N. Ben hadj,

S. Tounsi

R. Neji

F. Sellami

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Use of Evolutionary Approach for Multiobjective Optimization of Losses and Mass in Permanent Magnet Motor

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For Electric Vehicles (EVs), Weight and losses reduction are important factors not only in reducing the energy consumption and cost but also in increasing autonomy. Electric motor system is one of the key parts of electric vehicle that is why it is necessary to do some research on EVs performance evaluation by reducing its losses and mass. In this paper, we propose an approach based on the combination between an Evolutionary Algorithm (EA) and an analytical model of electric motor in order to reduce its losses and mass which are the objectives functions in a multiobjective problem (MOP). In this study, the weighted sum based approaches to multiobjective optimization is used because it is computationally very efficient. Also, Analytical simulation results for the multiobjective optimization are exhibited.

Keywords: Multiobjective optimization, Electric vehicle, Permanent Magnet Motor, Losses and Mass.

1. INTRODUCTION

Recently, the use of EVs especially in the urban environment offers a quite attractive solution against the problem of the atmospheric pollution due to the extended use of vehicles with internal combustion motors, also it solves many problems like noise, reliability, Low fuel consumption. However, the major shortcomings of an EV are the low autonomy and the high cost. Owing to this, Electric motor especially permanent-magnet synchronous motor (PMSM) is one of the key parts of EV that is why by reducing its mass and losses, we minimize not only the EV cost and consumption but also we increase considerably the autonomy and efficiency of EV [1,2].

In this paper, we use a systemically approach based on the coupling between the parameterized model of losses and mass in electric motor and the optimization program in order to optimize parameters influencing EV design. So, minimizing the electric motor losses and mass (EMLM) problem, is resolving a multiobjective optimization problem (MOP) when the motor losses is the first optimization function and the motor mass is the second optimization function. Next, we are fixed for purpose to resolve this multiobjective problem by using an Evolutionary Algorithms based on weighted sum method. In first section, a studied motor structure is clarified and a formulation of EMLM problem is presented. Then, the principle of multiobjective problem is defined and the proposed approach is developed. Finally, Analytical simulation results for the optimization are exhibited.

2. FORMULATION OF EMLM PROBLEM

2.1. Motor structure

The studied motor is a PMSM which is characterized by a reduced production cost, a strong power-to-weight-ratio and a high efficiency [3]. Figure 1 shows the geometry of PMSM example investigated in this study. The design is an inset permanent magnet motor topology [4], with radial magnetized magnets.

Laboratory of Electronic and Information Technology -LETI- Equip of Electric Vehicle and Power Electronics -VEEP- National Engineering School B.P.: W, 3038 Sfax-Tunisia

This motor has four pairs of poles, six principal teeth. Between two principal teeth an inserted tooth is added to improve the wave form of the electromotive force (E.M.F) and to reduce the flux leakages [5]. The slots are right and open aiming to facilitate the insertion of coils and to reduce the production cost. The concentrated winding is used. Each phase winding comprises two opposite diametrically coils [6].

Figure 1 shows the geometric input required by MAXWELL 2D.

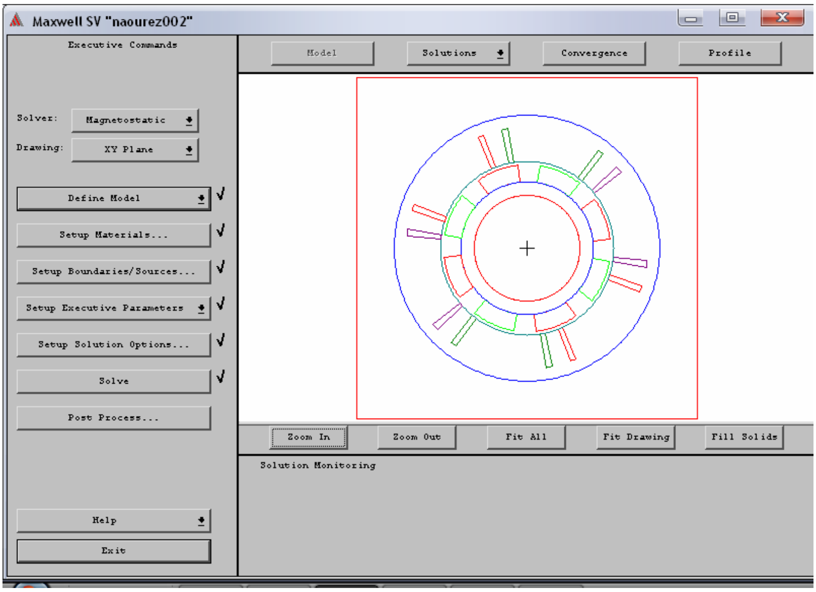

Figure 1: Geometric input required by Maxwell-2D

2.2. Sizing PMSM

The analytical stage of dimensioning is primarily based on various data such as: the schedule data conditions, the constant characterizing materials, the expert data and the motor configuration.

This last is characterized by a relation ship between the number of teeth and the number of poles pairs directly bound to the space percentage occupied by the slots compared to that occupied by the inserted tooth.

After applying our analytical model, we extract the geometrical and electromagnetic motor magnitudes. The geometrical sizes are determined from basic electromagnetism laws for a maximum flux position [7]. Of course, equations are written for a design approach. For example, the height of permanent magnets is found through Ampere law to have a flux density fixed in the air-gap.

On the other hand, the waveforms and magnetic leakage aren't computed by analytical calculation but determined by finite element simulations and introduced in the analytical computation.

The representation of the field lines when the motor operates at load is represented on the following figure:

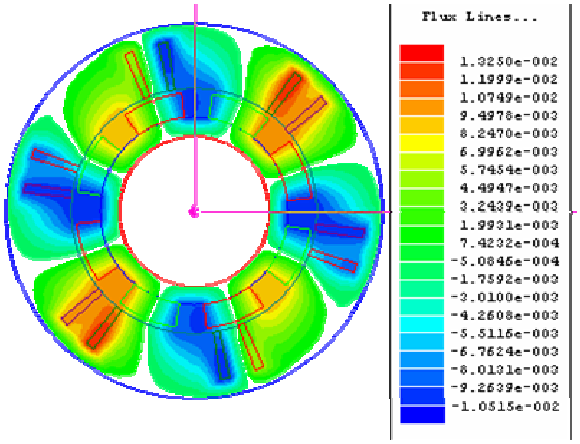

Figure 2: Field lines distribution at load

After analytical modeling and validation by finite elements method, we explain the optimization problem which consists on minimizing simultaneously the motor losses and the motor mass.

2.3. Objective functions

The resolution of EMLM problem consists in minimizing two given objectives functions which represent the motor mass and the motor losses. [8] gives the detail of modeling.

- PMSM mass function

The motor mass function F_m in Kg is represented by the following expression:

$$F_m = M_m + M_c + M_{sy} + M_{st} + M_{toothi} + M_{ry} \tag{1}$$

Where:

M_m is the magnets mass defined by:

$$M_m = pL_m W_m \left[\left(\frac{D_m - e}{2} \right)^2 - \left(\frac{D_m - e}{2} - H_m \right)^2 \right] M_{va} \tag{2}$$

M_c is the copper mass given by the equation:

$$M_c = \frac{3 I_n N_{sph} L_{sp}}{\sqrt{2} \quad \delta} M_{vc} \tag{3}$$

M_{st} is the stator teeth mass defined by the equation:

$$M_{st} = \left[\left(\frac{D_m + e}{2} + H_{tooth} \right)^2 - \left(\frac{D_m + e}{2} \right)^2 \right] L_m M_{vt} \tag{4}$$

M_{sy} is the stator yoke mass expressed by the equation:

$$M_{sy} = \pi \left[\left(\frac{D_m - e}{2} + H_{Tooth} + t_{sy} \right)^2 - \left(\frac{D_m + e}{2} + H_{tooth} \right)^2 \right] \cdot L_m M_{vt} \tag{5}$$

M_{ry} is the rotor yoke mass given by the equation:

$$M_{ry} = \pi\left[\left(\frac{D_m - e}{2} - H_m\right)^2 - \left(\frac{D_m - e}{2} - H_m - H_{ry}\right)^2\right] L_m M_{vt} \tag{6}$$

M_{toothi} is the inserted teeth mass defined by :

$$M_{toothi} = \frac{M_{st} W_{toothi}}{W_{tooth}} \tag{7}$$

- PMSM losses function

In the permanent magnet motor, the iron losses are given by the following expression [6]:

$$L_i = q\left(\frac{f_b}{50}\right)^{1.5}\left[M_{sy} B_{sy}^2 + M_{st} B_t^2\right] \tag{8}$$

The mechanical losses are given by the following expression [6]:

$$L_{me} = \frac{K_m . P_u}{\left(1 - r_p\right)\left(1 - K_m\right)} \tag{9}$$

The copper losses are given by the following expression:

$$L_c = 3 R_{ph} I_n^2 \tag{10}$$

The resistance per phase is expressed as follows:

$$\mathrm{R_{ph}} = \mathrm{R_{cu}}(\mathrm{t_b})\ \frac{\mathrm{N_{sph}}\ \delta\ \mathrm{L_{sp}}}{\mathrm{I_n}/\sqrt{2}} \tag{11}$$

The Motor rated current is given by the following expression:

$$I_n = \frac{T_{em}}{K_e} \tag{12}$$

Finally, the motor losses function F_L is given by the following equation:

$$F_L = L_i + L_m + L_c \tag{13}$$

2.4. Problem constraints

The different constraints of EMLM problem are established following technological, physical and expert considerations. For example: The wheel radius is delimited by the space reserved, the air-gap flux density variation beaches are defined starting from the iron B-H curve to avoid problem saturation and the current density is an expert data.

- The geometrical constraints:

$$\begin{aligned} &100\ mm \le D_m \le 250\ mm \\ &150\ mm \le L_m \le 200\ mm \\ &2\ mm \le e \le 8\ mm \end{aligned} \tag{14}$$

- The Technological constraints:

$$\begin{aligned} &2 \le r_d \le 8 \\ &0.25\ m \le R_w \le 0.35\ m \end{aligned} \tag{15}$$

Where r_d is the reduction ratio and R_w is the wheel radius.

- The magnetic constraint:

$$0.89T \le B_e \le 1.05T \tag{16}$$

Where B_e is the air-gap induction.

- The efficiency constraint:

$$R_{end} > 0.94 \tag{17}$$

Where R_{end} is the motor efficiency.

- The physical constraint:

$$I_m \le I_d \tag{18}$$

I_m is the motor current, and I_d is the demagnetization current.

The optimization problem is summarized as follow:

Minimizing simultaneously F_M and F_L with:

$$\left\{ \begin{array}{l} I_m \le I_d \ \ and \ \ R_{end} \succ 0.94 \\ 100\ mm \le D_m \le 250\ mm \\ 150\ mm \le L_m \le 200\ mm \\ 2\ mm \le e \le 8\ mm \\ 2 \le r_d \le 8 \\ 0.25\ m \le R_w \le 0.35\ m \\ 0.89\ T \le B_e \le 1.05\ T \end{array} \right\} \tag{19}$$

3. MULITIOBJECTIVE OPTIMIZATION

3.1. Principle

Engineering design often deals with multiple, possibly conflicting, objective functions or design criteria. For example, one may want to maximize the performance of a system while minimizing its cost. Such design problems are the subject of multiobjective optimization and can generally be formulated as follow [9]:

$$\left\{ \begin{array}{l} Minimizing \quad F(X) = (F_1(X), F_2(X), \ldots\ldots F_{Nobj}(X)) \\ \qquad\qquad\qquad\qquad With \\ \qquad\qquad g_j(X) = 0 \quad , j = 1, \ldots.M \\ \qquad\qquad h_k(X) \le 0 \quad k = 1, \ldots..K \end{array} \right. \tag{20}$$

where :

N_{obj}: Number of objectives,

M : Number of equality constraints,

K: Number of inequality constraints,

X: Decision vector.

Any two solutions X_1 and X_2 can have one of two possibilities: One covers or dominates the other or none dominates the other.

In minimization problem, without loss of generality, a solution X_1 dominates X_2 if the following two conditions are satisfied:

$$\begin{cases} \forall i \in \left\{1,2,....N_{obj}\right\}, & F_i(X_1) \le F_i(X_2) \\ \forall j \in \left\{1,2,.....N_{obj}\right\}, & F_j(X_1) \prec F_j(X_2) \end{cases} \tag{21}$$

X_f is the set of feasible solutions, i.e. $X_f = \left\{x \in X / g'(x) = 0 \ and \ h'(x) \le 0\right\}$.

where:

$g'(x) = \left(g_1(x), g_2(x),.....g_m(x)\right)^T$ and $h'(x) = \left(h_1(x), h_2(x),...h_k(x)\right)^T$.

A decision vector $x \in X_f$ is non-dominated with respect to a set $A \subset X_f$, if:

$$\nexists \ \ a \in A / a \prec x \tag{22}$$

The set of non-dominated decision vectors is known as the Pareto optimal set, while the corresponding set of objectives vectors constitutes the Pareto optimal front.

3.2. Weighted sum method for MOP

Most practical problems require the simultaneous optimization of multiple objectives. In applications of optimization techniques, the solution to such problems is usually computed by combining the objectives into a single one according to some utility function. To solve the MOP, the weighted sum method is used In case of a two objectives functions in the optimization problem where ,F_1 and F_2 can be weighted using weighting values, w_1, and w_2 respectively, so that [10]:

$$Minimize \quad F\left(F_1, F_2\right) = F\left(w_1, w_2\right) = w_1 F_1 + w_2 F_2 \tag{23}$$

We can divide the objective function by a positive number without altering the solution, after dividing (24) by w_1, w_2/w_1**,** can be redefined as w. Then (23) can be written as follows:

$$Minimize \quad F\left(w\right) = F_1 + wF_2 \tag{24}$$

where $w = \left[0,\infty\right[$.

Because it is difficult to realize according to the w in total range, objective function is reformed for covering the total range. The final objective function is represented by:

$$F\left(w\right) = wF_1\left(X\right) + \left(1-w\right)F_2\left(X\right) \tag{25}$$

where $\mathrm{w} = \left[0,1\right]$ and x is a set of design variables.

Using this method, only one Pareto optimal solution can be obtained with one run of the optimization algorithm.

3.3. Proposed approach

By replacing the motor various losses which is the first optimization function and the motor mass which is the second optimization function in (25), we note that this optimization function F depend primarily on the wheel radius R_w, the average motor diameter D_m, the average motor length L_m, the air-gap flux density B_e, the reducer ratio r_d and the air-gap thickness e, which are selected as parameters of optimization.

Consequently, our optimization problem consists on minimizing the EMLM by keeping efficiency higher or equal to 0.95 and respecting the following constraints (Table 1), in order to obtain the optimal values of optimisation parameters: R_{wopt}, r_{dopt}, L_{mopt}, D_{mopt}, e_{opt} and B_{eopt}.

The beach of each parameter variation $x_i \in (R_w, r_d, L_m, D_m, e, B_e)$ must respect the following constraint:

$$X_{imin} \leq X_i \leq X_{imax} \tag{26}$$

The values of the lower limit X_{imin} and the upper limit X_{imax} are established following technological, physical and expert considerations.

Table 1: Optimization constraints

Lower limit X_{imin}	Variables X	Upper limit X_{imax}
100	D_m(mm)	250
150	L_m(mm)	200
0.1	B_e(T)	1.05
3	r_d	8
4	e(mm)	8
0.25	R_W(m)	0.35

Figure 3 describes the optimization total process, associating algorithm and criteria in evaluation.

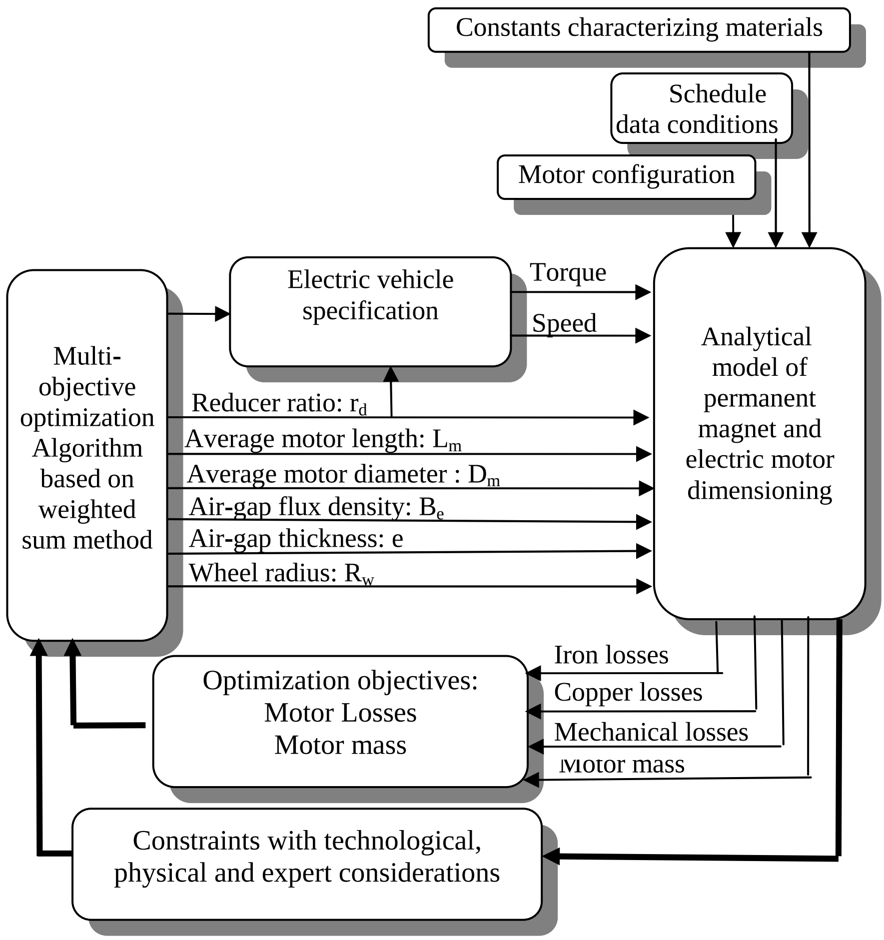

Figure 3: Optimization process

Figure 4 presents the used approach for multiobjective optimization Algorithm execution starts by requesting the user to enter critical data, which include design specifications, Constants characterizing materials, Motor configuration, Schedule data conditions, Analytical model of permanent magnet and electric motor dimensioning, objectives to be optimized and constraints. In addition, the optimization routine requires information on upper and lower values of optimization parameters, number of objectives and the number of generations.

The evolutionary settings required by the optimization routine include population size, initial population, selection method, probability of crossover, crossover method probability of mutation, mutation method.

Execution stops once the termination criterion is satisfied. The program stops execution once the termination criterion is satisfied (When optimal solution is obtained ten successive times). Optimization results can be saved manually in a text file for further processing. These results present the optimized variable values and objective values for each generation [11].

The user, as the decision-maker, has to select a desired result from the *result-set* (optimal in the sense of multiobjective optimization, obtained from execution of figure 4).

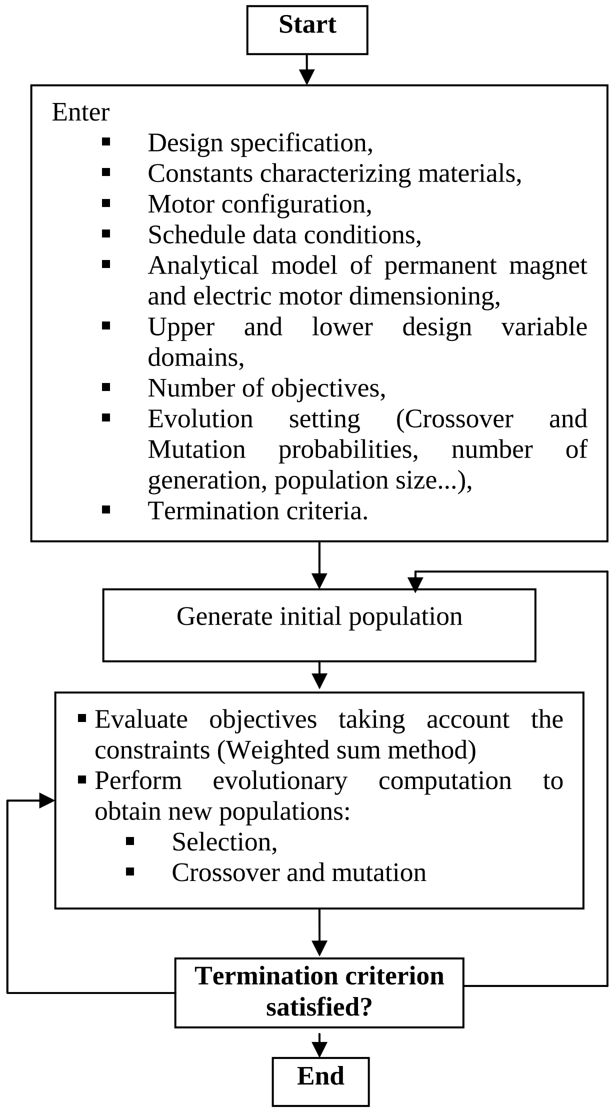

Figure 4: Multiobjective algorithm for motor losses and mass optimization.

In the following, the multiobjective stochastic design optimization approach is applied to the simultaneous minimization of losses and mass in the permanent magnet motor.

4. SIMULATION AND RESULTS

The simulation parameters as well as the vehicle components model have been set for an EV with the following specifications [12]:

- Body mass : 1200kg,
- Rolling resistance coefficient : 130.10^{-4},

- Body aerodynamic drag coefficient : 0.7,
- Vehicle front area : 1.4m^2,
- Basic speed of the electrical vehicle : 30km/h,
- Electric motor : 15kW.

4.1. Mono-objective optimization

To optimize the two functions, losses and mass in the motor. We use a Real Coded Genetic Algorithm (RCGA) with real coding which is a simulated evolution type optimization technique and good for finding global optimal solution [13]-[14]- [15].

The RCGA was programmed in MATLAB 7.0 and was run on a Pentium IV, 2.0 GHz, 128 MB RAM machine. The RCGA parameters are given by Table 2.

Table 2: RCGA parameters

Characteristics	Types or values
Type of selection	Tournement
Type of crossover operator	Arithmetic
Probability of crossover	0.95
Type of mutation operator	Uniform
Probability of mutation	0.01
Population size	350
Generation number	700

Figures 5 and 6 illustrate the evolution of two convergence objectives.

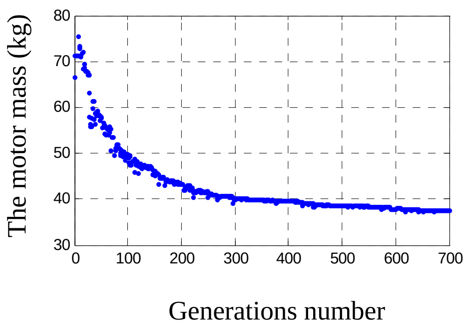

Figure 5: The motor mass function according the generations number

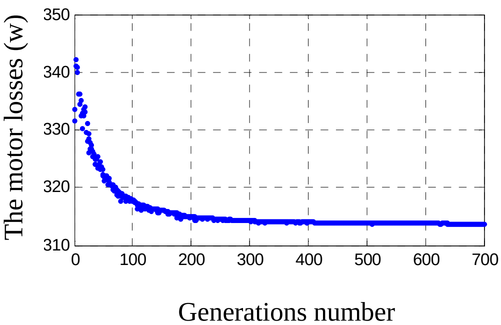

Figure 6: The motor losses function according the generations number

From figures 5 and 6, we notice that the motor losses function and the motor mass function are decreasing according to the generations number and converge toward their minimal values.

Also, we note that the population improvement is very fast on the beginning (total research) and becomes increasingly slow as the time pass (local research), consequently the algorithm converges for a good choice of the initial populations.

The motor losses function converges toward the value 313.69W and the motor mass function converges towards 37.24 kg.

Table 3 shows the results of mono-objective optimization for the motor mass, and the motor losses functions obtained under MATLAB simulation.

Table 3: Results of mono-objective optimization

	Motor mass optimization	Motor losses optimization
D_m(mm)	100.42	245.72
L_m(mm)	150.51	150.28
B_e(T)	0.99	0.99
e(mm)	7.97	7.96
R_w(mm)	250.70	250.33
r_d	7.98	7.97
Optimal value of objective function	37.24 Kg	313.69 W

4.2. Bi-objective optimization

After having an idea about the optimal values of the two mono-objectives optimizations, we use the proposed approach given in figure 3 when the parameters simulations are given by Table 4.

Figure 7 represents the evolution of the objective function given by (25) according the generations number, we note that this function reaches its optimum value in the 359 iterations.

The optimal Pareto set for a bi-objectives optimization of the motor losses and the motor mass functions is shown in figure 8.

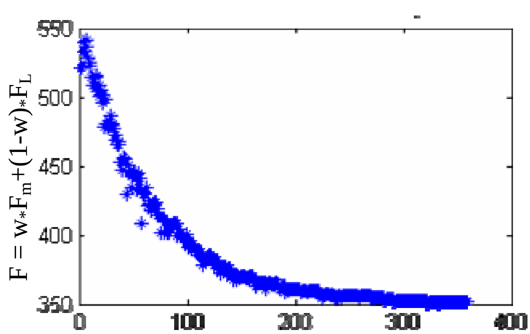

Figure 7: Evolution of the different objectives which are summed up to a single according the generations number.

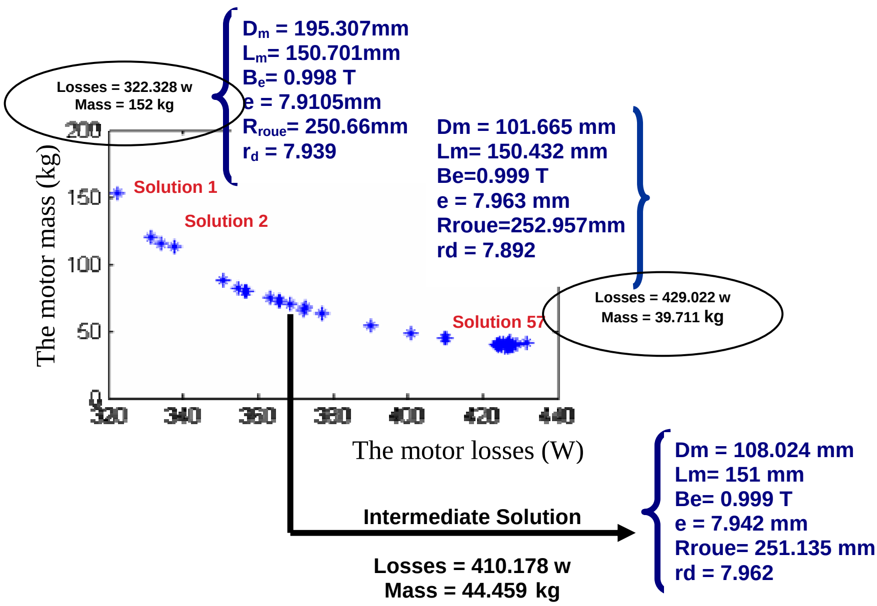

Figure 8: Pareto set mass/ losses

The result is collected from 50 runs of the optimization. From figure 8, we can take the optimal values of the objectives function with minimal motor losses and with minimal motor mass. This result is given by the following Table:

Table 4: The optimal solutions

	With minimal motor losses	With minimal motor mass	An intermediate solution
Motor losses	322.328	429.022	410.1786
Motor mass	152	39.711	44.459
D_m	195.307	101.665	108.024
L_m	150.701	150.432	151
B_e	0.998	0.999	0.999
e	7.9105	7.963	7.9421
R_w	250.66	252.957	251.135
r_d	7.939	7.892	7.962

Figure 9 and 10 show respectively the evolution of optimization parameters as a function of motor losses and the evolution of optimization parameters as a function of motor mass from 50 runs of the optimization. We note that the obtained values of optimization parameters are very near from the different runs in the two optimization functions.

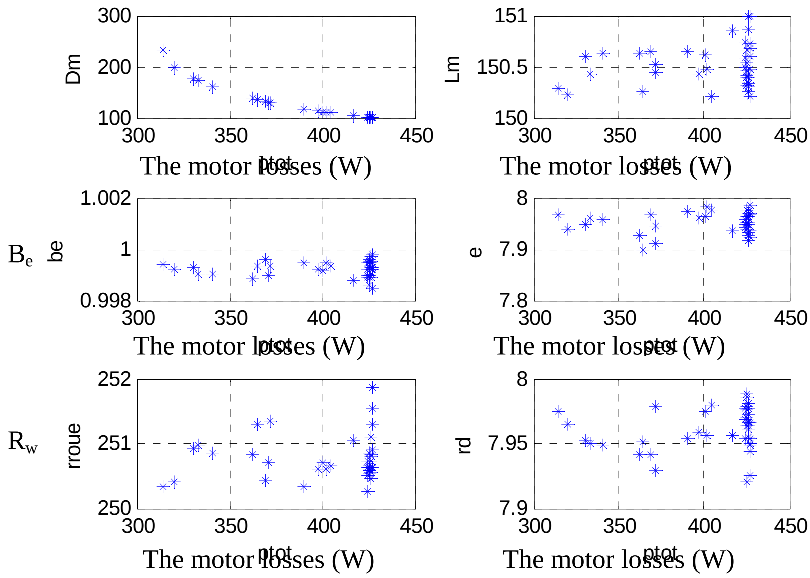

Figure 9: Evolution of optimization parameters as a function of the motor losses

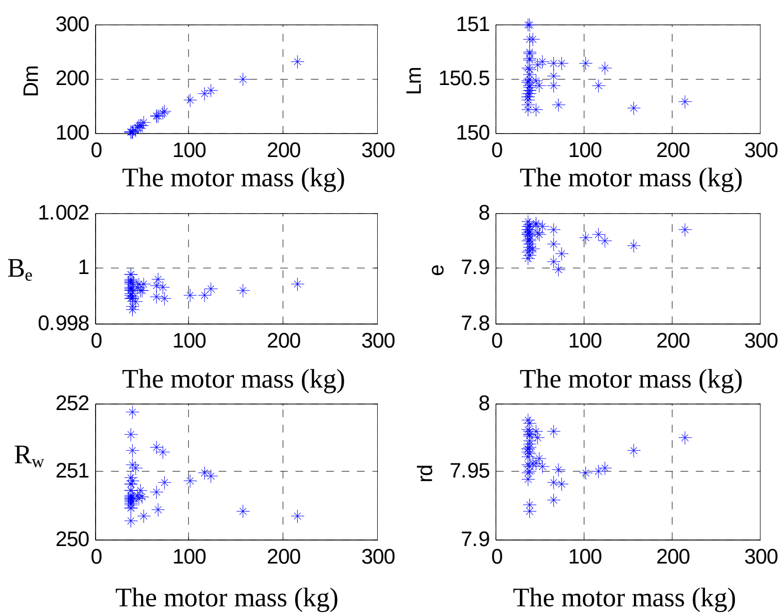

Figure 10: Evolution of optimization parameters as a function of the motor mass

Figure 11 shows the evolution of optimization parameters as a function of generations number in the 50 runs.

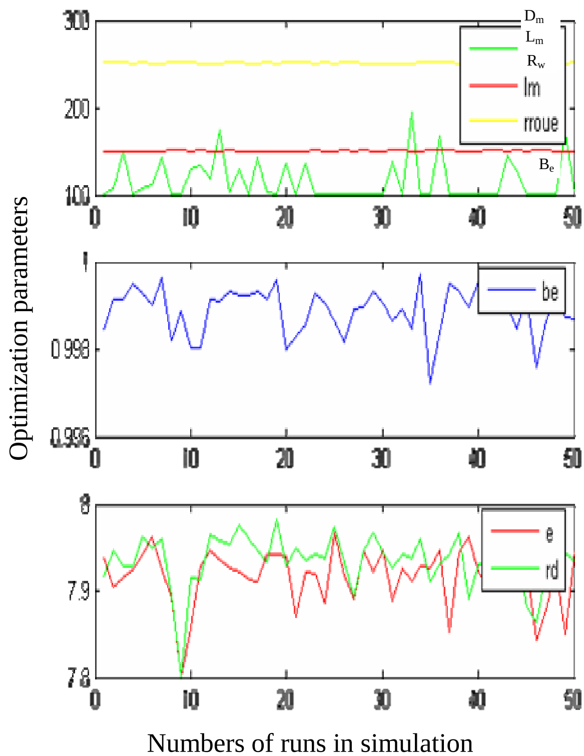

Figure 11: Evolution of optimization parameters

5. CONCLUSION

In this paper, a multiobjective optimization approach based on weighted sum method has been presented and applied to the multiobjective losses and mass problem of an electric vehicle.

The problem has been formulated as a multi objectives problem, while taking into account the motor losses, and the motor mass as objectives functions.

The results show that the proposed approach is efficient for solving the EMLM multiobjective problem. The non dominated solutions obtained are well distributed and have satisfactory diversity characteristics.

Finally the permanent magnet motor designed around its optimal parameters is an interest solution in EV world.

6. NOMENCLATURE

P :The number of poles pairs,
L_m :The motor length,
W_m :The magnet angular width,
D_m :The motor diameter,
E :The air-gap thickness,
H_m :The magnet height,
I_n :The motor rated current,
M_{va} :The volumic mass of magnet,
M_{vc} :The volumic mass of copper,
M_{vt} :The volumic mass of magnetic sheet,
L_{sp} :The average length of one spire,
N_{sph} :The number of spires per phase,
Δ :The current density accepTable in coil,
H_{tooth} :The principal tooth height,
t_{sy} :The stator yoke thickness,
H_{ry} :The motor rotor yoke height,
W_{toothi} :The inserted angular tooth width,
q :The coefficient quality metal sheets,
f_b :The base frequency of the motor,
B_{sy} :The stator yoke flux density,
B_t :The tooth flux density ,
K_m :The mechanical loss ratio,
r_p :The loss ratio, generally r_p= 2%,
$R_{cu(tb)}$:The resistance per phase at Temperature t_b,
T_{em} :The electromagnetic torque,
K_e :The motor electric constant.

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