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Research Article

Geometric Optimization of Permanent Magnet Synchronous Machines Using Grey Wolf and Teaching–Learning-Based Algorithms

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Abstract:

Permanent Magnet Synchronous Machines (PMSMs) are widely recognized for their high efficiency, low acoustic noise, and extended operational lifetime. This study presents an optimization framework based on two metaheuristic algorithms, namely Grey Wolf Optimizer (GWO) and Teaching–Learning-Based Optimization (TLBO), to determine the optimal geometric parameters of the machine. The proposed methodology combines finite element analysis with numerical optimization by coupling COMSOL Multiphysics and MATLAB in order to model and evaluate the machine performance. The effectiveness of the developed approach is assessed through comparisons with recently published reference studies. The obtained results demonstrate good accuracy and confirm the reliability, robustness, and efficiency of the proposed optimization strategy.

1. Introduction

Permanent Magnet Synchronous Machines (PMSMs) are widely used in modern applications such as electric vehicles, aerospace, and robotics due to their high efficiency, low noise, and long service life [1-14]. However, maximizing their performance involves a complex, multiobjective optimization process that must consider numerous geometric and operational parameters [15-27].In this context, metaheuristic optimization algorithms have emerged as powerful tools for addressing the intricacies of engineering design [22].This work presents the study of a radial-flux Permanent Magnet Synchronous Machine (PMSM). It first details its modeling through the computation of the electromagnetic field, including its physical characteristics, harmonic steady-state analysis, and the distribution of magnetic forces. Subsequently, geometric optimization tools are developed by adapting two stochastic methods.A design strategy is then established to define the parameters to be optimized. Finally, the obtained results are analyzed by distinguishing between simulations with and without constraints, in order to assess the impact of optimization on the machine's performance.To determine the optimal geometric characteristics of the machine while minimizing the overall force acting on the stator, the finite element analysis (FEA) will be coupled with the implementation of two stochastic optimization methods: the Teaching Learning Based Optimization (TLBO) and the Grey Wolf Optimizer (GWO). This approach will be carried out using MATLAB software. The proposed method is validated through comparison with recent benchmark studies, demonstrating its robustness, effectiveness, and strong potential for practical use in electric machine optimization.

2. Mathematical model

2.1 Machine modeling

In a rotating electrical machine, the resolution domain considered in the case of a two-dimensional study corresponds to the cross-section of this machine [22]. The electromagnetic equation, in terms of the magnetic vector potential A to be solved, can be written in magnetodynamics in this form:

$$\overrightarrow{Rot}(\nu\overrightarrow{Rot}\vec{A}) + \sigma\frac{\partial\vec{A}}{\partial t} = \vec{J_s} + \overrightarrow{Rot}(\nu\vec{B_r}) \qquad (1)$$

$\vec{A}$: Component of the magnetic vector potential,
$\vec{J_s}$: Imposed current density,
$\vec{B_r}$: Remanent induction,
σ, υ: Electrical conductivity and magnetic permeability respectively.

1.2 Determination of the distribution magnetic forces

The magnetic vector potential solution A is obtained in each node of the finite element mesh of the study domain. Therefore, the distribution of magnetic forces can be determined by calculating their nodal values from the nodal values of the magnetic vector potential [19-28]. The virtual work method was used to calculate the magnetic forces. These forces are determined by solving the equation below:

$$F = -\int_0^A A^T \frac{\partial[M]}{\partial S} dA \qquad (2)$$

S : is the virtual displacement

[M]: is the magnetic rigidity matrix.

2.3 Objective Function

Since we are seeking to minimize stator forces, the optimization problem can be described by minimizing the objective function fobj, given by the following equation:

$$f_{obj} = min(\sum_{i=1}^{nps} fstat_i(X_j)) \qquad (3)$$

With: nps : is the number of nodes in the stator and the vector of design parameters.

2.4 Constraints

In this problem, we considered two constraints: The torque and the joule losses. These are inequality constraints. Obtained by these equations:

$$\begin{cases} Torque = f * R_{rotor} \\ Joule\ losses = (3 * R_{phase}) * (J_s * C)^2 \end{cases} \qquad (4)$$

R_{roto}: Rotor radius, f : Tangential force exerted on the rotor,
R_{phase}: Stator resistance per phase,
C: Surface area of a slot,
Js: Current density in a slot.

3. Geometry & characteristics of the PMSM used

The machine studied is a permanent magnet machine. Its geometric configuration is presented in Figure.1 and its main characteristics are given in Table 1

Table 1. *Characteristics of the studied machine [22]*

Number of phases:	3
Number of pole pairs:	3
Inner stator diameter (mm):	44.7
Active machine length (mm):	160
Number of stator slots:	18
Number of magnets:	6
Connection type:	Star
Rated current (A):	5.3

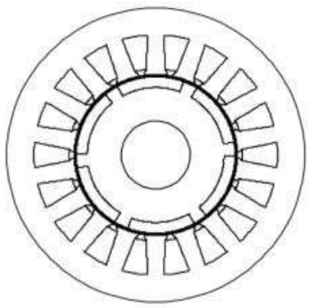

Figure 1. *Geometric configuration of the PMSM used*

4. Applications and results

4.2. Harmonic Regime Modeling

A study in the harmonic regime was carried out for the no-load operating condition of the motor, at a frequency of f=50 Hz. The ferromagnetic laminations of both the stator and the rotor are assumed to be linear. The RMS phase current is: $I_{\_eff}$=3.5*√2 A, and the phase resistance is: R_{phase}=0.5 Ω. The finite element mesh adopted for this study is shown in the figure 2.
The elements constituting this mesh are first-order triangular elements. This mesh consists of N=5161 nodes and NE=10280 elements. Figure.3 shows the equipotential lines of the magnetic vector potential. These lines exhibit a radial distribution in the air gap of the machine and tend to follow the paths of least reluctance (ferromagnetic regions).
The figures below show the distribution of magnetic forces in the stator. These magnetic forces are stronger in regions where the field lines are more

concentrated. Moreover, they exhibit a non-uniform distribution along the contour passing through the teeth, due to the presence of the slots (Figure 4).

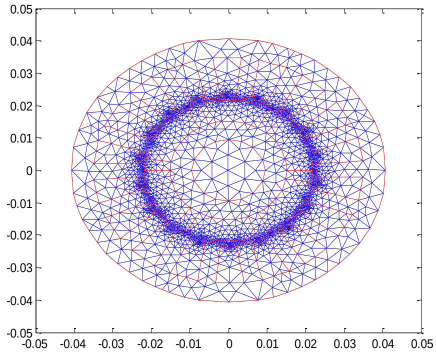

Figure 2. *Finite element mesh adopted in this study.*

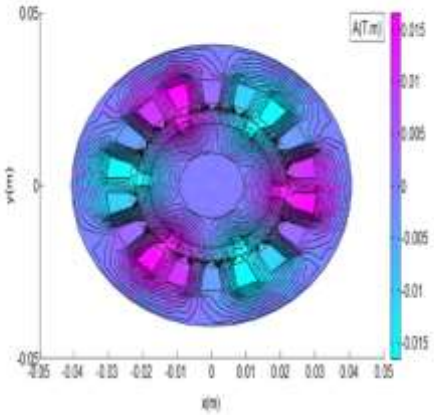

Figure 4. *Equipotential lines of the magnetic vector potential*

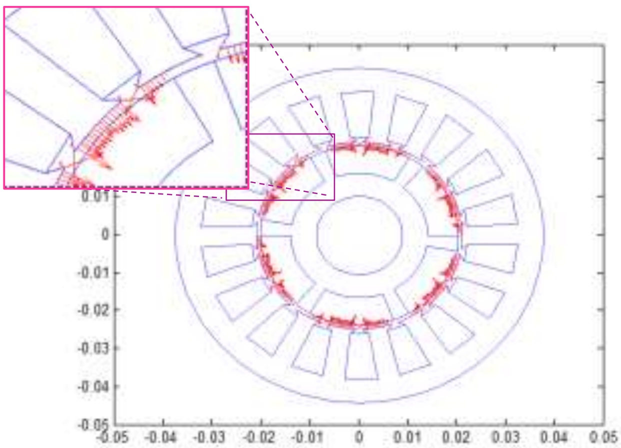

Figure 5. *Distribution of magnetic forces in the stator*

Since the magnetic forces acting on the stator have a non-uniform distribution, it is desirable to reduce them in order to minimize their effects (vibrations, etc.). To this end, a computational code based on two global optimization methods (TLBO and GWO) has been developed, aiming to determine the optimal geometric parameters of the machine that yield a minimum overall force on the stator.

4.3. Development of geometric optimization tools

An optimization process based on the numerical analysis of the studied system requires special handling, since evaluating the objective function at each iteration of the process necessitates at least one numerical analysis performed by an external routine to the optimization tool. The organization of an optimization tool associated with numerical modeling of electrotechnical systems is designed in such a way that the exchange of information and results between the two modules is possible [22][28][29].

4.3. Adaptation of the Grey Wolf Optimization (GWO) method

Before starting the search for the optimal solution using the Grey Wolf Optimization (GWO) algorithm, it is necessary to initialize the algorithm by defining several key parameters, such as:

- The population size (number of wolves in the pack).
- The number of dimensions of the optimization problem.
- The coefficients for updating the wolves' positions (a, A, and C), which influence the balance between exploration and exploitation.
- The maximum number of iterations or a defined convergence criterion.

A very small number of wolves may limit the exploration of the search space and lead to a local optimum. Conversely, a very large number increases the computational time and may slow down the convergence of the algorithm [22][30][33].

4.4 Adaptation of the Teaching–Learning-Based Optimization (TLBO) method

Before starting the search for the optimal solution using the TLBO algorithm, it is necessary to initialize the algorithm by defining several key parameters, such as:

- The population size (number of learners in the class).
- The number of dimensions of the optimization problem.
- The number of iterations representing the learning cycles.
- The definition of the two main phases of the algorithm: the Teacher Phase and the Learner Phase.

- The stopping criterion of the search process (maximum number of iterations or convergence condition).

The TLBO algorithm improves solutions through two main phases: in the Teacher Phase, learners are guided toward the best solution (the teacher), while in the Learner Phase, knowledge is exchanged among individuals to enhance their performance.A small number of learners may limit the diversity of solutions and lead to convergence to a local optimum. Conversely, a large number increases computational time without necessarily improving solution quality. One of the advantages of this algorithm is that it does not rely on many control parameters compared to other optimization algorithms, which facilitates its implementation and effectiveness in solving optimization problems [34-35].

4.5. Design strategy

The main objective of the developed design approach is to follow a numerical methodology in order to optimize the geometry of the magnets, the slots, and the stator yoke of a PMSM. The geometric parameters of these components are selected as design variables. This study aims to determine an optimal combination of values (geometric parameters) that ensures a high torque while minimizing the weight.

4.5.1. Geometric optimization variables

The study shows that several geometric parameters affect torque (saliency ratio) and Joule losses, but the most influential ones are the slot opening angle (β_{enco}), slot radius (R_{enco}), magnet radius (R_{aim}), outer and inner stator radius ($R_{statorext}$,) ($R_{statorint}$). Finally, the optimization variables and their bounds are given in (Table 2 & Figure 6):

Table 3. *Limits of the optimization parameters*

Parameter	Min Value	Max Value
$\boldsymbol{R_{aim}}$ (mm)	15	21
$\boldsymbol{\beta_{enco}}$ (Deg)	5.75	11.25
R_{enco} (mm)	25	35
$R_{statorext}$ (mm)	38	44
$R_{statorint}$ (mm)	22.2	22.8

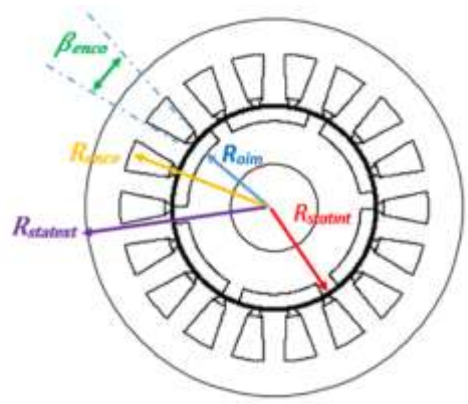

Figure 7. *The vector of parameters to be optimized*

4.6. Optimization Results and Simulation Scenarios

Two simulations were conducted to identify the optimal geometry that minimizes the global force at the stator level. First, a simulation was performed using four parameters. Second, a simulation with five parameters was carried out to maximize the machine torque.

4.6.1 Simulation with four parameters

The system below represents the optimization problem to be solved:

$$\begin{cases} \min\left(g = \sum_{i=1}^{nps} fstat_i\right) \\ 15 \le R_{aim} \le 21; 25 \le R_{enco} \le 35; 38 \le R_{statorext} \le 44 \\ 5.75 \le B_{enco} \le 11.25 \end{cases} \quad (5)$$

The figure 8 illustrates the evolution of the objective function with respect to the number of iterations for the two optimization methods (GWO & TLBO). The obtained optimal parameters, as well as the computational time and the corresponding torque, are summarized in Table 3. Furthermore, Figure 8 compares the initial geometry of the machine with the optimal geometry obtained by each optimization method.

Table 3. *Optimal parameters obtained*

Parameters	Initial Values	Optimal Values (TLBO)	Optimal Values (GWO)	Computation Time (TLBO)	Computation Time (GWO)	Torque (N•m)
R_{aim} (mm)	18.05	21.03	20.8	11h:52m:14s	06h:10m:35s	0.952
R_{enco} (mm)	30.8	35.10	34.7			
R_{aim} (mm)	18.05	21.03	20.8			
R_{enco} (mm)	30.8	35.10	34.7			

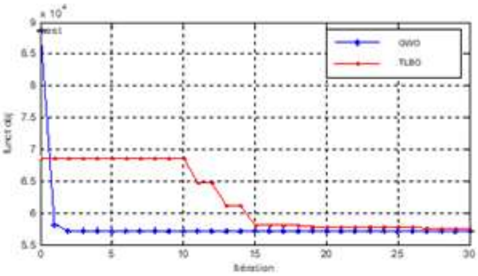

Figure 8. *Evolution of the objective function versus iterations (TLBO & GWO).*

Based on the observation of Figure 8, a significant difference can be noticed between the objective functions of the two methods. Indeed, the objective function of the Grey Wolf Optimizer (GWO) rapidly reaches the optimal value as early as iteration 2, and then remains stable at this level until the end. In contrast, the other method (TLBO) only converges to this value starting from iteration 15, where it then stabilizes definitively. This difference is also reflected in the program's execution time. Indeed, the Teaching Learning Based Optimization (TLBO) required approximately 12 hours to fully generate the results, whereas the Grey Wolf Optimizer (GWO) reduced this time by half. This remains valid despite the fact that the number of iterations was set identically for both algorithms.

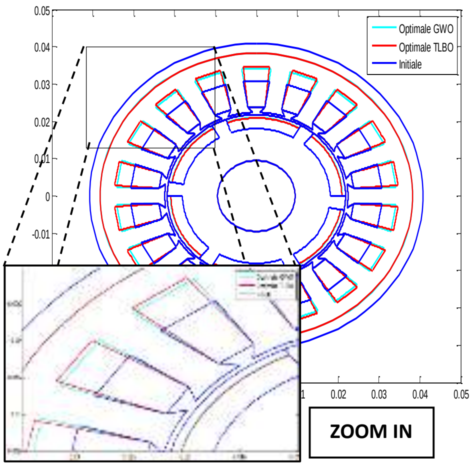

Figure 8. *Presentation of the three machines: initial, Optimale TLBO, and Optimale GWO.*

However, by analyzing the obtained results for the parameters to be optimized, we observe a strong convergence of the optimal values between the two methods, particularly with regard to the slot diameter and the permanent magnet thickness. Both approaches lead to a reduced permanent magnet thickness, which results in a lower machine torque. Thus, while a reduction in the machine weight was achieved, it came at the expense of torque. In order to maximize the torque, another simulation without constraints was carried out.

4.6.2 Simulation with five parameters for torque maximization

In this case, the optimization problem is formulated as follows:

$$\max(Tor)\quad \begin{cases} 15 \le R_{aim} \le 21;\, 25 \le R_{enco} \le 35;\, 38 \le R_{statorext} \le 44; \\ 5.75 \le B_{enco} \le 11.25;\, 22.2 \le R_{statorint} \end{cases} \quad (6)$$

Where:

Tor*:* objective function to be maximized.

The vector of parameters to be optimized is defined as follows: [R_{enco}, R_{aim}, β_{enco}, $R_{statoro}$, $R_{statorint}$]. The evolution of the objective function over the iterations is illustrated in Figure 9. The obtained optimal parameter values, as well as the corresponding computation time, are summarized in Table 4. Finally, Figure 10 presents the superposition of the three machine configurations: initial, TLBO-optimized, and GWO-optimized.

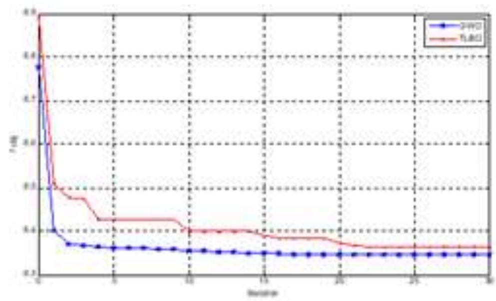

Figure 9. *Evolution of the objective function versus iterations (TLBO & GWO).*

Table 4. *Optimal parameters obtained*

Parameters	Initial Values	Optimal Values (TLBO)	Optimal Values (GWO)	Computation Time (TLBO)	Computation Time (GWO)	Torque (N•m)
R_{aim} (mm)	18.05	15.3	15.9	6h :24m :58s	6h :11m :34s	3.5050
R_{enco} (mm)	30.8	34.2	33.7	—	—	—
$R_{statorext}$ (mm)	40.8	40.4	39.6	—	—	—
β_{enco} (Deg)	8	6.8	6.29	—	—	—

From the obtained results in this case, it can be observed that the Teaching Learning Based Optimization (TLBO) converged faster than in the previous simulations. The execution time was reduced by nearly half, decreasing from 11 hours and 52 minutes to 6 hours and 25 minutes, making it comparable to that of the second method. In contrast, for the Grey Wolf Optimizer (GWO), the execution time remained almost unchanged.

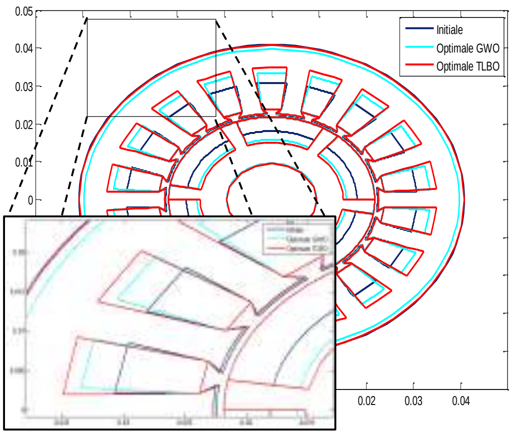

Figure 10. *Presentation of the three machines: initial, Optimale TLBO, and Optimale GWO.*

6.4.3 Discussion of Results and Comparison between the Two Methods:

6.4.3.1 Objective function :

The analysis of the objective function graph allows a comparison between the performance of the Teaching Learning Based Optimization (TLBO) and the Grey Wolf Optimizer (GWO) according to several criteria:

- **Convergence:** The GWO algorithm appears to reach an optimal solution more quickly compared to TLBO, which reflects a better balance between exploration and exploitation from the early iterations.
- **Stability:** The convergence of GWO is more stable with fewer oscillations, whereas the TLBO shows more fluctuations before reaching a steady plateau. This instability can be attributed to genetic operators such as mutation and selection.
- **Exploration vs exploitation:** The TLBO explores a wider search space at the beginning of the optimization process, while GWO focuses more on efficiently exploiting promising solutions, which explains its faster convergence.

In conclusion, if speed and stability are the main priorities, the Grey Wolf Optimizer (GWO) appears to be the most suitable choice. On the other hand, the Teaching Learning Based Optimization (TLBO) may prove to be more effective for problems that require a deeper exploration and a greater diversity of solutions.

6.4.3.2 Optimized parameters:

The analysis of the obtained results for the optimization parameters reveals a strong convergence of the optimal values between the two methods, particularly for the slot diameter and the permanent magnet thickness. In both cases, the optimization leads to a relatively small magnet thickness, which results in a reduction of the machine torque.

While this configuration allows a reduction in the machine weight, it is nevertheless accompanied by a loss in torque. To overcome this limitation, a new simulation without constraints was carried out in order to maximize the torque. However, by introducing constraints on torque and Joule losses, a more realistic solution was obtained, with optimal parameters closer to actual operating conditions. Regarding the constraints, they remain acceptable, especially for the second simulation, where they provide a satisfactory trade-off between performance and realism.

7. Conclusion

This paper addressed the determination of the optimal geometric parameters of an interior PMSM through a comprehensive optimization approach. The developed model incorporated electromagnetic field computation and magnetic force distribution, while considering practical constraints such as torque and Joule losses to minimize the force exerted on the stator.

The application of Teaching–Learning-Based Optimization and Grey Wolf Optimizer enabled an effective exploration of the design space and highlighted the significant influence of geometric optimization on machine performance. The comparative analysis demonstrated that both methods provide reliable solutions, with noticeable differences in convergence behavior and computational efficiency.

Overall, GWO proved to be more suitable for applications requiring fast convergence and high stability, whereas TLBO showed stronger capabilities in exploring the search space and generating diverse solutions. Therefore, the choice of the optimization method should be guided by the specific requirements of the problem, ensuring an appropriate balance between computational efficiency, solution quality, and physical constraints.

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
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- **Data availability statement:** The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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