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 \( \beta_s \) and \( \beta_r \) and the ratios \( K_{\alpha s} \) and \( K_{\alpha r} \) 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 PQRS 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, \( N_s \), and rotor, \( N_r \), 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 \((N_s/N_r)\) 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

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Symbol</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of stator poles</td>
<td>( N_s )</td>
<td>8</td>
</tr>
<tr>
<td>Number of rotor poles</td>
<td>( N_r )</td>
<td>6</td>
</tr>
<tr>
<td>Number of phases</td>
<td>( q )</td>
<td>4</td>
</tr>
<tr>
<td>Number of turns/phase</td>
<td>( N_t )</td>
<td>144</td>
</tr>
<tr>
<td>Air-gap length</td>
<td>( e )</td>
<td>0.3 mm</td>
</tr>
<tr>
<td>Stack length</td>
<td>( L )</td>
<td>114 mm</td>
</tr>
<tr>
<td>Outer diameter</td>
<td>( D_o )</td>
<td>190 mm</td>
</tr>
<tr>
<td>Rotor diameter</td>
<td>( D_r )</td>
<td>100 mm</td>
</tr>
<tr>
<td>Shaft diameter</td>
<td>( D_a )</td>
<td>28 mm</td>
</tr>
<tr>
<td>Back iron thickness</td>
<td>( b_{sy} )</td>
<td>12.5 mm</td>
</tr>
<tr>
<td>Stator pole arc</td>
<td>( \beta_s )</td>
<td>18 °</td>
</tr>
<tr>
<td>Rotor pole arc</td>
<td>( \beta_r )</td>
<td>22 °</td>
</tr>
</tbody>
</table>

Table 2
Physical parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Turns/phase</td>
<td>144</td>
</tr>
<tr>
<td>Wire cross section area</td>
<td>1 mm²</td>
</tr>
<tr>
<td>Coil fill factor</td>
<td>0.7</td>
</tr>
<tr>
<td>Coil cross section area</td>
<td>103 mm²</td>
</tr>
<tr>
<td>Peak current</td>
<td>12 A</td>
</tr>
<tr>
<td>Voltage</td>
<td>500 V (1 p.u.)</td>
</tr>
<tr>
<td>Lamination material</td>
<td>M19 steel</td>
</tr>
</tbody>
</table>

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

![Feasible triangle of the studied 8/6 SRM.](image)

The choice of $\beta_s$ and $\beta_R$ 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

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

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

$$\omega_{sp} > b_y > 0.5 \omega_{sp}$$  \hspace{1cm} (2)

With the ratio $K_{cs}$:

$$0.5 < K_{cs} = \frac{b_y}{\omega_{sp}} \leq 1$$  \hspace{1cm} (3)

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

$$0.5 \omega_{sp} < b_y < 0.75 \omega_{sp}$$  \hspace{1cm} (4)

With the ratio $K_{cr}$:

$$0.5 < K_{cr} = \frac{b_y}{\omega_{sp}} \leq 0.75$$  \hspace{1cm} (5)

3. Optimization of geometric parameters

A. Optimization process

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

$$\text{Minimize } F(\vec{x})$$

under constraints:

$$\vec{g}(\vec{x}) \leq 0$$

and $$\vec{h}(\vec{x}) = 0$$

$$\vec{x} = \{x_1, \ldots, x_n\}$$

$$\beta_s - \beta_r \leq 0; \quad \beta_s = \beta_R = \frac{\alpha}{2}$$

The vector $F(\vec{x})$ 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:

$$\text{Minimize } F_{eq}(\vec{x}) = \sum_{i=1}^{k} W_i F_i(\vec{x})$$

Under constraints:

$$\vec{g}(\vec{x}) \leq 0$$

and $$\vec{h}(\vec{x}) = 0$$

$$\vec{x} = \{x_1, \ldots, x_n\}$$

With the coefficients

$$W_i \geq 0 \text{ and } \sum_{i=1}^{k} W_i = 1$$

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:

$$F_2(\vec{x}) = -\frac{W_1}{W_2} F_1(\vec{x}) + C$$

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

\[ P_{\text{fer}} \left( \frac{W}{m^3} \right) = (k_{h1} \Delta B + k_{h2} \Delta B^2) f + \alpha_p \frac{1}{T} \int_0^T \left( \frac{dB(t)}{dt} \right)^2 dt \]  

(11)

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

\[ \alpha_p = \frac{\sigma_p}{12 \rho} \]  

(12)

Before any calculations one must first determine two types of variables: (i) specific material coefficients \( k_{h1}, k_{h2} \) and \( \alpha_p \), 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

<table>
<thead>
<tr>
<th>Part</th>
<th>( \Delta B )</th>
<th>( F )</th>
<th>( F_2 )</th>
<th>Volume</th>
</tr>
</thead>
<tbody>
<tr>
<td>stator</td>
<td>( \varphi_m ) ( E_{c}L_a ) ( N_r f_{rot} )</td>
<td>( \frac{U}{2 n_w E_{c}L_a} ) ( \frac{\pi (R_{\text{ext}} - (R_{\text{ext}} - E_{c^2})L_a)}{2} ) ( ( R_{\text{ext}} - E_{c^2})L_a )</td>
<td></td>
<td></td>
</tr>
<tr>
<td>yoke</td>
<td>rot</td>
<td>( \frac{\varphi_m}{W_r L_a} ) ( N_r f_{rot} )</td>
<td>( q \left( \frac{U}{n_w W_r L_a} \right)^2 ) ( N_r h_w W_r L_a )</td>
<td></td>
</tr>
<tr>
<td>teeth</td>
<td>( \frac{2 \varphi_m}{W_r F_a} ) ( \frac{1}{2} N_r f_{rot} )</td>
<td>( q \left( \frac{N_r}{n_w} \right) \left( \frac{U}{n_w F_a} \right)^2 ) ( N_r h_w W_r L_a )</td>
<td></td>
<td></td>
</tr>
<tr>
<td>rotor</td>
<td>( \frac{\varphi_m}{E_{c}L_a} ) ( N_r f_{rot} )</td>
<td>( \frac{U}{2 n_w E_{c}L_a} ) ( \frac{\pi (R_{\text{axe}} + E_{c^2})^2}{2} ) ( - R_{\text{axe}}^2 L_a )</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

C. Average Torque

The average torque is given by:

\[ T_{\text{avg}} = \frac{q N L}{2 \pi} W_c \]  

(13)

where \( q \) is the number of phases, \( N_r \) is the number of rotor poles and \( W_c \) 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.

\[ \Delta W_e = W_{\text{aligned}} - W_{\text{unaligned}} = \Delta l \left( \varphi_1 + \varphi_2 + \ldots + \frac{1}{2} \varphi_p \right) - \frac{1}{2} \varphi_s \times I_p \]  

(14)

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

\[ \Delta l = \frac{I_p}{n} \]  

(15)

The expression of the average torque is given by

\[ T_{\text{ave}} = \frac{q N}{2 \pi} \left( \Delta l \left( \varphi_1 + \varphi_2 + \ldots + \frac{1}{2} \varphi_p \right) - \frac{1}{2} \varphi_s \times I_p \right) \]  

(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:

\[
m_j = m_{j \text{min}} + \left( \frac{m_{j \text{max}} - m_{j \text{min}}}{2^n - 1} \right) \sum_{i=0}^{n-1} b_i 2^i \quad (17)
\]

The parameters \( m_j \) represent the design parameters. The set of values \( b_1, b_2, \ldots, b_n \), is the n-bit string of the binary representation of \( m_j \). \( m_{j \text{min}} \) and \( m_{j \text{max}} \) 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, minimax 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:

\[
v_{ij}^{t+1} = w v_{ij}^{t} + c_1 r_1 (pbest_{ij} - x_{ij}^{t}) + c_2 r_2 (gbest - x_{ij}^{t}) \quad (18)
\]

\[
x_{ij}^{t+1} = x_{ij}^{t} + v_{ij}^{t+1} \quad (19)
\]

for \( j \in 1 \ldots d \) where \( d \) is the number of dimensions, \( i \in 1 \ldots n \) where \( n \) is the number of particles, \( t \) is the iteration number, \( w \) is the inertia weight, \( r_1 \) and \( r_2 \) are two random numbers uniformly distributed in the range \([0,1]\), and \( c_1 \) and \( c_2 \) are 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 \( v_i \) to the new velocity \( v_i^{t+1} \). 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 \( v_{\text{min}} \leq v_i \leq v_{\text{max}} \). Likewise, the position of a particle is bounded as follows: \( x_{\text{min}} \leq x_i \leq x_{\text{max}} \).

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

\[
pbest_i^{t+1} = \begin{cases} pbest_i^t & \text{if } f(pbest_i^t) \leq f(x_i^{t+1}) \\ x_i^{t+1} & \text{if } f(pbest_i^t) > f(x_i^{t+1}) \end{cases} \quad (20)
\]

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

\[
\text{gbest}^{t+1} = \arg \min_i f(pbest_i^{t+1}) \quad (21)
\]

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 $\beta_s$, $\beta_r$ 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).](image)

![Fig. 11. Average distance between individuals (case 1).](image)

![Fig. 12. Average Torque and magnetic losses for SRM optimal](image)

**Table 4**  
Optimal solutions by GA (case 1).

<table>
<thead>
<tr>
<th>Index</th>
<th>$F_1$ [W]</th>
<th>$F_2$ [Nm]</th>
<th>$\beta_s$ [']</th>
<th>$\beta_r$ [']</th>
<th>$K_{cs}$</th>
<th>$K_{cr}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>234,145</td>
<td>18,911</td>
<td>23,801</td>
<td>28,133</td>
<td>0.896</td>
<td>0.723</td>
</tr>
<tr>
<td>2</td>
<td>189,718</td>
<td>15,428</td>
<td>19,102</td>
<td>27,255</td>
<td>0.907</td>
<td>0.744</td>
</tr>
<tr>
<td>3</td>
<td>245,439</td>
<td>20,093</td>
<td>25,902</td>
<td>27,746</td>
<td>0.884</td>
<td>0.731</td>
</tr>
<tr>
<td>4</td>
<td>161,417</td>
<td>13,134</td>
<td>17,255</td>
<td>26,560</td>
<td>0.512</td>
<td>0.744</td>
</tr>
<tr>
<td>5</td>
<td>138,764</td>
<td>11,387</td>
<td>15,059</td>
<td>25,352</td>
<td>0.501</td>
<td>0.747</td>
</tr>
<tr>
<td>6</td>
<td>180,191</td>
<td>14,340</td>
<td>17,801</td>
<td>25,946</td>
<td>0.804</td>
<td>0.747</td>
</tr>
<tr>
<td>7</td>
<td>231,040</td>
<td>17,954</td>
<td>23,015</td>
<td>27,446</td>
<td>0.603</td>
<td>0.734</td>
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<tr>
<td>8</td>
<td>213,993</td>
<td>16,976</td>
<td>22,290</td>
<td>26,551</td>
<td>0.521</td>
<td>0.743</td>
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<tr>
<td>9</td>
<td>149,710</td>
<td>12,206</td>
<td>16,102</td>
<td>25,564</td>
<td>0.503</td>
<td>0.744</td>
</tr>
<tr>
<td>10</td>
<td>216,590</td>
<td>17,322</td>
<td>21,636</td>
<td>27,193</td>
<td>0.897</td>
<td>0.728</td>
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<tr>
<td>11</td>
<td>252,137</td>
<td>20,751</td>
<td>27,062</td>
<td>28,306</td>
<td>0.901</td>
<td>0.722</td>
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<tr>
<td>12</td>
<td>199,781</td>
<td>16,084</td>
<td>20,158</td>
<td>27,765</td>
<td>0.907</td>
<td>0.730</td>
</tr>
</tbody>
</table>

**Table 5**  
Results for $W_1 = W_2$ by pso (case 1)

<table>
<thead>
<tr>
<th>Index</th>
<th>$F_1$ [W]</th>
<th>$F_2$ [Nm]</th>
<th>$\beta_s$ [']</th>
<th>$\beta_r$ [']</th>
<th>$K_{cs}$</th>
<th>$K_{cr}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>61.285</td>
<td>-18.79</td>
<td>23.864</td>
<td>25.851</td>
<td>0.703</td>
<td>0.781</td>
</tr>
</tbody>
</table>

**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.

Table 6

<table>
<thead>
<tr>
<th>Index</th>
<th>$F_1$ $[W]$</th>
<th>$F_2$ $[Nm/Kg]$</th>
<th>$\beta_1$ $[°]$</th>
<th>$\beta_f$ $[°]$</th>
<th>$K_{cs}$</th>
<th>$K_{cr}$</th>
</tr>
</thead>
<tbody>
<tr>
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<td>1,256</td>
<td>19,312</td>
<td>20,160</td>
<td>0,518</td>
<td>0,545</td>
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<td>1,258</td>
<td>21,200</td>
<td>21,643</td>
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<td>0,545</td>
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<td>24,357</td>
<td>25,032</td>
<td>0,532</td>
<td>0,548</td>
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<td>23,405</td>
<td>24,605</td>
<td>0,533</td>
<td>0,541</td>
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<tr>
<td>5</td>
<td>65,858</td>
<td>1,291</td>
<td>24,357</td>
<td>25,032</td>
<td>0,532</td>
<td>0,548</td>
</tr>
<tr>
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<td>15,621</td>
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<td>19,139</td>
<td>20,696</td>
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<tr>
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<td>21,042</td>
<td>21,156</td>
<td>0,517</td>
<td>0,545</td>
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<tr>
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<td>20,255</td>
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<td>0,540</td>
</tr>
<tr>
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<td>0,525</td>
</tr>
<tr>
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<td>1,072</td>
<td>15,192</td>
<td>24,580</td>
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</tr>
</tbody>
</table>

Table 7

<table>
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<th>$F_1$ $[W]$</th>
<th>$F_2$ $[Nm]$</th>
<th>$\beta_1$ $[°]$</th>
<th>$\beta_f$ $[°]$</th>
<th>$K_{cs}$</th>
<th>$K_{cr}$</th>
</tr>
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<tbody>
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<td>24,854</td>
<td>25,462</td>
<td>0,522</td>
<td>0,578</td>
</tr>
</tbody>
</table>

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

5. CONCLUSION

The optimization approach used in this work has proved its effectiveness because it has achieved its objectives, namely improving the performance of an 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.

REFERENCES


