Multi-objective Optimization Design of 8/6 Switched Reluctance Motor using GA and PSO Algorithms

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***Abstract** : In this work we tried to find the optimal values of the geometric parameters of a switched reluctance machine (SRM) such as the stator and rotor pole arc and ratios of the yoke thickness that satisfied two objectives functions: (i) minimizing the magnetic losses, (ii) and increasing the average torque. The weighting method was used to transform the multi-objective optimization into a single-objective problem. The approach using Particle Swarm Optimization (PSO) and Genetic Algorithms (GA) allowed finding the compromise surface of Pareto. The finite element analysis (FEA) was performed by coupling MATLAB with FEMM package software.*

Key words: *FEA, GA, multi-objective, optimization, PSO, switched reluctance motor (SRM).*

1. INTRODUCTION

The principle of switched reluctance machine (SRM) has long been known but its development has been manifested recently. Its advantages of robustness, reliability, and performance have enabled it multiple applications (air-conditioners, extractors, centrifugations, electrical vehicles, machines tools, flywheel energy storage, shipbuilding, aeronautics, wind generators...) [1-4].

New design and more efficient structures, and better adaption to the new requirements are the goal of manufacturers and researchers. To improve the performance of SRMs, the research shall focus in particular on optimizing geometric structure, control parameters, and material properties.

In this paper we will apply the multi-objective optimization which aims to improve the performance of a 8/6 SRM, to find the optimal parameters which meets two objectives: *(i)* the first one is to increase the average torque or torque to weight, *(ii)* and the second one is to minimize the magnetic losses. The geometric parameters to optimize are the stator and rotor poles arc β_s and β_r and the ratios K_{cs} and K_{cr} that defined the yoke thickness of stator and rotor [5].

The works which are is already made in the field of multi-objective optimization switched reluctance machine are numerous and different in the sense of improving the performance of these machines, the difference in this way is the choice of objective function, the algorithms and resolution method of a problem multi-objective optimization. In [6] the authors used the genetic algorithm for solving the problem in order to increase efficiency and minimize torque ripples. In [7] the authors studies the optimization of switching angles for two objective: increasing the average torque and minimizing torque ripple, they used the PQRSM algorithm calculation using the finite element method. In [8] the authors optimized three geometric parameters using the PSO optimization algorithm with SPEA method to get the Pareto front. In [9] the authors compared two methods to a 8/14 SRM aimed to optimized two objectives functions, increasing the average torque and minimizing torque ripples. In [10] the authors solved the optimization problem by using a differential evolution (DE) approach for three objective functions to increase the average torque, minimize copper losses and minimize torque ripple. In [11] the authors try to find a compromise between three objectives: increasing the average torque, maximizing the ratio average torque/copper losses, and maximizing the ratio average torque/volume. In [12] the authors applied an evolutionary methods NSGA and SPEA to increase the average torque and minimize torque ripples. In [13] the authors have designed a coupling of the finite element calculation method with an iterative method to solve the optimization problem with genetic algorithms in three steps. In [14] the authors used genetic algorithm coupled with finite element method to optimize the shape of a pole arc of a 8/6 SRM upon three criteria: increase the average torque, minimize the torque ripples and the copper losses. In [15] the authors present a design methodology for optimization based on a decomposition of the steps in the design process. In [16] the authors used the PSO algorithm to optimize the stator and rotor pole arc of a 8/6 SRM calculated analytically with the machine dimensions in order to increase the average torque and minimize torque ripples. In [17] the authors used a genetic algorithm to optimize the SRM design parameters, the calculation of variables was performed with the method of equivalent circuits; the optimization criteria are the improved efficiency and reduced torque ripples.

The aim of this work is to optimize numerous geometrical parameters of a doubly salient 8/6 SRM to improve the average torque under constraints and to reduce the core losses. The contribution of this work is on several levels:

- use of dimensionless parameters to be optimized

- FEA of the impact of these parameters on the electromagnetic characteristics using FEMM package software [18]
- coupling software FEMM to MATLAB multi-objective optimization based on PSO and GA algorithms under MATLAB environment.

2. STRUCTURE OF SRM TO OPTIMIZE

A. The studied SRM structure

There are different topologies of SRM according to the structure of stator and rotor poles (large or small), their numbers, the feeding mode... However, in order to pursue the work we have already done on another type of machine and to make a comparative study with other researchers, we opted for a doubly salient 8/6 SRM whose parameters are given in Table 1 and Table 2. [5]

The choice of number of poles of stator, *Ns*, and rotor, *Nr*, is important since they have significant implications on the torque. The speed, *N*, is related to the frequency of the power supply ($f=Nr*N/m$) according to the mode of supply, unidirectional ($m=1$) or alternative ($m=2$).

It is preferred to have a no integer ratio between stator and rotor poles. The most frequently ratios (*Ns/Nr*) are: 6/4, 8/6, and 12/8. The number of phases, *q*, frequently used is 3 or 4.
The flux and density plot by FEMM are depicted in Fig. 1.

Table 1
Parameters of the studied 8/6 SRM

Parameter	Symbol	Value
Number of stator poles	Ns	8
Number of rotor poles	Nr	6
Number of phases	q	4
Number of turns/phase	Nt	144
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	β_s	18 °
Rotor pole arc	β_r	22 °

Table 2
Physical parameters

Parameter	Value
Turns/phase	144
Wire cross section area	1 mm^2
Coil fill factor	0.7
Coil cross section area	103 mm^2
Peak current	12A
Voltage	500V (1 p.u.)
Lamination material	M19 steel

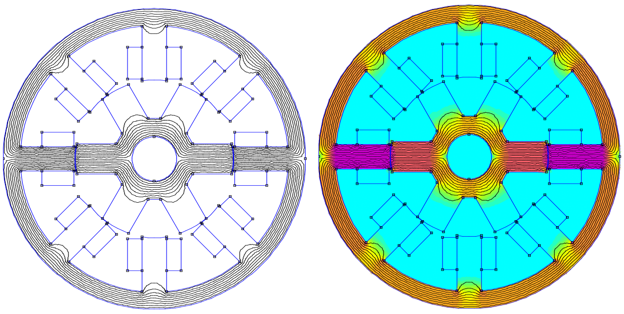

Fig. 1. Flux and density plot of the studied 8/6 SRM by FEMM.

For initial design, characteristics of static torque versus the rotor position, magnetic flux versus the excitation at aligned and unaligned positions, and phase inductance vs. rotor position at different level of excitations are represented in Fig. 2, Fig. 3 and Fig. 4 respectively.

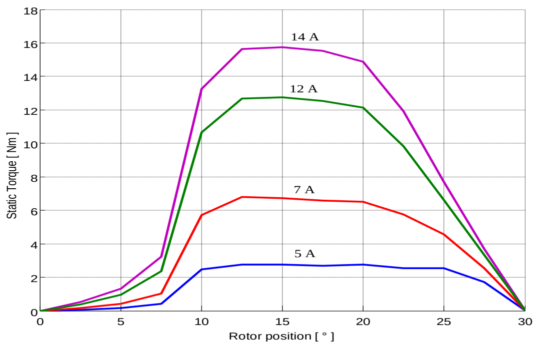

Fig. 2. Static torque vs. position for initial design.

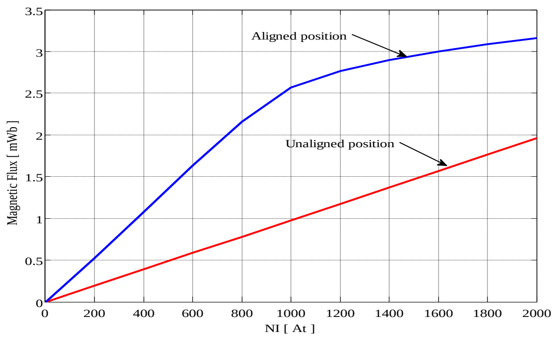

Fig. 3. Magnetic flux vs. excitation for initial design.

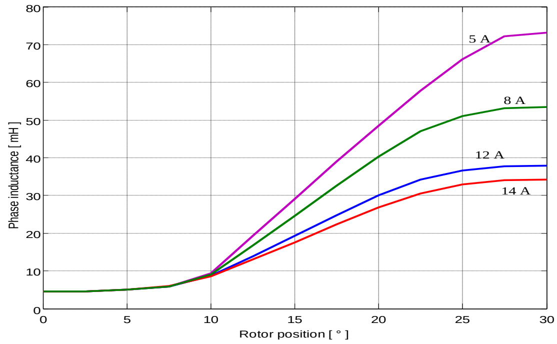

Fig. 4. Phase inductance for initial design.

B. The selection of poles angles

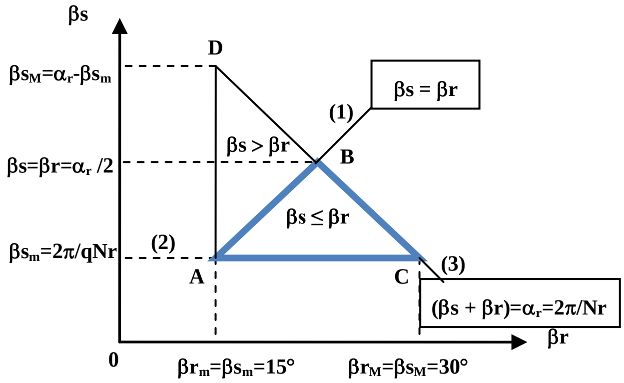

Fig. 5. Feasible triangle of the studied 8/6 SRM.

The choice of βs and βr has significant effects on the torque ripple, duration of output torque, winding space and is an important factor in motor design optimization.

To start an optimization process, one can select them in the middle of the lower half of the feasible triangle where $\beta s \leq \beta r$ (Fig. 5).

C. Choice of back iron thickness [5]

The expression of the stator pole width is

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

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

$$\omega_{sp} > b_{sy} \geq 0.5\, w_{sp} \quad (2)$$

With the ratio K_{cs}:

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

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

$$0.5\omega_{sp} < b_{ry} < 0.75\omega_{sp} \quad (4)$$

With the ratio K_{cr}:

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

3. Optimization of geometric parameters

A. Optimization process

The formulation of a multi-objective problem is written as follows:

$$\begin{cases} Minimise \;\; \vec{F}(\vec{X}) \\ under \;\; contraints: \\ \quad \vec{g}\,(\vec{X}) \leq 0 \\ and \quad \vec{h}\,(\vec{X}) = 0 \\ \vec{X} = \{x_1, \dots, x_n\} \end{cases} \quad (6)$$

$$\beta_s - \beta_r \leq 0; \quad P_{co} = Cte; x_{imin} \leq x_i \leq x_{iMax} \quad (7)$$

The vector $\vec{F}(\vec{X})$ includes several objective functions, the goal is to seek to minimize (or maximize) the objective functions that are often contradictory, as the minimization of an objective leads to an increase of another goal, so the solution we seek is always a compromise between these objectives [14]. There are several methods of solving a problem of multi-objective optimization; these methods allow us to select the best solutions.

The weighting method to solve a multi-objective optimization problem is most evident (Fig. 6). Moreover, this method is also called the "naive approach" of the multi-objective optimization. The goal here is to return to a mono-objective optimization problem, of which there are many methods of resolution. The easiest way process involves taking each of the objective functions, in applying a weighting and summing the weighted objective functions. This gives a new objective function [19].

The formulation of the problem returns a single-objective problem:

$$\begin{cases} Minimize \;\; F_{eq}(\vec{X}) = \sum_{i=1}^{k} W_i . F_i(\vec{X}) \\ \quad Under \; Contraints: \\ \quad \quad \vec{g}\,(\vec{X}) \leq 0 \\ \quad and \quad \vec{h}\,(\vec{X}) = 0 \\ \quad \vec{X} = \{x_1, \dots, x_n\} \end{cases} \quad (8)$$

With the coefficients

$$W_i \geq 0 \text{ and: } \sum_{i=1}^{k} W_i = 1 \quad (9)$$

This is an expression of the right in the F_1, F_2 plan. Indeed, if one tries to minimize $F_{eq}(\vec{X})$, it is necessary to determine the smallest constant C on the following linear equation:

$$F_2(\vec{X}) = -\frac{W_1}{W_2} . F_1(\vec{X}) + C \quad (10)$$

For several values of W_i we can plot the compromise surface Pareto as depicted in Fig. 7.

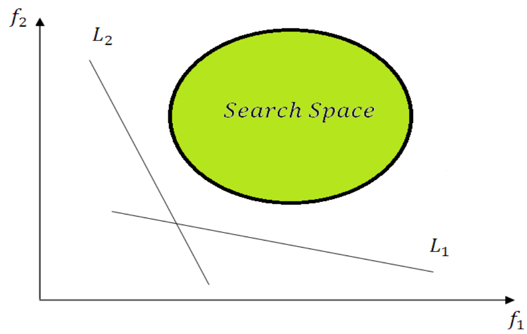

Fig. 6. Layout of weighting method.

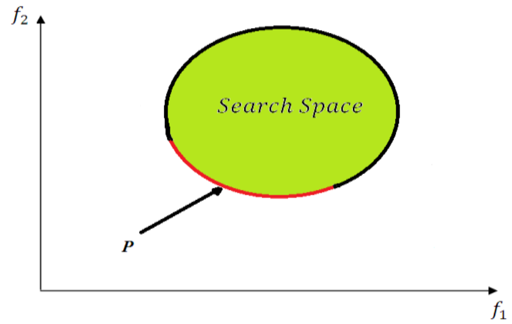

Fig. 7. Layout of compromise surface Pareto.

Finite-element modeling (FEM) of the machine was chosen because of its accuracy to model complex geometry and to take into account physical phenomena like saturation. The FEMM package software was used because it offers the possibility to parameterize the machine geometry and to automate the computer-aided design (CAD) drawing by means of a MATLAB script.

Optimization GA and PSO codes were carried out under MATLAB software coupled to FEMM as shown in Fig. 8. The function takes the geometrical parameters of the machine as input, builds the corresponding FEM model, and then computes the average static torque.

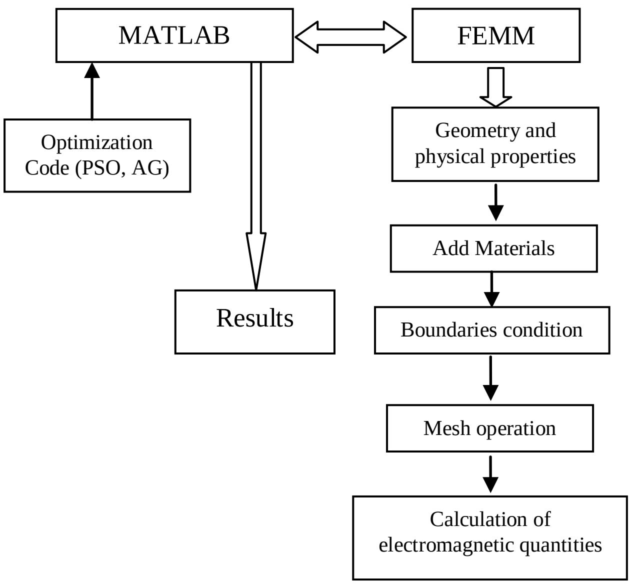

Fig. 8. Flowchart of coupling software MATLAB – FEMM.

B. Magnetic losses

The calculating the magnetic losses are calculated by the model proposed by Emanuel Hong [20]

$$P_{fer}\ (W/m^3) = (k_{h1}\Delta B + k_{h2}\Delta B^2)f + \alpha_P \frac{1}{T}\int_0^T \left(\frac{dB(t)}{dt}\right)^2 dt \quad (11)$$

The full suite $\frac{1}{T}\int_0^T \left(\frac{dB(t)}{dt}\right)^2 dt$ will be appointed F_2.

$$\alpha_p = \frac{e_p^2}{12\ \rho} \quad (12)$$

Before any calculations one must first determine two types of variables: *(i)* specific material coefficients $kh1, kh2$ and α_P, given by the manufacturer of the materials; *(ii)* the second variable is the density of flux which will be calculated by the finite element method using the FEMM software, iron losses depending on the maximum flux.

Table 3

Calculation of flux density, volume losses in four parts.

Part	ΔB	F	F_2	**Volume**
stator yoke	$\frac{\varphi_m}{E_c L_a}$	$N_r\ f_{rot}$	$\left(\frac{U}{2n_s E_c l_a}\right)^2$	$\pi(R_{ext} - (R_{ext} - E_c)^2)L_a$
stator teeth	$\frac{\varphi_m}{W_r L_a}$	$N_r\ f_{rot}$	$q\left(\frac{U}{n_s w_s l_a}\right)^2$	$N_s h_s\ W_s\ l_a$
rotor teeth	$2\frac{\varphi_m}{W_r L_a}$	$\frac{1}{2}N_s\ f_{rot}$	$q\left(\frac{N_s}{N_r}\right)\left(\frac{U}{n_s W_r l_a}\right)^2$	$N_r h_r\ W_r\ l_a$
rotor yoke	$\frac{\varphi_m}{E_{cr} L_a}$	$N_r\ f_{rot}$	$\left(\frac{U}{2n_s E_{cr} l_a}\right)^2$	$\pi((R_{axe} + E_{cr})^2 - {R_{axe}}^2)l_a$

C. Average Torque

The average torque is given by:

$$T_{moy} = \frac{q.N_r}{2\pi} W_c \quad (13)$$

where q is the number of phases, N_r is the number of rotor poles and Wc is the co-energy.

To compute the difference of co-energies at aligned and unaligned positions as depicted in Fig. 9 and expressed by (9) a comprehensive program is written in MATLAB coupling with FEMM.

$$\partial W_c = W_{caligned} - W_{cunaligned} = \Delta i\left(\varphi_1 + \varphi_2 + \ldots + \frac{1}{2}\varphi_n\right) - \frac{1}{2}\varphi_u \times I_p$$

(14)

is calculated using n points of the magnetic flux versus the mmf curve with the trapezoidal integration algorithm and

$$\Delta i = \frac{I_p}{n} \quad (15)$$

The expression of the average torque is given by

$$T_{moy} = \frac{q.N_r}{2\pi}\left(\Delta i\left(\varphi_1 + \varphi_2 + \ldots + \frac{1}{2}\varphi_n\right) - \frac{1}{2}\varphi_u \times I_p\right)$$

(16)

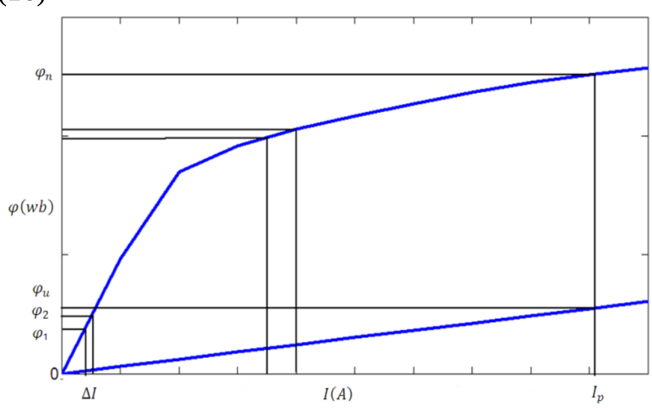

Fig. 9. Extremes magnetic characteristics flux vs. excitation mmf.

D. Genetic algorithm method

GA is a global optimization method based on genetic recombination and evolution in nature [21]. GAs use an approach that commonly involves starting with a random selection of design space points of M populations. The system is discretized into P parameters in a model vector m called a chromosome. Each parameter m_j, ($j = 1 \ldots P$) is called a gene in accordance with the natural terminology of the genetic theory. A gene is a binary encoding of a parameter given by:

$$m_j = m_j^{\min} + \frac{(m_j^{\max} - m_j^{\max})}{2^n - 1} \cdot \sum_{i=0}^{n-1} b_i 2^i \qquad (17)$$

The parameters m_j represent the design parameters. The set of values $b_1, b_2 \ldots b_{n-1}$ is the n-bit string of the binary representation of m_j, $m_j^{\min}$ and $m_j^{\max}$ are the minimum and maximum admissible values for m_j, respectively. Using a sufficient number of bits per parameter provides a fine-grained set of values.

The genes of these initial individuals are combined in meaningful ways to produce new solutions, and these are evaluated and ranked by an objective function value. Finally, the GA iteratively generates a new population, which is derived from the previous population through the application of the genetic operations which are: selection, crossing and mutation. The role of the selection is to select individuals in the population from their fitness. The crossover operation combines the features of two parent chromosomes to form two offsprings. The mutation implies small random changes to one or several of genes in a chromosome in order to promote variation and diversity in the population [22]. Selection, mutation and crossing each operation are controlled with probabilities P_s, P_m, and P_c respectively, that allow the algorithm to explore new regions of the problem space. The new population will contain increasingly better chromosomes (best individuals or parameters) and will eventually converge to an optimal population that consists of the optimal chromosomes.

E. Particle swarm optimization method

PSO is an evolutionary algorithm for the solution of optimization problems. It belongs to the field of Swarm Intelligence and Collective Intelligence and is a sub-field of Computational Intelligence. It was developed by Eberhart and Kennedy and inspired by social behavior of bird flocking or fish schooling [23]. Several modifications in the PSO algorithm had been done by various researchers [4]. PSO is simple in concept, as it has a few parameters only to be adjusted. It has found applications in various areas like constrained optimization problems, min-max problems, multi-objective optimization problems and many more [24].

The PSO method is regarded as a population-based method, where the population is referred to as a swarm [25]. The swarm consists of n individuals called particles, each of which represents a candidate solution [26]. Each particle i in the swarm holds the following information: *(i)* it occupies the position x_i, *(ii)* it moves with a velocity v_i, *(iii)* the best position, the one associated with the best fitness value the particle has achieved so far $pbest_i$, and *(iv)* the global best position, the one associated with the best fitness value found among all of the particles *gbest*.

Similarly to the GA, in our application, the positions of particles x_i represent the lengths of the branches L_i. The fitness of a particle is determined from its position. The fitness is defined in such a way that a particle closer to the solution has higher fitness value than a particle that is far away. In each iteration, velocities and positions of all particles are updated to persuade them to achieve better fitness according to the following equations:

$$v_{i,j}^{t+1} = wv_{i,j}^t + c_1 r_{1\,i,j}^t \left(Pbest_{i,j} - x_{i,j}^t\right) + c_2 r_{2\,i,j}^t \left(gbest_j^t - x_{i,j}^t\right) \qquad (18)$$

$$x_{i,j}^{t+1} = x_{i,j}^t + v_{i,j}^{t+1} \qquad ? \qquad (19)$$

for $j \in 1..d$ where d is the number of dimensions, $i \in 1..n$ where n is the number of particles, t is the iteration number, w is the inertia weight, $rand_1$ and $rand_2$ are two random numbers uniformly distributed in the range [0,1], and c_1 and c_2 the acceleration factors. c_1 is the cognitive acceleration constant. This component propels the particle towards the position where it had the highest fitness. c_2 is the social acceleration constant. This component steers the particle towards the particle that currently has the highest fitness.

In equation (14), the inertia weight w affects the contribution of v_{ij}^t to the new velocity v_{ij}^{t+1}. If w is large, it makes a large step in one iteration (exploring the search space), while if w is small, it makes a small step in one iteration, therefore tending to stay in a local region [27].

Typically, the velocity of a particle is bounded between properly chosen limits $v_{\min} < v_{id} < v_{\max}$ (in most cases $v_{\min} = -v_{\max}$). Likewise, the position of a particle is bounded as follows: $x_{\min} < x_{id} < x_{\max}$.

Afterwards, each particle updates its personal best position using the following equation:

$$pbest_i^{t+1} = \begin{cases} pbest_i^t & \text{if } f(pbest_i^t) \le f(x_i^{t+1}) \\ x_i^{t+1} & \text{if } f(pbest_i^t) > f(x_i^{t+1}) \end{cases} \qquad (20)$$

Finally, the global best of the swarm is updated using the following equation:

$$gbest^{t+1} = arg \ min \ f(pbest_i^{t+1}) \qquad (21)$$

where f is a function that evaluates the fitness value for a given position.

The PSO process is repeated iteratively until one of the following termination criteria occurs [28]: if the maximum number of iterations has been reached, an acceptable solution has been found or no improvement is observed over a number of iterations.

4. Optimization results

The results obtained in this work were very satisfactory because the percentage of performance improvement is very important. This study allows us to find the optimal values of the optimized parameters that satisfied our objectives functions, four parameters was optimized in this study stator pole angle, rotor pole angle β_s, β_r and ratios which define the stator yoke and rotor thicknesses K_{cs} and K_{cr}, This optimization was done in two cases, the first case is optimized for two objectives functions, the objective one is the magnetic losses and the objective two is the average torque, in the second case the objective one is the magnetic losses and the objective two is the Torque-to-weight.

In this work the weighting method was applied to solve our multi-objective problem with the use of GA and PSO optimization algorithms. The genetic algorithm GA was used to plot the surface compromise Pareto who includes the optimal solutions that satisfied the two objective functions. The PSO algorithm is used in a particular case with $W_1 = W_2$.

Case 1 : in this first case the objective one is the 'magnetic losses' and the objective two is the 'average torque'.

In this case the results were presented in tables and figures. Figure 10 shows the compromise area in the sense of Pareto front. Figure 11 represents the average distance between individuals over generations. Table 4 summarizes the optimal solutions of optimized parameters that satisfy the two objective functions: average torque and magnetic losses. Figure 12 shows the two objective functions for each point found by applying the optimization with the genetic algorithm. Table 5 summarizes the results obtained with application of the PSO algorithm for equal weights.

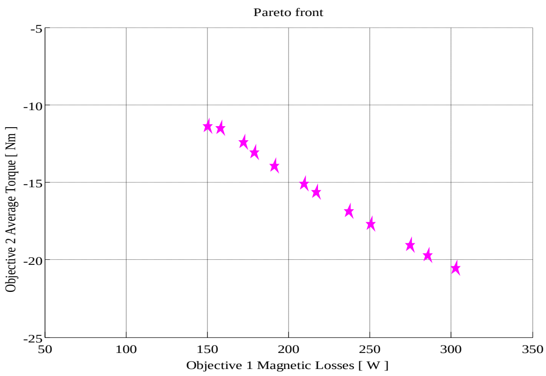

Fig. 10. Compromise surface Pareto using GA (case 1).

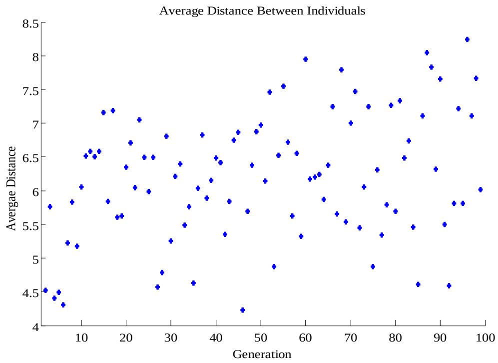

Fig. 11. Average distance between individuals (case 1).

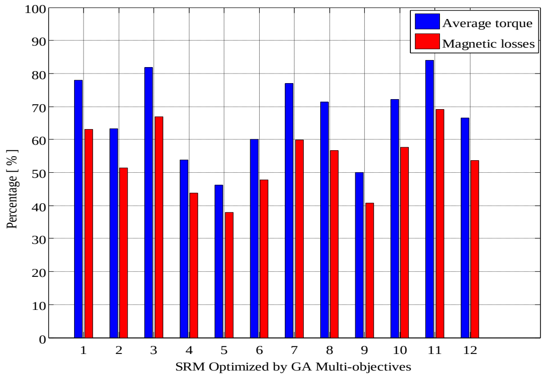

Fig. 12. Average Torque and magnetic losses for SRM optimal

Table 4
Optimal solutions by GA (case 1).

Index	F_1 [W]	F_2 [Nm]	β_s[°]	β_r [°]	K_{cs}	K_{cr}
1	234,145	18,911	23,801	28,133	0,896	0,723
2	189,718	15,428	19,102	27,255	0,907	0,744
3	245,439	20,093	25,902	27,746	0,884	0,731
4	161,417	13,134	17,255	26,560	0,512	0,744
5	138,764	11,387	15,059	25,352	0,501	0,747
6	180,191	14,340	17,801	25,946	0,804	0,747
7	231,040	17,954	23,015	27,446	0,603	0,734
8	213,993	16,976	22,290	26,551	0,521	0,743
9	149,710	12,206	16,102	25,564	0,503	0,744
10	216,590	17,322	21,636	27,193	0,897	0,728
11	252,137	20,751	27,062	28,306	0,901	0,722
12	199,781	16,084	20,158	27,765	0,907	0,730

Table5
Results for $W_1 = W_2$ by pso (case 1)

Index	F_1 [W]	F_2 [Nm]	β_s[°]	β_r [°]	K_{cs}	K_{cr}
1	61.285	-18.79	23.864	25.851	0.703	0.781

Case 2 : in this second case the objective one is the 'magnetic losses' and the objective two is the 'torque to weight'.

Figures 13, 14 and 15 present the optimization results obtained with the use of the genetic algorithm. Table 6 summarizes the optimal values of the optimized parameters and their objective functions, the magnetic losses and torque to weight. Figure 16 shows the two objective functions for optimal points obtained by genetic algorithm. Table 7 shows the results for equal weighting coefficients obtained by the application of PSO algorithm

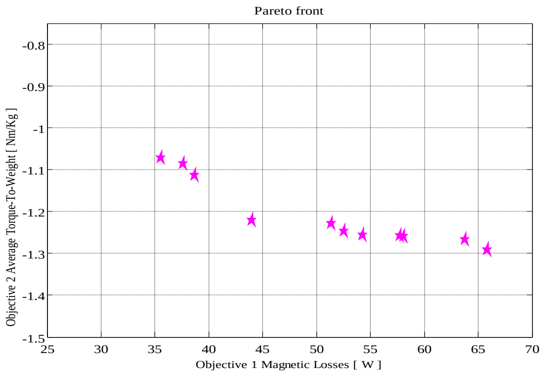

Fig. 13. Compromise surface Pareto (case 2).

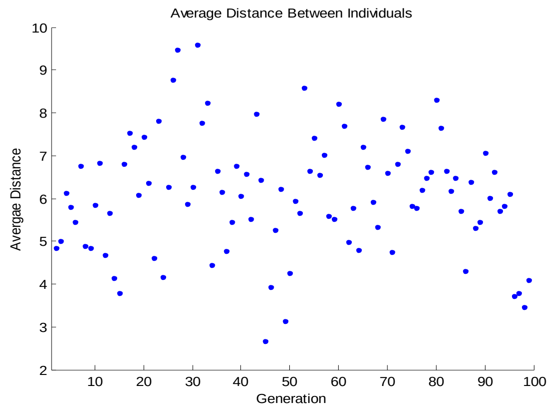

Fig. 14. Average distance between individuals (case 2).

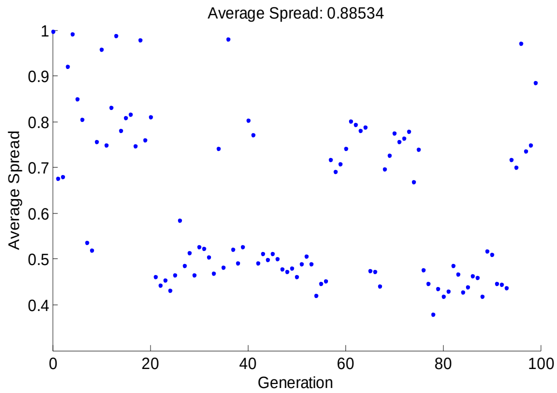

Fig. 15. Average spread (case 2).

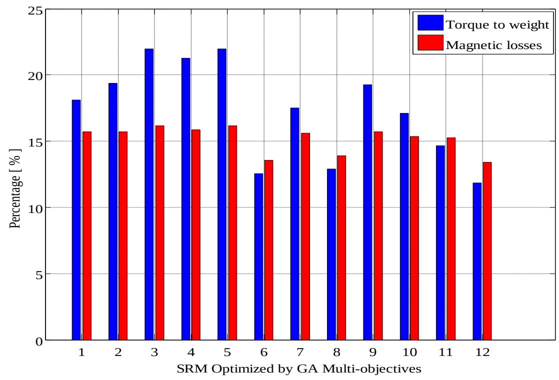

Fig. 16. Torque to weight and magnetic losses for SRM optimal

Table 6
Optimal solutions by GA (case 2)

Index	F_1 [W]	F_2 [Nm/Kg]	β_s[°]	β_r [°]	K_{cs}	K_{cr}
1	54,268	1,256	19,312	20,160	0,518	0,545
2	58,041	1,258	21,200	21,643	0,515	0,545
3	65,858	1,291	24,357	25,032	0,532	0,548
4	63,780	1,267	23,405	24,605	0,533	0,541
5	65,858	1,291	24,357	25,032	0,532	0,548
6	37,595	1,085	15,621	24,737	0,530	0,728
7	52,508	1,247	19,139	20,696	0,518	0,590
8	38,670	1,114	15,146	22,245	0,521	0,644
9	57,736	1,258	21,042	21,156	0,517	0,545
10	51,383	1,228	17,955	20,255	0,530	0,540
11	43,963	1,221	20,677	18,494	0,528	0,525
12	35,558	1,072	15,192	24,580	0,507	0,739

Table 7
Results for $W_1 = W_2$ by pso (case 2)

Index	F_1 [W]	F_2 [Nm]	β_s[°]	β_r [°]	K_{cs}	K_{cr}
1	69,758	- 1,291	24,854	25,462	0,522	0,578

5. Conclusion

The optimization approach used in this work has proved its effectiveness because it has achieved its objectives, namely improving the performance of a 8/6 SRM prototype through the optimization of various geometrical parameters under constraints. These parameters were chosen so as to satisfy two objective functions: (i) the first is the minimization of the magnetic losses, which is an important criterion which depends on the geometrical and electrical parameters; (ii) the second is the increase of the average torque.

The hybrid approach using the Particle Swarm Optimization (PSO) and the Genetic Algorithms (GA) has provided inconclusive results. The finite element formulation using FEMM to MATLAB software has improved the accuracy of the calculations. Finally, one obtained several values of the optimized parameters which include a compromise surface Pareto; this variety of values increases the space of choice that depends on load specifications.

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