms), a swarm [9, 10] (swarm methods), a colony (bat algorithm), and even a pack [11, 12] (grey wolf method). If considering successive iterations, the optimization procedure tries to find the optimal solution by moving a group of "agents" around the permissible area.

When executing calculations for successive iterations and subsequent individuals, the objective function for each variant of the device (individual), i.e. repeatedly determining the distribution of the electromagnetic field for the optimized object, must be calculated.

Applying a very complex mathematical model extends computation time for a single individual. For heuristic algorithms, the determination of each successive position of an individual depends on a random coefficient. The optimization process must be repeated several times to obtain reliable and good-quality results [13, 14].

In order to minimize the number of calls to the objective function corresponding with the total computation time, scientists are looking for newer and more effective optimization algorithms. These new methods may allow for obtaining the optimal solution faster, with fewer iterations of the algorithm.

In the last few years, many new methods have been developed, including the bat method, the grey wolf method, the salp swarm algorithm [9], the whale optimization algorithm [15] and the sparrow optimization algorithm [16]. These methods use various mathematical models and may have different performance properties [17].

In the case of a solution optimization task concerning the optimal designing of a permanent magnet motor, classical optimization algorithms were most frequently applied, including genetic algorithms [18–21] and particle swarm optimization algorithm [22]. Moreover, the authors dealing with the optimization of PM motors use heuristic (metaheuristic) algorithms [2, 4, 11] or others [23]. Hybrid optimization algorithms are very rarely applied to the optimization of PM motors.

The aim of this research is to develop a novel hybrid optimization algorithm. The hybrid algorithm connects the heuristic cuckoo search (CS) optimization algorithm and Hooke–Jeeves deterministic method. For each iteration, new cuckoo positions for part of the population are determined randomly. Additionally, for the selected pair of cuckoos, the new position is looked for by the Hooke–Jeeves method. The hybrid procedure thus elaborated will be applied to optimize the LSPMSM rotor.

*e-mail: lukasz.knypinski@put.poznan.pl

Manuscript submitted 2022-08-16, revised 2022-12-21, initially accepted for publication 2022-12-22, published in February 2023.

2. HYBRID OPTIMIZATION ALGORITHM

Nowadays, research on the development of new heuristic algorithms to solve optimization problems is carried out very intensively. New methods are being created based on the observations of behavior of various social groups of animals living in the Earth's ecological system. In order to improve the performance of the optimization algorithm being developed, the authors very often combine two different approaches [24–27].

A new hybrid optimization algorithm, combining the heuristic algorithm (cuckoo search) and deterministic method (Hooke–Jeeves) is proposed to obtain optimal design of the LSPMSM.

2.1. Classical cuckoo search algorithm

The SC algorithm was introduced in 2009 by Xin-She Yang and Suash Deb [28]. The method was developed based on the reproductive behavior of the common cuckoo. The cuckoo is a reproductive predator. Cuckoos lay their eggs in the nests of other birds.

They favor two potential reproduction scenarios: (a) to lay their own egg in the nest of another species after removing the owner's egg from the nest, (b) to take over another species' nest for their own reproduction purposes. The CS algorithm was developed taking into account the following assumptions [29]:

(a) The selected cuckoo lays one egg in a randomly chosen nest;
(b) The nest with the best eggs is moved to the next iteration of the algorithm;
(c) The number of nests is constant and assigned before starting the optimization process. A host can also find and recognize the "foreign" egg. Therefore, a certain probability $p_a \in (0, 1)$ is assumed. The assumed probability describes the possibility of removing a cuckoo's egg from the host's nest (the solution is eliminated), or the host will abandon the nest and build a new nest in a different location (the new nest is added in a random place).

In the classical CS algorithm, we use the following terms: a cuckoo, nest and egg. The nest is a point (potential solution) in a permissible area of a problem being solved. Each cuckoo randomly selects the nest and lays an egg. The nest with an egg is one solution of the analyzed problem. All cuckoos lay the selected number of eggs in the single iteration.

2.2. Hybrid cuckoo search algorithm

The nomenclature of the hybrid algorithm developed was modified. The nest, i.e. the potential locations where the cuckoo can lay an egg, was omitted. For the sake of simplicity, the author decided to use the term "cuckoo" as an acceptable solution.

A new position for the randomly selected half of the cuckoo group in the k-th iteration is determined:

$$\mathbf{x}_k^j = \mathbf{x}_{k-1}^j + \lambda\sigma\left(\mathbf{x}_b - \mathbf{x}_{k-1}^j\right), \tag{1}$$

where: j is the randomly selected cuckoo, $\mathbf{x}_b$ is the position of the best cuckoo, λ is the step size scaling factor [30], and σ is the distribution probability density function for non-negative random variables (Levy flight coefficient).

The value of the probability density function is calculated as:

$$\sigma = \sqrt{\frac{c}{2\pi}}\,\frac{e^{-\frac{c}{2\mathbf{x}_{k-1}^j}}}{\left(\mathbf{x}_{k-1}^j - \mathbf{x}_b\right)^{1.5}}, \tag{2}$$

where c is the constant factor.

In the next stage of the proposed algorithm – $(N/2)$ times, where N is the number of cuckoos in the population – two cuckoos are randomly selected. The values of the objective function for both cuckoos are compared, and the position of the better cuckoo is determined. The best displacement $(\hat{\tau})$ of the worse cuckoo in the direction of the better cuckoo is determined by the use of the Hooke–Jeeves method. A new position of the worse cuckoo is calculated by the following equation:

$$\mathbf{x}_k^2 = \mathbf{x}_k^2 + \hat{\tau}\left(\mathbf{x}_k^1 - \mathbf{x}_k^2\right), \tag{3}$$

where $\mathbf{x}_k^2$ is the position vector of the worse cuckoo, $\mathbf{x}_k^1$ is the position vector of the better quality cuckoo from a randomly selected pair, respectively, and $\hat{\tau}$ is the length of the "optimal" displacement of the worse cuckoo towards the better cuckoo, determined by the Hooke–Jeeves method.

In the optimization procedure being developed, probability p_a, for the beginning stage of the optimization process, is taken into consideration (only for the first 10 iterations). Probability p_a determines how many new cuckoos in random positions will be created in the current iteration.

Moreover, in the proposed hybrid approach, a simple elitism procedure is applied [31]. This strategy prevents the position of the best cuckoo from changing in each iteration.

The block diagram of the thus developed hybrid optimization procedure is presented in Fig. 1.

3. HYBRID CS VERSUS CLASSICAL CS

To compare the advantages and disadvantages of the proposed hybrid CS optimization algorithm, comparative calculations were executed for two analytical benchmark functions: (a) the Matyas function, and (b) the Himmelblau function.

Matyas function has one global minimum equal to $f_M(0,0) = 0$, and is described by the formula below:

$$f_M(x,y) = 0.26\left(x^2 + y^2\right) - 0.48xy, \tag{4}$$

where x and y are in the range of (–10, 10).

The Himmelblau function has four global minima equal to 0. It is defined by the following equation:

$$f_H(x,y) = \left(x^2 + y - 11\right)^2 + \left(x + y^2 - 7\right)^2, \tag{5}$$

where $-6 \le x \le 6$ and $-6 \le y \le 6$.

Optimization calculations for the classical CS procedure [30] were made for the following parameters: number of nests equal to $n = 125$, number of cuckoos $N = 100$ and $p_a = 0.25$. For the hybrid CS algorithm, the calculations were performed for $N = 100$, $p_a = 0.15$ and $k_{\max} = 50$. The optimization process

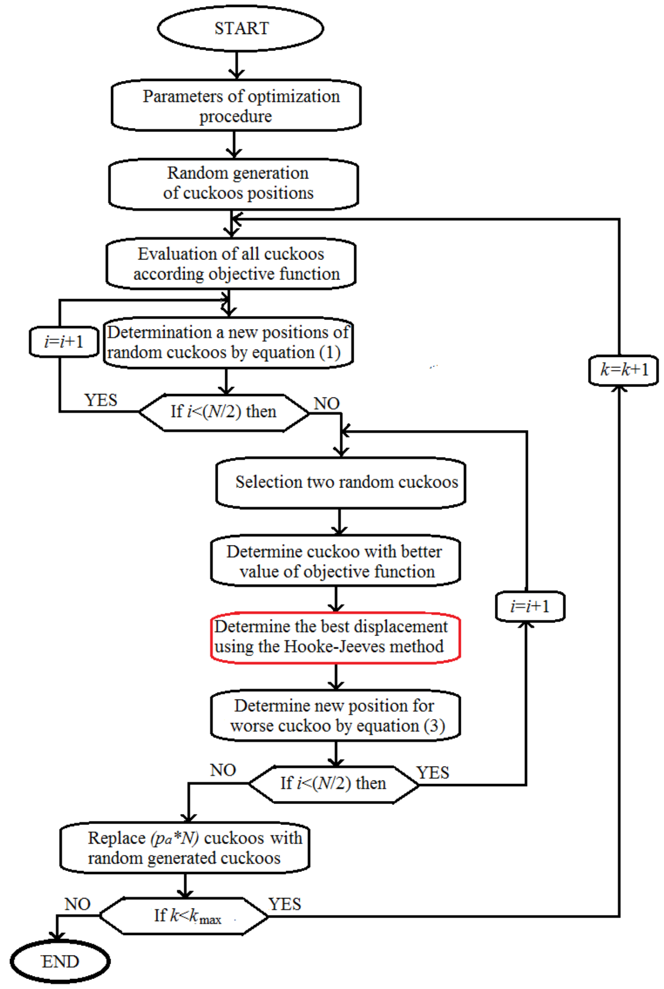

Fig. 1. Flow chart of an optimization procedure

Table 1

Course of the optimization process for CS

k	x	y	$\Delta f(x,y)$	N_{of}
1	2.8881171	2.45504721	3.710164	100
2	3.7677678	−1.9077475	1.825653	225
4	3.7453086	−1.8046252	1.495028	475
8	3.5913946	−1.8473621	0.003278	975
10	3.5913946	−1.8473621	0.002378	1225
20	3.5913946	−1.8473621	0.003278	2325
40	3.5909618	−1.8480482	0.002914	4525
50	3.5909618	−1.8480482	0.002914	5656

Table 2

Results for hybrid CS

k	x	y	$\Delta f(x,y)$	N_{of}
1	2.6948872	0.7289877	32.4437263	100
2	3.1861291	2.3086872	4.43066841	268
4	–2.8998311	3.0901732	0.3721568	592
8	3.0342150	1.8713965	0.2210426	1358
10	3.0001121	1.9497031	0.0418830	1850
20	3.0056238	2.0199493	0.0102512	3170
40	3.0013331	1.9949794	0.0003595	6290
50	3.0002560	1.9999081	0.0000021	7922

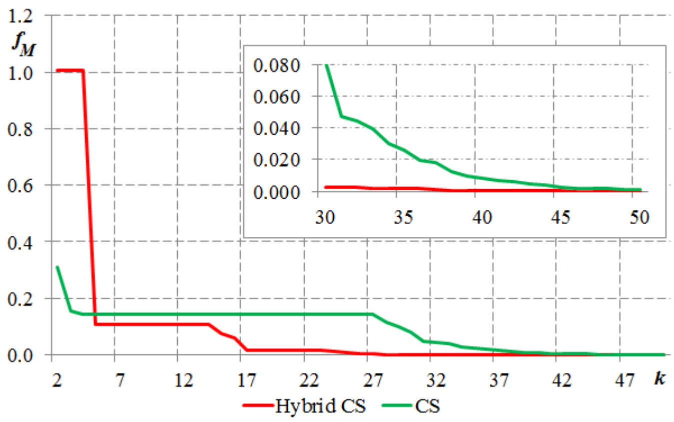

Fig. 2. Comparison of the convergence curves for both algorithms

was repeated 20 times for random starting cuckoo populations. Performing a series of optimization calculations allows for statistical evaluation of the quality of the proposed algorithm.

Table 1 presents results from the best-adapted cuckoo in successive iterations according to classical CS and Himmelblau function. In successive columns, the values of coordinates x and y, the difference $\Delta f(x,y)$ between the value for the objective function and global minima and the numbers of call functions N_{of} are all listed.

From the comparison results presented in Table 2, it can be concluded that the hybrid CS algorithm obtains better quality results. It is worth noting that after 20 iterations a better value of objective function was obtained for the classical CS procedure. However, after 30 iterations much better computation results were obtained for the hybrid CS algorithm. The disadvantage of the hybrid optimization algorithm is the distinctly higher number of calls in the function.

Then, computations were performed for the Matyas function. The convergence curves for the classical CS algorithm (green) and the hybrid CS algorithm (red) for the best optimization process were compared (see Fig. 2).

It can be observed that despite the worse starting positions in cuckoos in the initial population, the hybrid method provides better convergence. For the Matyas function, the hybrid CS algorithm obtained better results after six iterations. Moreover, the optimal solution for the hybrid CS was 0.000026 and for classical CS it was 0.0009.

In order to perform a solid evaluation of the quality and reliability of both the optimization algorithms being compared, a statistical analysis was carried out. Using the results of 20 runs for both optimization procedures, the best, worst, average and standard deviations (SD) were determined for both test functions. Results of the statistical analysis are given in Table 3.

Table 3
Results of statistical analysis

	Classical CS		Hybrid CS	
	f_M	f_H	f_M	f_H
Best	0.000069	0.001441	0.000092	0.000002
Worst	0.059978	0.089610	0.008060	0.006309
Average	0.008318	0.009611	0.001545	0.000602
SD	0.015212	0.019985	0.002217	0.001537

According to the results presented in Table 3, it can be seen that for both the analytical functions analyzed the classical cuckoo search algorithm obtained better results only for the Matyas function (best results from all runs of optimization procedure). It is worth noting that the hybrid CS algorithm ensures better values of standard deviation in comparison to the classical CS algorithm.

In order to compare advantages of the hybrid CS (HCS) being developed with other heuristic algorithms, the calculation has been made for following algorithms: (a) genetic algorithms (GA), (b) particle swarm optimization (PSO), and (c) bat algorithm (BA) [32]. The calculations have been executed for the Himmelblau function. All optimization procedures (hybrid CS, GA, PSO and BA) were started 20 times for random initial populations. The results of statistical analysis are presented in Table 4.

Table 4
Results of statistical analysis for selected heuristic algorithms

	HCS	GA	PSO	BA
Best	0.21E–04	4.50E–04	1.29E–05	6.76E–04
Worst	6.3E–03	73.6E–03	9.13E–03	80.3E–03
Average	0.6E–03	27.1E–03	1.77E–03	22.5E–03
SD	1.53E–03	23.9E–03	3.28E–03	29.4E–03

Based on the results presented in Table 4, it can be concluded that the HCS algorithm allows to obtain better statistical values than the other compared heuristic algorithms. Additionally, the standard deviation for hybrid CS algorithm is the best among the compared algorithms.

According to the author, hybrid algorithms can be interesting tools in comparison to other nature-inspired algorithms.

4. OPTIMIZATION OF LINE-START PM SYNCHRONOUS MOTOR

The hybrid procedure developed was added to the computer software in order to optimize LSPMSM [33]. The software developed consists of two main parts: (a) the optimization procedure, and (b) the mathematical model of the LSPMSM.

The optimization script and mathematical model of LSPMSM were developed in Delphi Tiburón and Ansys Maxwell, respectively. Various optimization procedures can be used in the optimization module. The hybrid procedure developed was added to the computer software and the tested optimization problem was solved.

The optimization problem consisted in searching the rotor structure for the dimensions that ensure good functional parameters. The stator dimensions were adopted from earlier research works [33]. The rotor has been described by five design variables describing the motor excitation system: $x_1 = r$, $x_2 = g$, $x_3 = l$, $x_4 = O_1$ and $x_5 = O_2$, where r is the distance between poles, g and l are the permanent magnet thickness and length, respectively, and O_1 and O_2 are the parameters responsible for the location of the magnets (see Fig. 3).

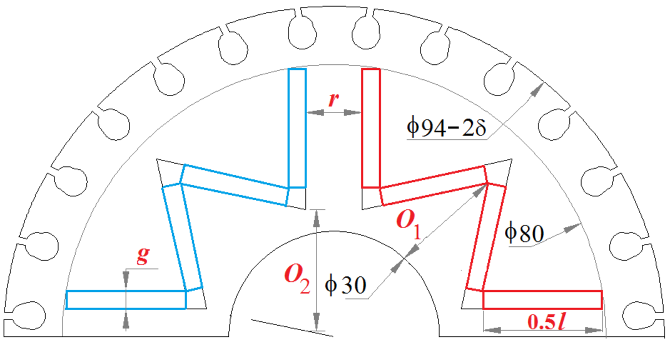

Fig. 3. Rotor structure with marked design variables

The following stator dimensions were adopted during the optimization process: (a) outer stator diameter $D_o = 154$ mm, (b) inner stator diameter $D_i = 94$ mm, (c) stack length $L_i = 140$ mm, (d) the number of slots $N_s = 36$, (e) stator yoke length $h_{jS} = 16.2$ mm, and (f) air gap length $\delta = 0.82$ mm.

During the solution of the optimal designing problems of line-start motors, especially LSPMSM, the parameters taken into account in the objective function must be selected carefully. The authors point out [34] that the researchers often focus on including only the steady-state operation parameters or transient parameters during start-up operation states. According to the author's experience, it is necessary to search for a compromise between both types of parameters. Taking into account only the parameters' steady-state operation or the parameter's transient operation leads to the deterioration of the parameters of the other type [35].

A compromise objective function was adopted as an optimality criterion. The description of objective function has been taken into account for both types of parameters: (a) parameters related to energy consumption, and (b) parameters tied to proper synchronizing ability. The objective function for i-th cuckoo has the following form:

$$f^i(\mathbf{x}) = \left(\left(\frac{\eta^i(\mathbf{x})}{\eta_0} \right) \left(\frac{\cos^i \varphi(\mathbf{x})}{\cos_0 \varphi} \right) \right)^{\alpha} \cdot \left(\frac{T^i_{80}(\mathbf{x})}{T_{80\_0}} \right)^{\beta}, \tag{6}$$

where $\mathbf{x} = [r, g, l, O_1, O_2]^T$ is the vector composed of design variables, $\eta(\mathbf{x})$ and $\cos^i \varphi(\mathbf{x})$ are the efficiency and power factor for i-th cuckoo, respectively, $T_{80}^{i}(\mathbf{x})$ is electromagnetic torque at the speed equal to 0.8 of synchronous speed [36], η_0, $\cos_0 \varphi$ and T_{80_0} are average values of efficiency, power factor and electromagnetic torque calculated as average values from several initial cuckoo populations, and α and β are the weighting coefficients.

The α and β coefficients were determined on the basis of the first three iterations of the optimization algorithm for random positions of the cuckoo. Both coefficients were chosen using a Microsoft Excel spreadsheet (64-bit version). The weighting factor for steady state parameters was selected to obtain a product (power factor and efficiency) greater than 75 for the first three iterations of the optimization algorithm. Moreover, the beta factor was chosen to guarantee T_{80_0} bigger than 12 Nm.

The optimization procedure was run 8 times for random initial cuckoo populations. The number of cuckoos in the population was $N = 30$, the probability was $p_a = 0.1$ and the maximum number of iterations was $k_{\max} = 20$. The weighting coefficients of the objective functions were assumed as $\alpha = 2$ and $\beta = (2/3)$. The average values of functional parameters (η_0, $\cos\varphi_0$ and T_{80_0}) were calculated as an average from 10 runs of the optimization software for the random positions of cuckoo in the initial population. During optimization calculation, the following values of these parameters were adopted: $\eta_0 = 86.63$, $\cos\varphi_0 = 0.852$ and $T_{80\_0} = 14.49$. The results of computation in the selected iterations are listed in Table 5.

Table 5
Results of LSPMSM optimization

k	r	l	g	O_1	O_2	$\eta(\mathbf{x})$	$\cos\varphi(\mathbf{x})$	$T_{80}(x)$
	[mm]	[mm]	[mm]	[mm]	[mm]	[%]	[–]	[Nm]
1	3.98	20.17	2.87	16.8	16.66	89.57	0.863	13.83
3	3.35	25.79	2.70	18.7	8.13	89.89	0.880	15.76
5	3.93	21.23	2.75	16.6	12.10	91.08	0.894	16.53
8	3.55	37.85	3.48	18.6	14.08	92.12	0.981	15.64
10	3.93	21.82	2.66	16.6	17.10	91.06	0.925	17.76
11	3.93	21.54	2.88	16.5	16.86	90.63	0.934	17.62
12	3.93	21.28	2.93	16.6	17.10	90.10	0.952	17.54
13	3.93	21.23	2.95	16.6	17.10	90.08	0.954	17.53
15	3.93	21.23	2.95	16.6	17.10	90.08	0.954	17.53
20	3.93	21.23	2.95	16.6	17.10	90.08	0.954	17.53

It can be noted that the optimal solution was obtained after the 13-th iteration of the optimization process. The optimal solution of the optimization process depends on the values of weighting coefficients (α and β) and also on the mean values of functional parameters in the initiation procedure (η_0, and T_{80_0}) [37]. The obtained results of the calculations show that the power factor and the value of electromagnetic torque at 80% of synchronous speed are opposite criteria [38]. They also point out that regardless of the iteration parameters r, O_1 and O_2 do not change.

Next, the start-up process was computed for the optimal structure of LSPMSM obtained from optimization. The load torque was equal to 0.5 rated torque. The velocity waveform during the start-up process is presented in Fig. 4.

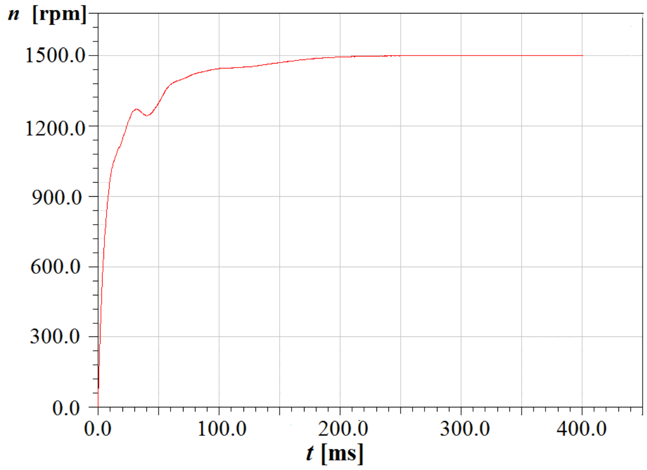

Fig. 4. Velocity waveform for optimized motor

Next, the impact of the load torque on the motor electromagnetic (functional) parameters, such as the line current and motor efficiency, was analyzed. The calculation for the optimal values of design variables has been executed with the use of Maxwell. The 2D FEA has been employed to compute the value of efficiency and line current. The optimized LSPMSM has rated power $P_N = 4$ kW. The value of rated electromagnetic torque is about 25.5 Nm.

Figure 5 illustrates the efficiency characteristic for an optimal solution (LSPMSM) as a function of electromagnetic torque.

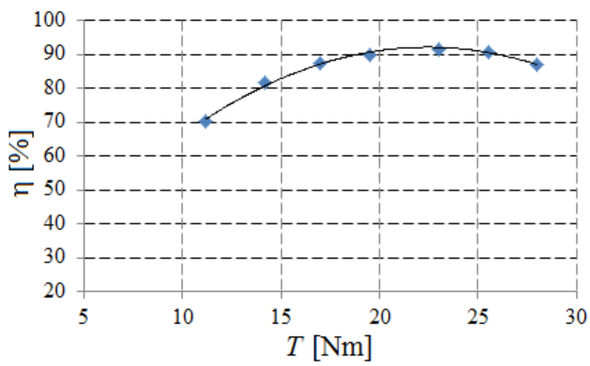

Fig. 5. Characteristic of $\eta = f(T)$ for optimal LSPMSM

The efficiency characteristic in the function of electromagnetic torque is similar to that of the classical induction motor. The maximum value of the efficiency is obtained for load torque smaller than the rated torque.

The characteristic of line current as a function of output torque for the optimal solution is presented in Fig. 6.

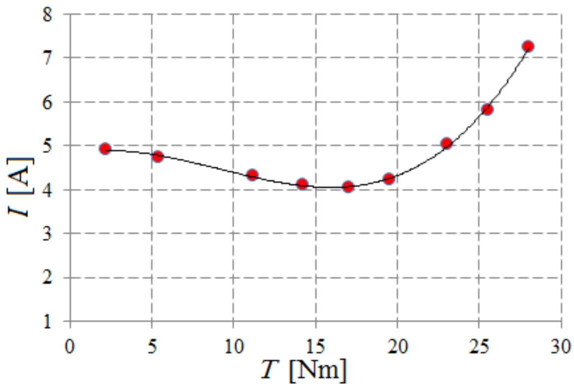

Fig. 6. Characteristic of $I = f(T)$ for optimal LSPMSM

Next, the characteristic of the power factor as a function of electromagnetic torque for the optimal solution was determined. The chart of $\cos\varphi = f(T)$ is presented in Fig. 7.

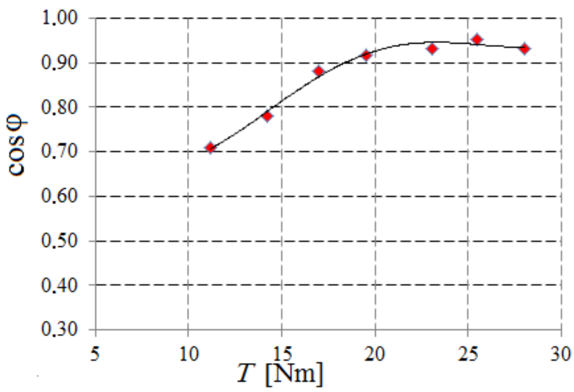

Fig. 7. Characteristic of $\cos\varphi = f(T)$ for optimal LSPMSM

In the case of the line current, a shape similar to V-curve can be observed. The better values of efficiency and the power factor in the optimized LSPMSM decrease the line current for the same loading torque. This phenomenon was described in detail in [39].

5. CONCLUSIONS

The computer software supporting the process of optimal designing of the LSPMSM was developed. A proposed hybrid optimization procedure was employed in the optimization module. The hybrid procedure is a combination of (a) a heuristic (cuckoo search) algorithm, and (b) a deterministic (Hooke–Jeeves) method.

The optimization algorithm developed has better accuracy in comparison with the classical CS algorithm. Moreover, it allows for determining solutions with better quality. The results obtained show that the algorithm developed is characterized by better values of mean and standard deviation. Also, the hybrid CS procedure allows to achieve a better convergence curve for the selected test function.

The proposed hybrid CS algorithm showed high precision during searching for a global extremum in the Himmelblau function. The present results of comparative calculations for selective optimization algorithms (HCS, GA, PSO and BA) proved that the developed algorithm as good convergence and reliability and can be successfully applied for the optimal design of electromagnetic devices.

The main disadvantage of the hybrid CS algorithm is the large number of calls of the objective function. A single call of the objective function consists in determining the distribution of the electromagnetic field distribution and calculating all components of the objective function. Therefore, the algorithm should be used for the optimization of electromagnetic devices described by simplified models, i.e. models with lumped parameters.

On the other hand, the proposed hybrid CS algorithm can provide acceptable results faster (see convergence curve in Fig. 2). Obtaining a result close to the optimal one after executing a smaller number of iterations in the case of time-consuming field models describing phenomena in an optimized motor allows for significant reduction of the total computation time. If a more accurate optimal solution is needed, it is possible to perform the optimization process on a reduced range of decision variables near to optimal point from the previous optimization process.

ACKNOWLEDGEMENTS

This research was funded by the National Science Centre – NCN (Poland), under the MINIATURA 3 program, grant number: 2019/03/X/ST7/01004.

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