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Optimization design of a doubly salient 8/6 SRM based on three computational intelligence methods

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Abstract: The aim of this paper is to optimize an 8/6 doubly salient switched reluctance machine using three computational intelligence methods, which include particle swarm optimization, a genetic algorithm, and differential evolution. Three cases are investigated where different parameters are considered like the stator pole arc, rotor pole arc, and ratios, which define the stator yoke and rotor thickness. The objective functions considered are the average torque and the torque-to-weight functions. The simulations are carried out using MATLAB and FEMM software. The optimal results found are compared with the initial design, and it is shown that high improvements are achieved.

Key words: Computational methods, design, optimization, switched reluctance machine

1. Introduction

To meet challenging requirements, the performance improvement of electrical machines is necessary, and this is a subject of much investigation by many research teams worldwide. Performance improvement concerns not only conventional asynchronous or synchronous machines, but also new machine structures, such as the switched reluctance machine (SRM), which is the main concern of this paper.

The robustness, reliability, performance, and cost of SRMs have enabled them to develop multiple applications (air conditioners, extractors, centrifugations, electrical vehicles, machine tools, flywheel energy storage, shipbuilding, aeronautics, wind generators, etc.) [1–4].

New designs, more efficient structures, and better adaptation to new requirements are the goals of manufacturers and researchers. To improve the performance of SRMs, this research will focus specifically on optimizing the geometric structure, control parameters, and material properties.

In [5], the authors used particle swarm optimization (PSO) to optimize the geometric parameters of an 8/6 SRM with two objective functions: to increase the average torque and to minimize the ripple. In [6], torque production is improved using a PSO algorithm to optimize the stator and rotor angles of an 8/6 SRM. In [7], the authors maximized the geometric parameters of a 6/4 SRM coupled to a compressor, using a genetic algorithm (GA) to increase the average torque. In [8], PSO was applied to the rotor pole arc of a 4/2 SRM to minimize the torque ripple. In [9], the augmented Lagrangian method was used to determine optimum magnetic circuit parameters to minimize torque ripple. In [10], high efficiency and low torque ripple were investigated using a genetic fuzzy algorithm.

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The aim of this work is to optimize the geometrical parameters of an 8/6 doubly salient switched reluctance machine (DSSRM) in order to maximize the average torque and torque-to-weight. This was performed using three computational intelligence (CI) methods: PSO, a GA, and differential evolution (DE).

The main contribution of this work is related to the following aspects: the high number of the studied geometrical parameters; their impact on the magnetic characteristics, i.e. the average torque and torque-to-weight; the comparative study of the three optimization algorithms, GA, PSO, and DE; and the hybrid simulation using FEMM [11] coupled to MATLAB software [12].

The paper is organized as follows. Section 2 describes the structure of the studied DSSRM prototype. Section 3 discusses the CI methods used in this paper. The results obtained are discussed in Section 4. A conclusion with a synthesis of the most significant results obtained in this work is drawn in Section 5.

2. Structure of the SRM to be optimized

2.1. The studied SRM structure

There are different topologies of SRMs according to the structure of the stator and rotor poles (large or small), their numbers, feeding mode, etc.

The choice of number of poles per stator, *Ns*, and rotor, *Nr*, is important since they have significant influence on the torque. The speed, N, is related to the frequency of the power supply ($f = Nr \times N/m$) according to the mode of supply: unidirectional ($m = 1$) or alternative ($m = 2$). It is preferred to have the ratio between stator and rotor poles as a noninteger. The most frequently used structures (*Ns/Nr*) are 6/4, 8/6, and 12/8 [13]. The number of phases frequently used, q, is 3 or 4.

In order to pursue our previous work on a type of machine and conduct a comparative study of other research, we opted for an 8/6 DSSRM, as depicted in Figure 1, with the parameters given in Tables 1 and 2 [14].

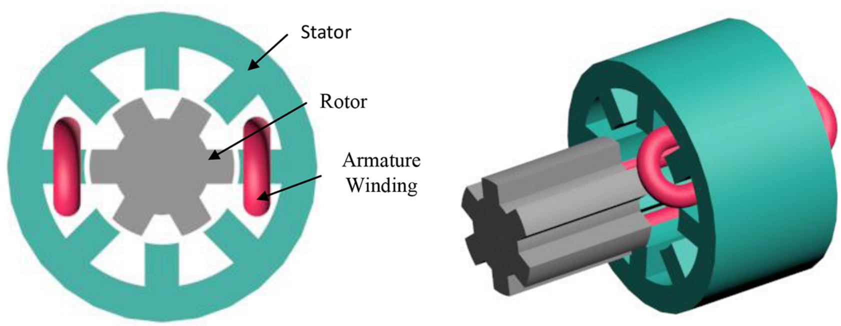

Figure 1. The investigated 8/6 DSSRM.

2.2. Selection of pole angles

The choice of stator pole arc and rotor arc pole βs and βr has significant effects on the torque ripple, duration of output torque, and winding space and is an important factor in motor design optimization. To start an optimization process, one can select pole angles in the middle of the lower half of the feasible triangle, where $\beta s \leq \beta \mathrm{r}$ (Figure 2).

Table 1. Parameters of the studied 8/6 DSSRM.

Parameter	Symbol	Value
Number of stator poles	Ns	8
Number of rotor poles	Nr	6
Number of phases	q	4
Air gap length	E	0.3 mm
Stack length	L	114 mm
Outer diameter	Do	190 mm
Rotor diameter	Dr	100 mm
Shaft diameter	Da	28 mm
Back iron thickness	b_{sy}	12.5 mm
Stator pole arc	βs	18°
Rotor pole arc	βr	22°

Table 2. Physical parameters of the studied 8/6 DSSRM.

Parameter	Value
Turns/phase n_s	144
Wire cross-section area	1 mm^2
Coil fill factor	0.7
Coil cross-section area	103 mm^2
Peak current	12 A
Voltage	500 V (1 p.u.)
Lamination material	M19 steel
Density of M19 ρ	7600 kg/m^3

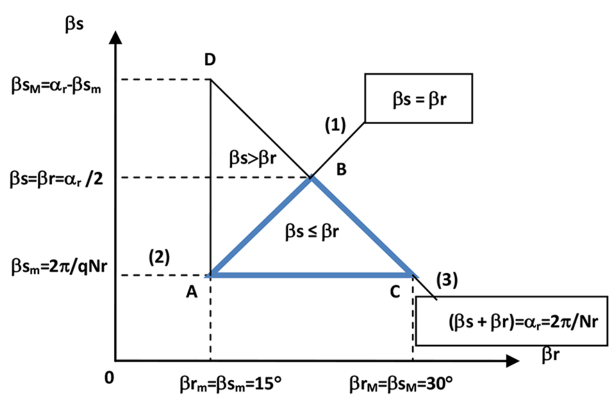

Figure 2. Feasible triangle of the studied 8/6 DSSRM.

2.3. Choice of back iron thickness

The expression of the stator pole width is given by:

$$\omega_{sp} = D_s \sin\left(\frac{\beta_s}{2}\right) \tag{1}$$

Due to mechanical and vibration considerations, the stator yoke thickness could have a value in the range of:

$$\omega_{sp} > b_{sy} \geq 0.5\, w_{sp} \tag{2}$$

With the ratio K_{cs}:

$$0.5 < K_{cs} = \frac{b_{sy}}{\omega_{sp}} \leq 1 \tag{3}$$

The rotor yoke thickness could have a value in the range of:

$$0.5\omega_{sp} < b_{ry} < 0.75\omega_{sp} \tag{4}$$

With the ratio K_{cr}:

$$0.5 < K_{cr} = \frac{b_{ry}}{\omega_{sp}} \leq 0.75 \tag{5}$$

3. Optimization of geometric parameters

3.1. Optimization process

The optimization problem can be formulated as follows:

$$\begin{array}{rl} \text{Minimize} & \mathrm{f}\,(\mathrm{x}) \\ \text{Subject to} & g\,(\mathrm{x}) = 0 \\ \text{and} & h\,(\mathrm{x}) \leq 0 \end{array} \tag{6}$$

Where:

x: vector of design variables;

f (x) : objective function;

g (x) : set of equality constraints;

h (x) : set of inequality constraints.

The imposed constraints are given by the following equation:

$$\begin{cases} \beta_s - \beta_r \leq 0 \\ P_{co} = Cte \\ x_{imin} \leq x_i \leq x_{iMax} \end{cases} \tag{7}$$

Finite element software FEMM was used because it offers the possibility of parameterizing the machine geometry and automating the computer-aided design drawing by means of a MATLAB script. Optimization PSO, GA, and DE codes were carried out with MATLAB coupled to FEMM, as shown in Figure 3. The function takes the geometrical parameters of the machine as input, builds the corresponding finite element method (FEM) model, and then computes the average static torque and the torque-to-weight.

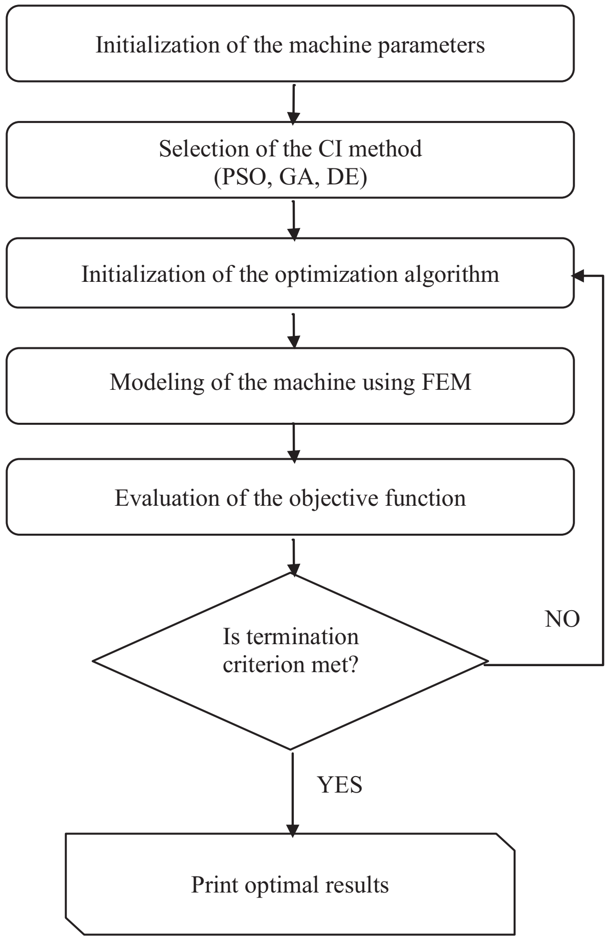

Figure 3. Flowchart of coupling software MATLAB–FEMM.

3.2. Objective functions

3.2.1. Average torque

As mentioned previously, the first objective is to maximize the average torque of the machine. The average torque is expressed as:

$$T_{av} = \frac{q\,N_r}{2\pi} W_c \tag{8}$$

where q is the number of phases, N_r is the number of rotor poles, and W_c is the converted coenergy.

The difference between coenergies at aligned and unaligned positions, as depicted in Figure 4, is expressed by Eq. (9):

$$W_c = W_{aligned} - W_{unaligned} = \Delta i \left(\varphi_1 + \varphi_2 + \ldots \frac{1}{2}\varphi_n \right) - \frac{1}{2}\varphi_u I_p \tag{9}$$

where W_c is calculated using n points on the magnetic flux versus mmf curve with the trapezoidal integration algorithm, and

$$\Delta i = \frac{I_p}{n} \tag{10}$$

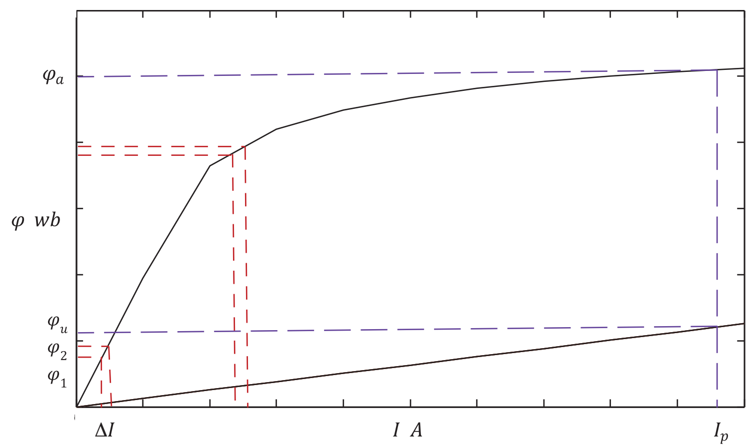

Figure 4. Aligned and unaligned magnetic flux vs. excitation.

3.2.2. Torque-to-weight

The second objective of this work is the maximization of the torque-to-weight. The torque-to-weight is expressed as:

$$T_{Wei} = \frac{T_{av}}{m} \tag{11}$$

and

$$m = \rho\, v \tag{12}$$

3.3. Optimization of computational intelligence methods

In this paper, three CI methods are used. These methods are explained in the following sections.

3.3.1. Particle swarm optimization

PSO is a population-based stochastic optimization method developed by Eberhart and Kennedy in 1995, inspired by the social behavior of bird flocking or fish schooling [15,16]. PSO starts with an initial randomly generated population, known as particles. Each particle has a particular position and velocity and keeps track of its coordinates in hyperspace. The coordinates are associated with the best solution (fitness) it has achieved at a certain point, called pbest, the overall best value, and its location, called gbest, obtained thus far by any particle in the population. Then, at each iteration, the velocity of each particle is updated toward pbest and gbest, and, consequently, the position of that particle is also updated.

3.3.2. Genetic algorithm

The GA was first used by Holland [17]. The GA is the most famous global optimization method and is based on Darwin's theory of evolution. The GA is a population-based method that starts with a randomly generated chromosome and then evolves to better solutions. The GA iteratively generates a new population based on the previous population through the application of genetic operations, which include selection, crossing, and mutation. The selection aims to select individuals from the population based on their fitness. The crossover operation combines the features of two parent chromosomes to generate two new offspring. The role of mutation is to introduce diversity to the population [18,19].

3.3.3. Differential evolution

DE was initially developed by Price and Storn in 1995 while trying to solve the Chebyshev polynomial fitting problem [20]. It stems from the genetic annealing algorithm, which was also developed by Price [21]. DE starts with an initial randomly generated population. Then this population evolves until the termination conditions are fulfilled. While the population is evolving, the three evolutionary operations, namely differential mutation, crossover, and selection, are executed in sequence [22].

4. Optimization results

The results obtained in this work were very satisfactory because the percentage of performance improvement was significant. This study allowed us to find the optimal values of the parameters that would optimize our objective function. In this work, three cases are investigated.

4.1. Case 1

In this case, the stator pole arc and rotor pole arc βs and βr are taken as design variables, and the objective function is the average torque T_{av}. The optimal results, found using PSO, GA, and DE, are given in Table 3. Figure 5 shows the T_{av} and the weight for the initial and optimized machine. It is worth mentioning that the optimal results improved the T_{av} by more than 30%. Furthermore, the GA and DE gave almost the same results, which were better than the ones found using PSO.

Table 3. Optimal results for CASE 1.

	Initial design	Optimal design		
		PSO	GA	DE
Generations size		50	50	50
Population size		20	20	50
Average torque [Nm]	14.168	18.87	19.56	19.47
Stator pole arc β_s°[15°–30°]	18	24.32	25	25.88
Rotor pole arc β_r°[15°–30°]	22	26.04	26.66	26.83
Weight [kg]	11.808	14.665	14.968	15.294

Figure 6 presents the evolution of the objective function during each iteration for the GA. Figure 7 shows the influence of the optimized values on the torque characteristics–rotor position. Figure 8 presents the characteristic of the phase inductance–rotor position. There is an increase in the maximum phase inductance unaligned position.

4.2. Case 2

In this case, the stator pole arc and rotor pole arc βs and βr are taken as design variables, whereas the objective function is the torque-to-weight T_{Wei}. The optimal results found for this case are given in Table 4, and the torque-to-weight and weight for the initial and optimized machine are shown in Figure 9. We can note that the T_{Wei} has been improved using PSO, GA, or DE compared to the initial design.

4.3. Case 3

In this case, the stator pole arc and rotor pole arc, βs and βr, and the ratios that define the stator yoke and rotor thicknesses, K_{cs} and K_{cr}, are taken as design variables, while the objective function is the torque-to-weight T_{Wei}.

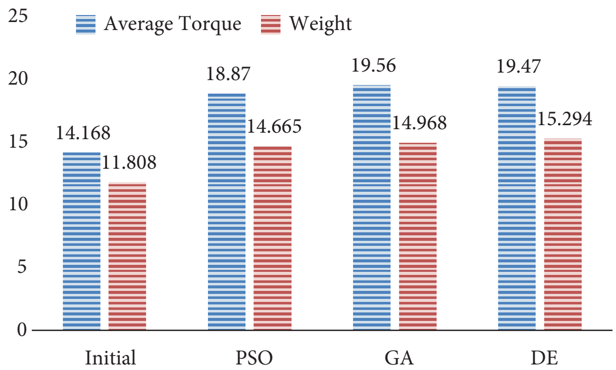

Figure 5. Average torque and weight for CASE 1.

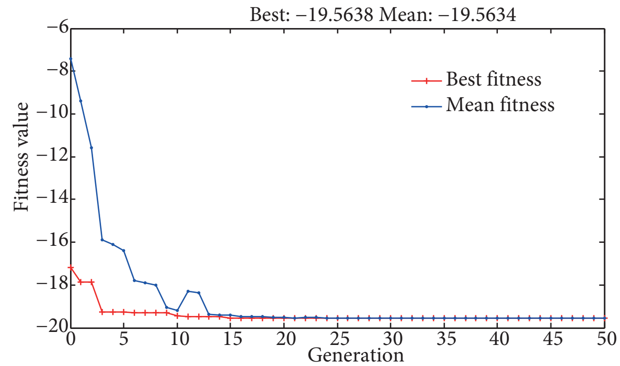

Figure 6. Evolution of the best and the mean fitness using GA for Case 1.

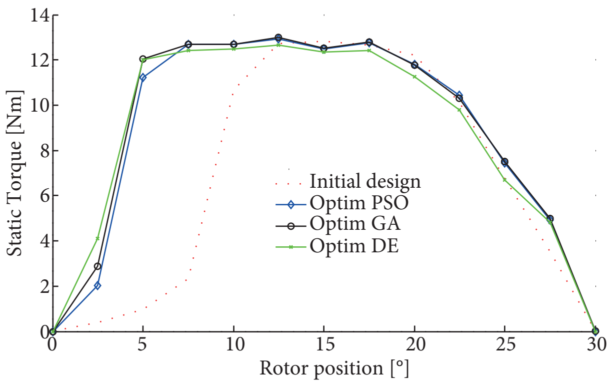

Figure 7. Static torque vs. position for initial and optimal designs.

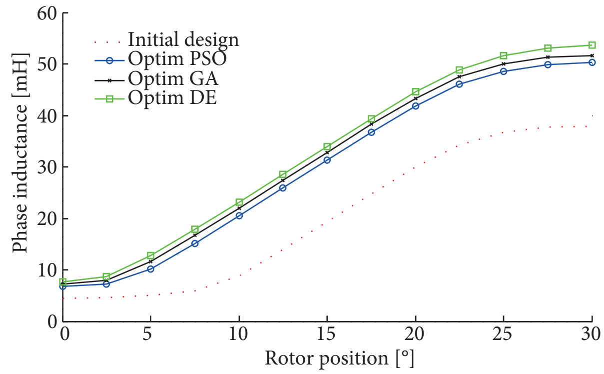

Figure 8. Phase inductance for initial and optimal designs.

Table 4. Optimal results for CASE 2.

	Initial design	Optimal design		
		PSO	GA	DE
Generations size		50	50	50
Population size		20	20	50
Torque-to-weight [Nm/kg]	1.199	1.231	1.239	1.287
Stator pole arc β_s° [15°–30°]	18	23.7	24.44	24.87
Rotor pole arc β_r° [15°–30°]	22	25.12	25.4	25.63
Weight [kg]	11.808	14.438	14.645	14.822
Average torque [Nm]	14.168	17.663	18.145	19.076

The average torque and the weight for the initial and optimized machine are shown in Figure 10. The plots of the static torque vs. rotor position shown in Figure 11, the plot of the inductance phases shown in Figure 12, and the magnetic flux vs. excitation for both aligned and unaligned positions shown in Figure 13 indicate an improvement of the electromagnetic characteristics of the initial structure with optimized parameters using PSO, GA, and DE. The results of the optimized parameters are given in Table 5.

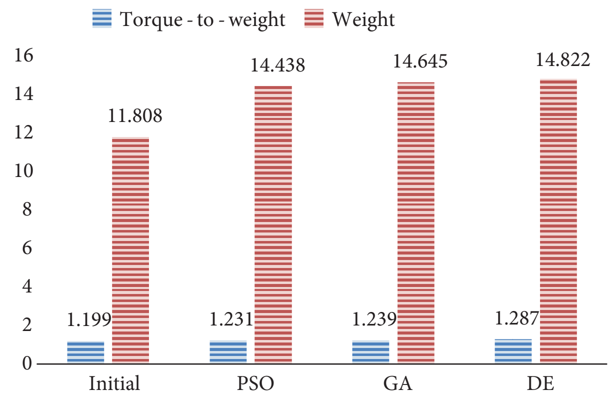

Figure 9. Torque-to-weight and weight for Case 2.

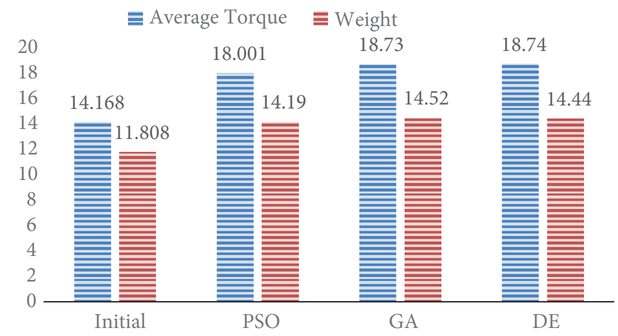

Figure 10. Average torque and weight for 8/6 SRM initial and optimal design for Case 3.

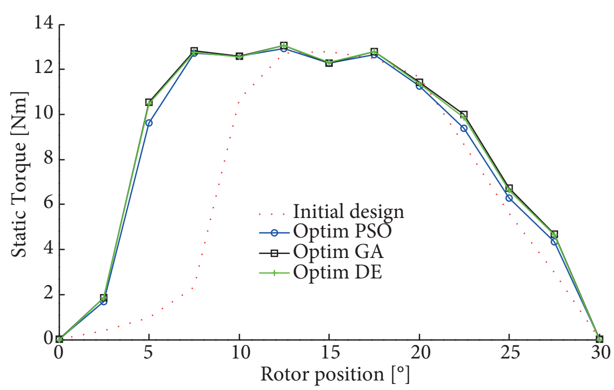

Figure 11. Static torque vs. position for initial and optimal design.

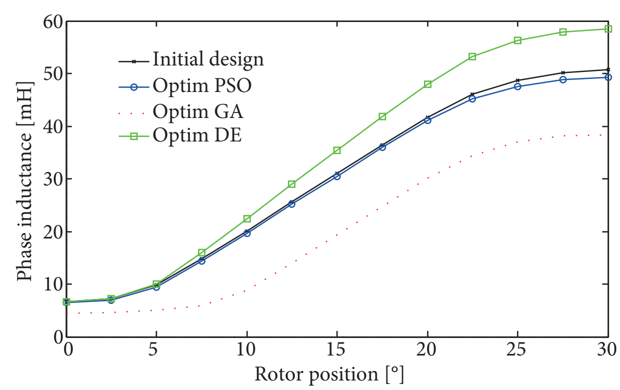

Figure 12. Phase inductance for initial and optimal design.

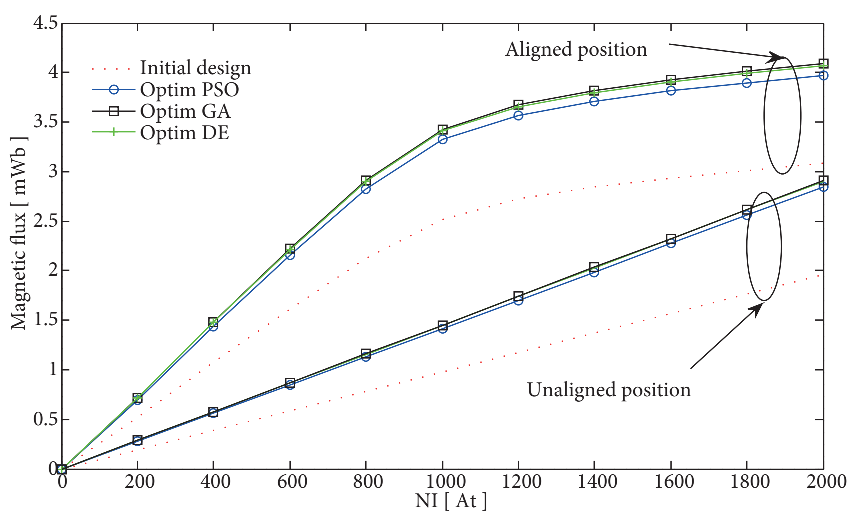

Figure 13. Magnetic flux vs. excitation for initial and optimal design.

Table 5. Optimal results for CASE 3.

	Initial design	Optimal design		
		PSO	GA	DE
Generations size		50	50	50
Population size		20	20	50
Torque-to-weight [Nm/kg]	1.199	1.268	1.29	1.298
Stator pole arc β_s° [15°–30°]	18	24.34	24.99	24.99
Rotor pole arc β_r° [15°–30°]	22	25.31	25.05	25.02
K_{cs} [0.25–0.6]	0.56	0.510	0.53	0.518
K_{cr} [0.25–0.75]	0.63	0.498	0.50	0.494
Weight [kg]	11.808	14.19	14.52	14.44
Average torque [Nm]	14.168	18.001	18.73	18.74

5. Conclusion

This paper discusses the results of a comparative study dealing with optimizing various geometrical parameters of an 8/6 SRM prototype based on three computational methods (GA, PSO, and DE). As the studied machine is strongly saturated, the finite element model has been used in a FEMM environment. The advantage of this free access software is that it offers the possibility to parameterize the SRM geometry and automate the computer-aided design drawing by means of a MATLAB script. A user-friendly program was implemented to couple FEMM to MATLAB.

The optimization process considers the objective function 'torque' with two main constraints to be related to the inequality of stator and rotor pole arcs ($\beta s < \beta r$) and constant copper losses. According to simulation results where the electromagnetic torque is deduced from the flux characteristics, we conclude that:

- Case 1: The optimization of the two pole arcs ($\beta s, \beta r$) improved the average torque by 39%, but with an increase in weight of 30% (not interesting case).
- Case 2: The optimization of the two pole arcs ($\beta s, \beta r$) improved the torque-to-weight by 7% (interesting case).
- Case 3: The optimization of four geometric parameters (two pole arcs and two yoke thicknesses) improved the torque-to-weight by 8% (very interesting case, because the increase in ratio is due to a decrease in weight, which results in a lower cost).

Work that studies the effects of geometric and control parameters on torque ripple is in progress.

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