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Swarm Intelligence Algorithms in Function of Efficiency Optimisation of PM Synchronous Motor

***Abstract**. This paper presents a novel approach to the efficiency improvement of permanent magnet synchronous motor using several swarm intelligence algorithms (particle swarm optimisation, cuckoo search, grey wolf algorithm and dragonfly optimisation algorithm) as an optimisation tool. The idea is to implement those novel optimisation algorithms for the efficiency improvement of permanent magnet synchronous motor, where the objective function in the optimisation process is the efficiency of the investigated motor. Comparative optimisation analysis results are given.*

***Streszczenie.** W artykule przedstawiono nowatorskie podejście do poprawy wydajności silnika synchronicznego z magnesami trwałymi przy użyciu kilku algorytmów inteligencji roju (optymalizacja roju cząstek, wyszukiwanie kukułki, algorytm szarego wilka i algorytm optymalizacji ważki) jako narzędzia optymalizacyjnego. Ideą jest wdrożenie tych nowatorskich algorytmów optymalizacyjnych do poprawy sprawności silnika synchronicznego z magnesami trwałymi, gdzie funkcją celu w procesie optymalizacji jest sprawność badanego silnika. Podano wyniki porównawczej analizy optymalizacyjnej. (**Algorytmy inteligencji roju w funkcji optymalizacji wydajności silnika synchronicznego PM**)*

Keywords: swarm intelligence algorithms, cuckoo search, grey wolf algorithm, dragonfly optimisation algorithm.
Słowa kluczowe: algorytmy inteligencji roju, wyszukiwanie z kukułką, algorytm szarego wilka, algorytm optymalizacji ważki.

Introduction

The electric motor is the device that transforms electrical energy into mechanical energy. Nowadays, electric motors are the cause of a considerable share of the use of electricity and therefore of the energy consumptions (70% in the industrial sector and 25-30% in the tertiary sector). Faced with ever-increasing energy demand and the overall strategy to reduce energy consumption in all the involved sectors, the use of efficiency enhanced electric motors is required. Generally, the efficiency of an electric motor depends on the type of motor, its size, the utilization factor, but also on the quality and quantity of the materials employed. In order all of this to be integrated into one energy efficient solution a good and reliable optimal design procedure is needed. To achieve this goal in the past three or four decades a variety of optimization methods have been used as tools for optimal design of power devices. Following this trend, a variety of optimization methods are used today for optimal design of electrical machines.

In general, the optimization methods can be divided into two groups: deterministic and stochastic methods. Deterministic methods are optimization methods that mostly relay on the variation and values of the optimization parameters. The quality of the solution depends on the definition of the starting point that is user dependent. Some of the deterministic methods need a determination of the gradient of the objective function. The term stochastic methods generally refer to the use of randomness in the optimization algorithm performance. They are challenging optimization algorithms that can be very successfully applied in high-dimensional nonlinear objective problems, problems that contain multiple local optima in which deterministic optimization algorithms may get stuck in a local optimum. Stochastic optimization algorithms provide an alternative approach that permits less optimal local decisions to be made within the search procedure that may increase the probability of the procedure locating the global optima of the objective function. They can be also divided in two general groups of methods such as: direct search methods and nature inspired algorithms. The nature inspired method are divided in the following groups: evolutionary algorithms, swarm intelligence algorithms, human based algorithms and physics-chemistry based algorithms, as presented in Fig. 1. In this paper the application of swarm intelligence algorithms in the optimal design of a permanent magnet synchronous motor is presented and analysed. A graphical presentation of some of those methods is shown in Fig. 2. From the presented swarm intelligence algorithms, the following methods have been selected for the research work in this paper: Particle Swarm Optimization Algorithm (PSOA), Cuckoo Search Algorithm (CSA), Grey Wolf Algorithm (GWA) and Dragonfly Algorithm (DFA). In the following text a brief introduction to the above mentioned algorithms is presented.

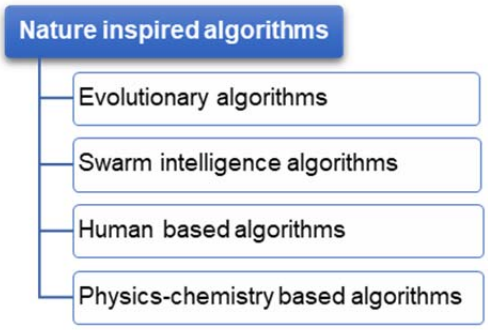


Fig.1. Nature inspired algorithms

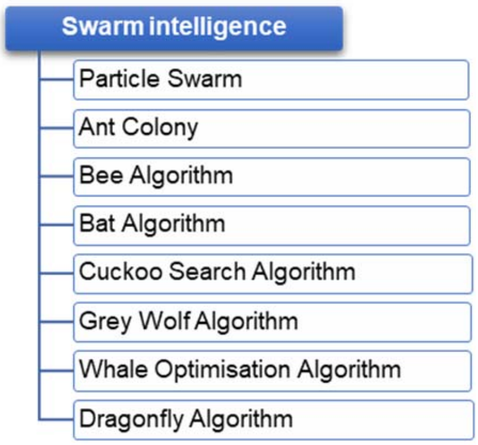


Fig.2. Swarm intelligence algorithms

2 Swarm Intelligence Algorithms

In the past two or three decades the stochastic optimisation methods have been successfully used in optimisation and optimal design of various power devices.

The use of randomness in the algorithms often means that the techniques are referred to as “heuristic search” as they use a rough rule-of-thumb procedure that may or may not work to find the optima instead of a precise procedure. Many stochastic algorithms are inspired by a biological or natural process and may be referred to as “metaheuristics” as a higher-order procedure providing the conditions for a specific search of the objective function. They are also referred to as “black box” optimization algorithms. There are many stochastic optimization algorithms and their number has reached over 150 and is rising day by day.

The stochastic nature of the procedure means that any single run of an algorithm will be different, given a different source of randomness used by the algorithm and, in turn, different starting points for the search and decisions made during the search. The pseudorandom number generator used as the source of randomness can be seeded to ensure the same sequence of random numbers is provided each run of the algorithm. This is good for small demonstrations and tutorials, although it is fragile as it is working against the inherent randomness of the algorithm. Instead, a given algorithm can be executed many times to control for the randomness of the procedure. This idea of multiple runs of the algorithm can be used in two key situations: comparing algorithms and evaluating final result. Algorithms may be compared based on the relative quality of the result found, the number of function evaluations performed, or some combination or derivation of these considerations. The result of any one run will depend upon the randomness used by the algorithm and alone cannot meaningfully represent the capability of the algorithm. Instead, a strategy of repeated evaluation should be used.

Here are some examples of stochastic optimization algorithms [1,2]: Iterated Local Search, Stochastic Hill Climbing, Stochastic Gradient Descent, Tabu Search, Greedy Randomized Adaptive Search Procedure. In the following text some examples of stochastic optimization algorithms that are inspired by biological or physical processes include: Simulated Annealing, Evolution Strategies, Genetic Algorithm, Differential Evolution, Particle Swarm Optimization etc. As mentioned previously those methods can be grouped in four groups:

- Evolutionary algorithms, (Genetic algorithms, Evolutionary strategies, Differential evolution, etc.)
- Swarm intelligence algorithms, (Particle swarm, Cuckoo search, Grey wolf, Dragonfly, Ant colony, etc.)
- Human based algorithms (Harmony search, Cooperative search, Cultural evolution, etc.)
- Physics-chemistry based algorithms (Simulated annealing, Gravitational search, Artificial chemical process, Multi-verse optimizer, etc.).

The aim of this research work is to implement four different particle swarm optimisation algorithms in the optimal design of permanent magnet synchronous motor. Therefore, a brief presentation of the investigated algorithms (Particle swarm optimisation, Cuckoo search, Grey wolf and Dragonfly) is presented in the text below.

2.1 Particle Swarm Optimization Algorithm

Particle Swarm Optimization algorithm (PSOA) is a swarm intelligence algorithm that is based on the analogy of swarm of bird and school of fish [3]. PSOA mimics the behaviour of individuals in a swarm to maximize the survival of the species. In PSO, each individual makes his decision using his own experience together with other individuals’ experiences. The algorithm, which is based on metaphor of social interaction, searches a selected space by adjusting the trajectories of moving points in a multi-dimensional space. The individual particles are drawn stochastically toward the position of present velocity of each individual, their own previous best performance, and the best previous performance of their neighbours.

2.2 Cuckoo Search Algorithm

Cuckoo search algorithm (CSA) is inspired by the egg-laying and parasitic behaviour of the Cuckoo bird [4]. The adult birds lay their eggs in other birds’ nests. They choose nests where the host bird just laid its eggs. The optimization algorithm follows three main hypotheses. The first is that each adult bird lays only one egg each time. The second is that the adult Cuckoo bird puts its eggs in randomly chosen nest and the best found nest is saved for the next generation. The last hypothesis is that the host bird can discover the strange egg with a probability $p_d \in [0, 1]$. It is known that animals search for food follows a random or at least a quasi-random pattern in nature. The foraging path can be seen as a random walk as it is affected by the current location and the transition probabilities to neighbouring locations. For Cuckoo, and many birds and insects, this random walk has characteristics of a Levy flight where the step sizes are evaluated according to a heavy-tailed probability distribution.

2.3 Grey Wolf Algorithm

Grey wolf algorithm (GWA) is a relatively new metaheuristic algorithm developed in 2014 [5]. It is a population-based stochastic algorithm for finding the optimal result from the solution set (population). GWO algorithm is inspired from grey wolves that belong to Canidae family which simulates the behaviour of leadership quality and the social hunting mechanism of grey wolves in three steps as tracking, encircling and attacking. There are particularly four types of grey wolves namely alpha (α), beta (β), delta (δ) and omega (ω) having a strict social dominant hierarchy.

2.4 Dragonfly Algorithm

The main inspiration of the Dragonfly algorithm (DFA) [6] originates from the dragonflies that are considered as small predators that hunt almost all other small insects in nature. The interesting fact about dragonflies is their unique and rare swarming behaviour. Dragonflies swarm for only two purposes: hunting and migration. The former is called static (feeding) swarm, and the latter is called dynamic (migratory) swarm. The two essential phases of optimization, exploration and exploitation, are designed by modelling the social interaction of dragonflies in navigating, searching for foods, and avoiding enemies when swarming both ways.

All the previously presented optimization algorithms in the work that follows are implemented in the optimisation procedure for efficiency improvement of the investigated permanent magnet synchronous motor and the optimization results are presented and compared.

3 Efficiency Improvement Results Using PSOA, CSA, GWA and DFA

The efficiency of the motor is selected as an objective function in the efficiency improvement of the permanent magnet motor. The investigated object in this work is a brushless three-phase permanent magnet synchronous motor (PMSM) that has a laminated stator with 36 slots and a rotor with 6-skewed $SmCo_5$ surface-mounted permanent magnets with Br = 0.95 T. The rated data of the motor are: I=18 A, T=10 Nm and n=1,000 rpm at frequency of 50 Hz.

The following motor parameters have been selected as optimisation parameters in the optimization procedure realised with the different swarm intelligence algorithms: outside radius of the rotor iron core R_{ro}, permanent magnet fraction f_m, permanent magnet radial height h_m, air-gap g, and axial active length of the motor L. The presentation of the optimized motor and the optimization parameters are presented in Fig. 3.

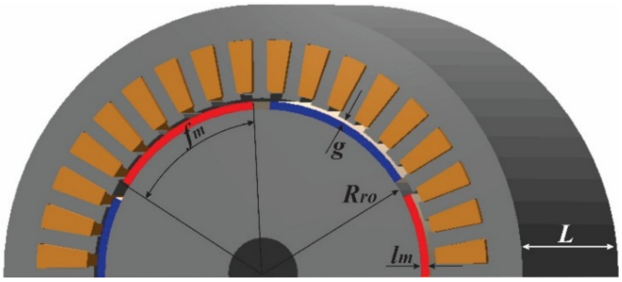


Fig.3. Presentation of the PMSM and its optimization parameters

The efficiency of the motor used for the optimisation in general can be defined with the following equation:

$$Efficiency(R_{ro}, f_m, h_m, g, L) = \frac{T \cdot \omega_m}{T \cdot \omega_m + P_{Cu} + P_{Fe} + P_{wf}} \tag{1}$$

where: T–rated torque, ω_m –rated speed, P_{Cu} – ohmic power loss, P_{Fe} – iron core power loss and P_{wf} – windage and friction power losses. In motor for the efficiency improvement each of the Power losses are properly defined in the mathematical model [7] of the motor in which all the losses are defined in relation to the optimization parameters. The same mathematical model and objective function is applied in all the swarm optimization algorithms, such as: PSO, CSA, GWA and DFA. In the case of the PSOA the objective function is defined to be the function of the efficiency of the motor, while in the case of CSA, GWA and DFA the objective function is defined as an inverse value of the efficiency, because those three optimization methods are defined as minimization methods. In such case the minimization of the objective function maximizes the efficiency of the motor.

In order to get a feasible solution each optimization parameter is defined in its upper and lower bounds. There values as well as the values for the initial solution are shown in Table 1.

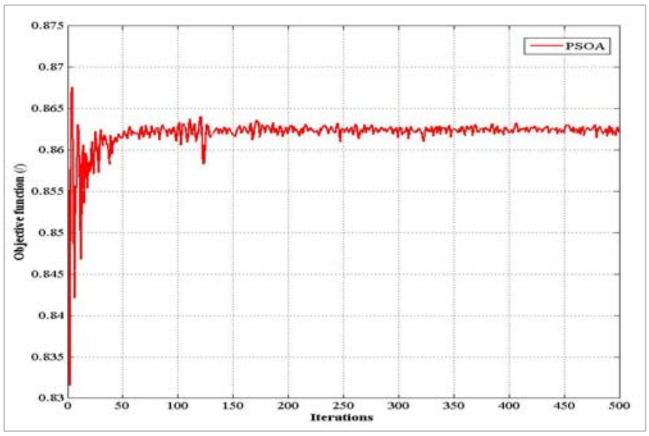
Table 1. Optimization parameters and their boundaries

Variables	Lower boundary	Upper Boundary	Initial model
R_{ro} (m)	0.03798	0.4642	0.042
g (m)	0.00072	0.00088	0.0008
f_m (/)	0.81	0.99	0.90
h_m (m)	0.0018	0.0022	0.002
L (m)	0.081	0.099	0.09
Efficiency	-	-	0.8489

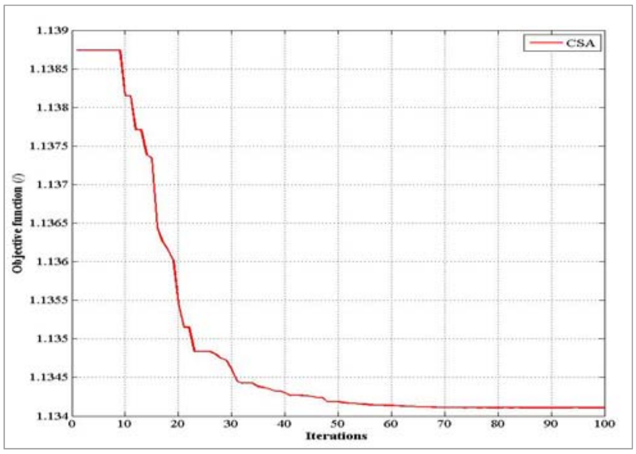
The optimisation process, due to the stochastic nature is realised for a large number of runs for all algorithms. A presentation of the objective function value change during the iterations for the best search for the analysed algorithms is presented in Fig. 4.

The results of the optimisation procedure realised with the investigated optimisation algorithms are presented in Table 2. The presented data includes the values for each optimization parameter, the value of the objective function as well as the value of the efficiency of the motor for each search best solution.

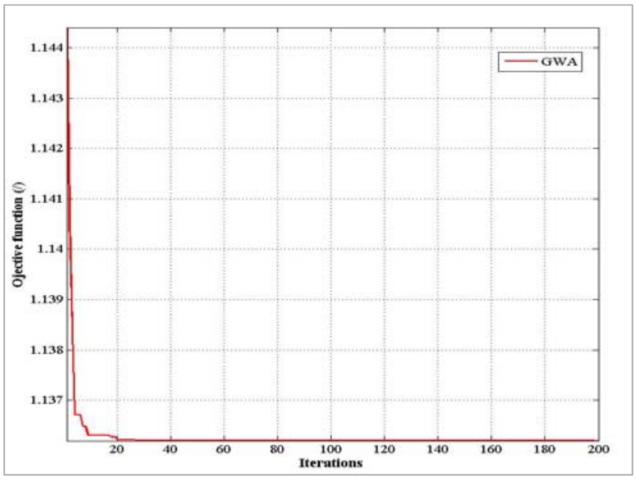
For further solution analysis additional motor parameters and quantities are presented in Fig. 5 and Fig. 6. The presented parameters and their values are: N – number of turns per phase of the stator winding, B_g – air gap flux density, R_{ph} – stator winding phase resistance, P_{Cu} – stator winding copper power losses, P_{Fest} – stator core iron power losses, m_{Cu} – total mass of the stator winding, m_{FeS} – total mass of stator iron core, m_{FeR} – total mass of rotor iron core, and m_{PM} – total mass of permanent magnets.



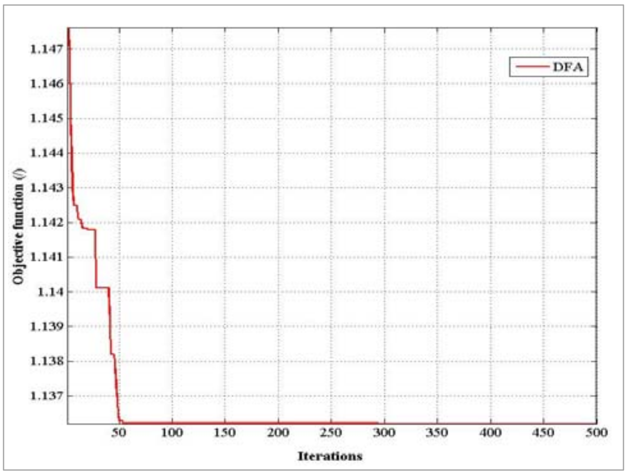
a) Particle swarm optimization algorithm



b) Cuckoo search algorithm



c) Grey wolf algorithm



d) Dragonfly algorithm

Fig. 4. Objective function value change during iterations

Table 2. Optimization results using different optimisation methods

Optimization parameters	Initial motor	PSOA	CSA	GWA	DFA
R_{ro} (m)	0.042	0.0412	0.0378	0.03798	0.03798
f_m (/)	0.9	0.82	0.9143	0.90705	0.9070
h_m (m)	0.002	0.00195	0.0022	0.0021	0.0021
g (m)	0.0008	0.00072	0.00072	0.00076	0.00076
L (m)	0.09	0.09813	0.099	0.0945	0.0945
Objective function (/)	-	0.8676	1.13624	1.1362	1.1362
Efficiency	0.8489	0.8676	0.8801	0.88013	0.88013

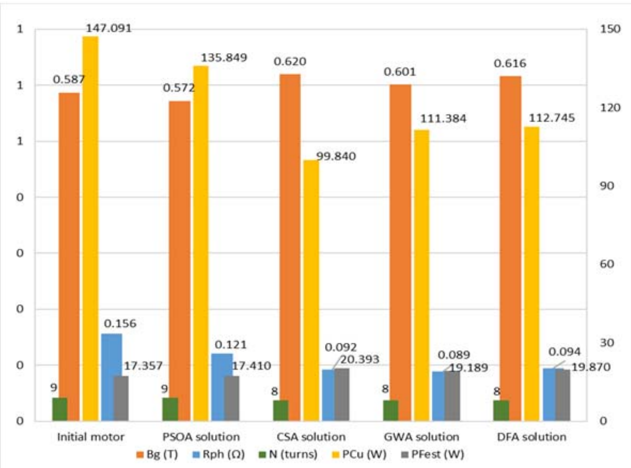


Fig. 5. Comparative analysis of motor parameters – part one

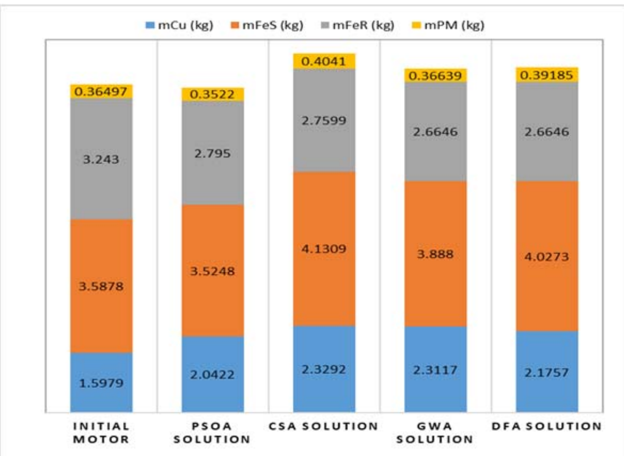


Fig. 6. Comparative analysis of motor parameters – part two

Based on the presented data in Table 2 and Table 3 and Fig. 5 it can be noticed that the GWA and DFA in their optimization process have reached the highest values of the objective function (0.88013), and CSA reached a value (0.8801) very close to the values of the previously mentioned algorithms. In this analysis the PSOA unfortunately reached the smallest value of the objective function (0.8676). Generally speaking, all investigated methods have reached a higher value of the motor efficiency in relation to the efficiency of the initial solution (0.8489). In relation the efficiency improvement of the presented solutions, the other motor parameters also face certain improvement as well.

4 Conclusion

In this paper the authors are giving a brief presentation, as well as implementation of different swarm-based optimization algorithms. Particle swarm optimization algorithm, cuckoo search algorithm, Frey wolf algorithm and Dragonfly algorithm are the investigated and implemented algorithms in the efficiency improvement of the permanent magnet synchronous motor. Selected results from the application of the four different optimization methods and a comparative analysis are presented. Finally, the several motor solutions in relation to the initial solution have been analysed based on the presented values and few solutions have been proposed.

Additionally, for a more detailed investigation a traditional finite element method analysis for the initial solution and a selected number of optimized solutions will be performed in other near future works.

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