



Research Article

Comparison of random search and gradient-based optimization techniques on design improvement of permanent magnet synchronous motor

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ABSTRACT

Electric machines are one of the tools that humanity has used for a long time and have become indispensable in the modern world. Electric machines produced in the form of transformers, motors, and alternators are designed in various groups. Permanent magnet synchronous motors (PMSM) belong to the group of motors in which the magnetic field is generated by permanent magnets, although they have a synchronous operating principle. Optimization studies are carried out to make PMSMs more efficient and develop them in different topological structures. Today, many optimization techniques are used in this field. Random search and gradient-based optimization algorithms are preferred for the optimization of electrical machines, as in many other fields. In this study, the efficiency optimization of a surface-mounted permanent magnet synchronous motor is performed using genetic algorithm (GA) and adaptive multiple-objective (AMO), which are random search methods, and sequential non-linear programming (SNP) and adaptive single-objective optimization (ASO), which are gradient-based algorithms. In addition to more than a 5% efficiency increase is achieved in all these methods, it was also found that random search techniques achieve faster results, while gradient-based systems produce more feasible results within the constraints. In addition, the model that provides the best efficiency value in accordance with the constraints was analyzed with the 2D finite element method and it was seen that it gave positive results in terms of air gap distance, air gap flux density and torque ripple. Demonstrating the success of this research is an acceptable efficiency increase rate was obtained compared to similar studies. Results of this study will contribute to lack of studies in literature examining random search and gradient-based optimization methods together among electrical machine optimization research.

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INTRODUCTION

In the quest for efficient and sustainable energy use, optimization of electric motors has emerged as an important area of research and development. Electric motors are the actuators of modern industrial, commercial and residential applications, driving machines, vehicles and appliances with various efficiency ratings. Among the numerous types of electric motors, PMSMs are of great interest due to their high efficiency, power density and precise control characteristics. Therefore, improving the performance of PMSMs through optimization methodologies has become a focus for researchers and engineers.

PMSMs represent a subset of synchronous motors in which the rotor's magnetic field is generated by permanent magnets instead of electromagnets. This configuration offers several advantages over other motors, such as induction motors, including higher efficiency, higher power density and improved dynamic response [1]. Due to these advantages, PMSMs are widely used in sectors ranging from automotive drive systems to renewable energy generation.

In order to exploit the full potential of PMSMs, researchers have aimed to improve performance metrics such as efficiency, torque ripple and transient response, and have also turned to cost, size and weight minimization techniques. For example, Avşar et al. have conducted an optimization study involving genetic algorithm and finite element method to increase the efficiency and reduce torque ripple of an internal rotor motor used in elevator systems. After the study, researchers evaluated the performance of the motor with a test setup and obtained results compatible with finite element method (FEM) analysis results [2]. In this study, the subject of electric motor optimization with a special emphasis on optimization techniques used to improve the efficiency and operating characteristics of PMSMs is investigated.

Random search methods, which explore the solution space without relying on differential information, encompass a variety of algorithms such as evolutionary algorithms, genetic algorithms and particle swarm optimization. These methods provide a robust framework for global optimization and are particularly well suited for problems with complex, nonlinear objective functions and constraints.

On the other hand, gradient-based optimization methods use derivative information to improve the solution toward the optimum point iteratively. Gradient-based optimization techniques, including gradient descent, Newtonian and quasi-Newtonian methods, exploit the mathematical properties of the objective function to achieve fast convergence to local optima.

A review of the works based on the techniques mentioned in this paper shows that in recent years, approaches based on the random search method have become more preferred in optimizing electric motors. Xu et al. aimed to increase the overall performance of a permanent magnet linear synchronous motor (PMLSM) planned to be used in elevator systems,

to reduce the torque ripple and to improve the torque density. In the study, the Particle Swarm Optimization algorithm based on random search method and multi-objective optimization technique using response surface model were preferred. They determined that the overall performance of the motor was effectively improved compared to the initial design by finite element analysis method and electromagnetic performance experiments [3]. In another study by Gholamian and Gholinejad, a controlled random search technique based on an ant colony algorithm was used to improve the torque-to-volume ratio of internal permanent magnet synchronous motors (IPMSMs) and validated with the 2D SEY technique. This approach demonstrates the potential of random search algorithms in achieving multi-objective optimization goals for PMSMs [4]. Moreover, Cui proposes a design optimization approach to achieve maximum efficiency, torque and minimum torque ripple for permanent magnet synchronous motors by integrating Design of Experiments (DOE) with a novel Gray Wolf Optimization algorithm. In this work, Cui demonstrates the effectiveness of combining different optimization strategies with a focus on addressing multi-objective optimization challenges in motor design [5]. In addition, the research by Cheng presents an optimization method based on an improved operator genetic algorithm, which emphasizes the improvement of global search capability through random numbers, to reduce the disturbance caused by the variation of mechanical parameters for efficient speed control of Permanent Magnet Synchronous Wind Generators (PMSWGs). This method contributes to optimizing PMSWGs by efficiently determining the key parameters [6]. Furthermore, Kwon and Lim investigate the optimal design of permanent magnet-assisted synchronous reluctance motor (PMA-SynRM) used in electric vehicles by combining random forest and genetic algorithm techniques. By identifying the design variables through sensitivity analysis, this study highlights the importance of integrating advanced algorithms for motor optimization. As a result of the experiments, it is observed that torque increases and torque ripple decreases [7].

There are also studies in literature where gradient-based algorithms are used in the optimization process of electric machines. For example, Bazzo et al. [8] used sequential quadratic programming (SQP) algorithm for multi-physics design optimization to reduce the cost of a permanent magnet synchronous generator (PMSG) used as a medium-power class wind turbine. Chen et al. [9] have studied a multi-objective optimization process to increase the output torque, efficiency and reduce torque ripple of a dual-stator permanent-magnet doubly salient (DS-PMDS) motor, planned for electric vehicles. They completed the optimization process, which carried out using parametric sensitivity analysis and sequential quadratic programming (NLPQL) methods, with FEM analysis. Although known algorithms are often used in electrical machine optimization processes, there are also studies that aim to find optimum values according to the gradual changes of some parameters affecting machine efficiency. Kurt and Fenercioğlu planned

to determine the model with the best performance by increasing rotor slot depth (Hs2) in the range of 3-7 mm with 0.25 mm steps while keeping the other parameters constant of the single-phase asynchronous motor. In their designs, which they were analyzed with 2D finite element method, they determined the model with a rotor slot depth of 4 mm provided the best performance [10].

In a review of studies in different disciplines, some papers are tests of the performance of both methods. For example, Rukolaine used a combination of pure random search method and conjugate gradient method in his study for shape optimization of radiant enclosures with specular-diffuse surfaces [11]. Bastrikov et al. [12] compared the performance of gradient-based methods and random search techniques in their study on land surface models for future climate forecasting. Finally, Miller et al. [13] compared the gradient-based SQP algorithm with two random search-based algorithms, a genetic algorithm and simulated annealing, to predict athletes' muscle strength. They found that random search algorithms produced more meaningful predictions due to the difficulty of the SQP algorithm in finding the global minimum.

There are many valuable papers on optimization using random search and gradient-based techniques in the literature. Although studies compare these two techniques in different disciplines, there is a lack of similar studies in electric machines. In this study, results of random search and gradient-based methods are examined and compared in the efficiency optimization of electric motors. At the end of study, model with the best efficiency result in accordance with size constraints was analyzed with 2D finite element method. According to analysis results, it was determined that the air gap distance, air gap flux density and torque ripple values were suitable for purpose of the machine. Thus, advantages and disadvantages of both methods were presented in electrical machine optimization process. In addition, by obtaining more than 5% efficiency increase in all methods used, electrical machine studied was improved and new results were added to literature for researchers working in this field. Efficiency increase rate of PMSM obtained is quite successful compared to similar studies in literature.

RANDOM SEARCH AND GRADIENT-BASED OPTIMIZATION TECHNIQUES

Optimization techniques preferred to find the optimal solution to a given problem, play an important role in various fields such as machine learning, engineering design and scientific computing. Optimization methods are generally based on gradient-based mathematical methods such as Newton and Quasi-Newton and random search-based algorithms such as genetic algorithm, water cycle algorithm, and annealing simulation [14]. Random Search and Gradient-based optimization techniques, widely used optimization approaches, aim to minimize or maximize the objective function.

Random Search

Random Search is a simple but effective optimization method based on sampling random points from the search space and evaluating them to find the best solution [15]. Unlike gradient-based methods, Random Search does not require knowledge about the gradient of the objective function. Instead, it explores the search space by randomly selecting candidate solutions and iteratively improving them [16]. Figure 1 shows the pseudocode for random search.

Random search, a member of the global optimization and stochastic optimization techniques, uses the direct search method because it does not require derivatives to scan a given space continuously. When it was first developed, only best-fit algorithms with a fixed step size were used [17], and later, direct random search and adaptive random search versions were studied [18]. Since the algorithm with a fixed step size has the disadvantage of converging to the minimum, it has been proposed to reduce the steps for high accuracy. Adapting the step size is more efficient than adapting the search direction and combining the two methods is considered more appropriate [19]. Studies show that random search is more likely to find the optimum value than manual and grid searches, especially in high-dimensional search spaces [20, 21]. Figure 2 shows the comparison between grid search and random search. The nine points in the figure show the candidate solutions, and the curves on the left and top show the model accuracy of the function in the relevant search dimension.

```

Input: NumIterations, ProblemSize, SearchSpace
Output: Best
1 Best ← ∅;
2 foreach  $iter_i \in \text{NumIterations}$  do
3    $candidate_i \leftarrow \text{RandomSolution}(\text{ProblemSize}, \text{SearchSpace});$ 
4   if  $\text{Cost}(candidate_i) < \text{Cost}(\text{Best})$  then
5     | Best ←  $candidate_i$ ;
6   end
7 end
8 return Best;

```

Figure 1. Pseudocode for random search [17] [created by author]

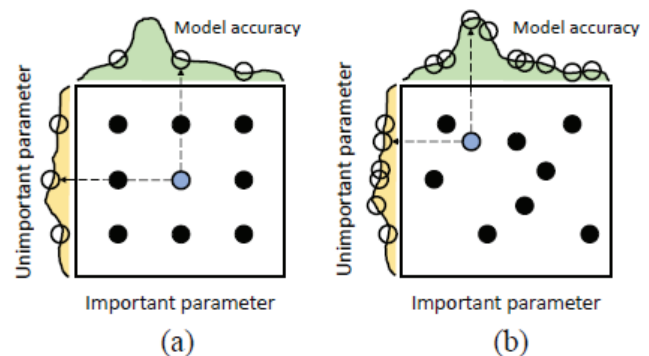


Figure 2. Comparison of grid search (a) and random search (b) [22] [created by author].

Furthermore, by exploring various candidate solutions, Random Search can avoid local optima and find globally optimal or near-optimal solutions in complex, high-dimensional spaces. In addition, random search is computationally inexpensive and easy to implement compared to other population-based methods such as particle swarm optimization or genetic algorithms. Therefore, random search is suitable for problems where computational resources are limited, or the evaluation of the objective function is expensive [22].

However, random search may require a large number of iterations to converge of optimal solution, especially in high-dimensional search space. The inherent randomness of the algorithm may lead to inefficient exploration of search space, leading to suboptimal solutions or high computing resource requirements [23]. In addition, suboptimal results may be found if there are not enough iterations, and the search intervals are not well chosen [24].

Genetic Algorithm (GA)

Genetic algorithm, which uses a random search technique, is part of the class of stochastic optimizers. It uses a form of random selection to determine where to explore the design space and applies it in a structured way. The random evaluation system used to generate the next generation may contain many random solutions that do not progress toward the optimization goal so that the local minimum is not skipped. Sometimes the GA can be extremely slow as it will run many more iterations [25].

Adaptive Multiple-Objective (AMO)

Adaptive multi-objective optimization (AMO) is developed as a combination of Kriging and multi-objective genetic algorithm (MOGA). AMO technique builds or uses a collection of existing instances to approach the problem better than passive search. It evaluates design points where necessary. Part of the population can be simulated by grading Kriging response surfaces. Therefore, Kriging error estimation reduces the number of evaluations used in finding Pareto environment solutions [26].

Gradient-Based Optimization

Gradient-based optimization techniques, widely preferred for solving optimization problems, rely on the gradient or approximation of the objective function to guide the search for the optimal solution. In this technique, the solution is iteratively updated according to the direction of the gradient to minimize or maximize the objective function efficiently. To determine an optimal solution using gradient-based methods, an endpoint must be defined where the gradient equals zero. Newton, quasi-Newton, Levenberg Marquardt and conjugate direction methods are the most popular gradient-based optimization techniques [14].

One of the most important advantages of Gradient-Based Optimization Techniques is their ability to exploit the local structure of the objective function to converge faster to the optimal solution. By exploiting knowledge about the gradient, these methods can efficiently navigate the search

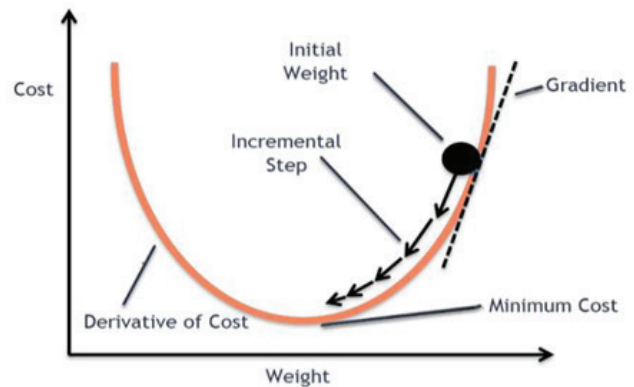


Figure 3. Gradient descent algorithm [29] [created by author]

space and converge towards the optimal solution along the steepest descent direction. As with most other optimization methods, a search direction is chosen, and the search process proceeds toward the optimum solution [27]. Search directions can be explored by determining the derivatives of the objective function with constraints. This type of optimization approach has two main disadvantages: slow convergence speed and no guarantee of reaching the optimal solution [28]. Gradient-based algorithms, which have different types such as Gradient Descent, Gradient Ascent and Stochastic Gradient Descent, play an important role in the training process of models in applications such as Machine Learning and Deep Learning [29]. Figure 3 shows the step movements of the gradient-based search from the starting point to the intended minimum.

Sequential Nonlinear Programming (SNP)

SNP assumes that the optimization variables spread over a continuous domain. There is no “Minimum Step Size” to be specified, and variables can take any value within the allowed constraints and numerical precision of the simulator. Like Quasi-Newton, the SNP optimizer assumes that noise is not important. It reduces the impact of noise, but noise filtering is not strong. SNP has a good approximation of the cost function in terms of optimization variables with a Finite Element Analysis (FEA) approach and lightweight cost function evaluation. Its main advantage over Quasi-Newton is that it deals with optimization problems more deeply [30].

Adaptive Single-Objective Optimization (ASO)

Adaptive Single Objective Optimization algorithm is a mathematical optimization method that combines experimental Optimal Space Filling (OSF), Kriging and MISQP optimization algorithms. The ASO method is a response surface-based gradient algorithm that provides global and refined results [31]. Since the algorithm is designed using a single-objective logic, it can be used for continuous input parameters but only addresses one output parameter objective. Since the other output parameters can be

defined as constraints, they are suitable for optimizing very constrained problems [32]. ASO automatically adjusts the design space improved in the previous iteration and performs the experimental design, response surface generation, and optimization process again to find the global optimum using incremental improvement logic [33].

In summary, random search and gradient-based optimization techniques have advantages and limitations for different optimization problems. Although it requires many iterations, random search is well suited for exploring complex and high-dimensional search spaces. Gradient-based optimization efficiently converges towards the optimal solution for smooth and well-functioning objective functions.

The size of search space and computational resources are decisive in choosing between random search and gradient-based optimization methods, as well as factors such as the nature of the objective function. In practice, combining the strengths of both methods, a hybrid approach can yield successful results by exploiting the flexibility of random search for global exploration and the efficiency of gradient-based optimization for local improvement.

SURFACE MOUNTED PMSM

The structure of permanent magnet synchronous motors mainly consists of stator, rotor, windings, permanent magnets and shaft. PMSMs are widely used in aerospace applications, electric vehicles and industrial control applications due to their favorable features such as low torque ripple coefficient, high torque-to-inertia ratio, high power density and good overload capacity [34]. Surface-mounted PMSMs are vulnerable to demagnetized fields but are particularly preferred for ease of manufacture. Since the permanent magnets are placed on the surface of the rotor, this design model is suitable for low speeds [1]. Surface mounted permanent magnet synchronous motors are becoming more and more popular to replace asynchronous motors, brushless DC motors and universal motors due to their advantages such as reliability, high efficiency,

less acoustic noise, small size, high air gap flux density and good dynamic response [35]. In addition to radial flux models, permanent magnet synchronous motors can be produced with different designs such as axial flux [36] and linear motor [3]. A cross-sectional view of a synchronous motor with surface-mounted permanent magnets is shown in Figure 4.

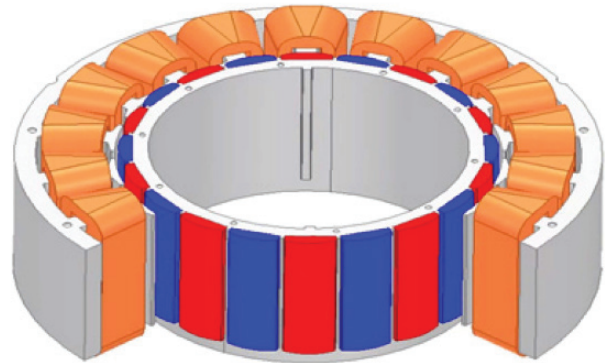


Figure 4. Surface-mounted permanent magnet synchronous motor [37] [created by author]

Table 1. Characteristics of the PMSM used in the study

Parameter	Value
Output power	550 W
Voltage	220 V
Nominal speed	5000 rpm
Outer diameter	72.17 mm
Package length	33 mm
Number of poles	8
Rated torque	1.20 N.m
Efficiency	%86.67

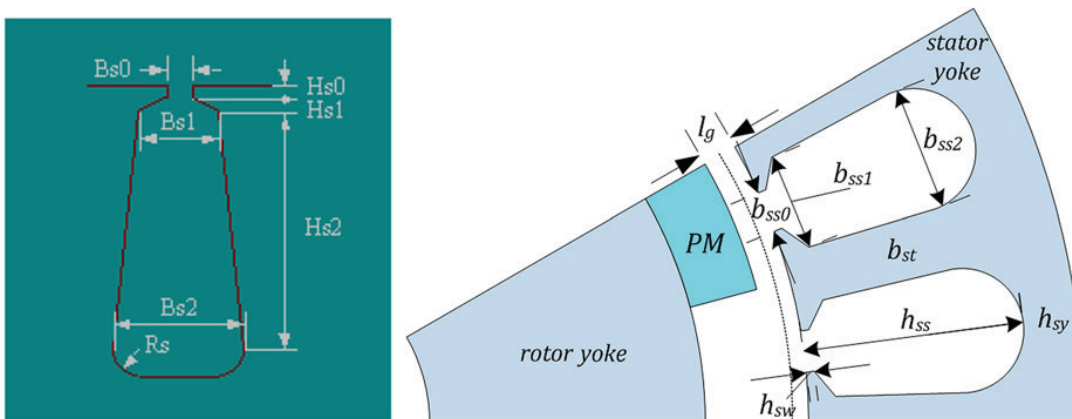


Figure 5. Rotor and stator geometry of PMSM [38] [created by author].

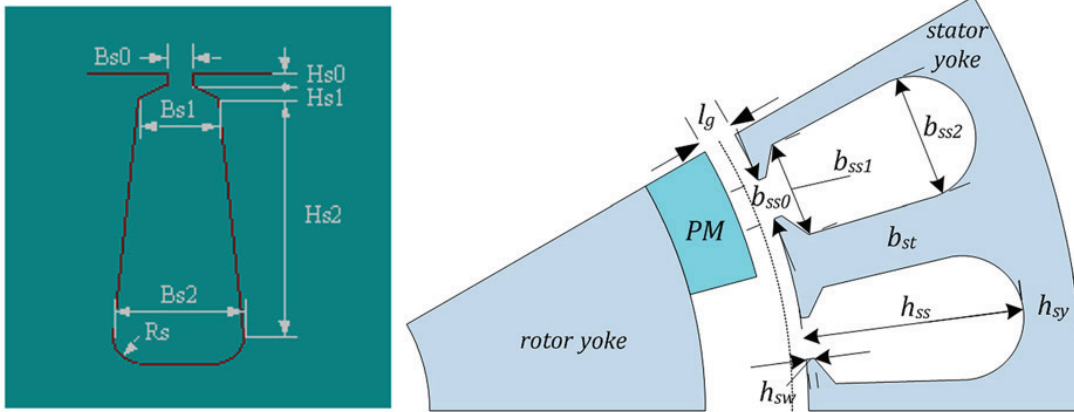


Figure 6. Slot structure stator.

In this study, a PMSM type servo motor was used, the important features of which are shown in Table 1. This motor is preferred in CNC machines and robotic applications as an automatic tool changer. It is aimed to increase efficiency of PMSM, which is currently 86.67%, by making changes to some design parameters.

Rotor and stator geometry of the motor used in this study can be seen from a cross-section in Figure 5, and the slot structure on the stator can be seen from the detailed image in Figure 6.

Outer diameter of rotor can be found with the following equation. In the initial design, this value is 44.9 mm.

$$shaft + 2 \times (rotor_{yoke} + magnet_{thickness}) \quad (1)$$

Stator's outer diameter can be found with the equation below. In initial design, this value is 72.17 mm. Shaft diameter in both equations is 25 mm.

$$shaft + 2 \times (rotor_{yoke} + magnet_{thickness} + hs0 + hs1 + hs2 + rs + stator_{yoke}) \quad (2)$$

PMSM efficiency equation, which will be used as the objective function, consists of input power, output power and loss components. Minimizing losses has a positive effect on efficiency value.

$$\eta = \frac{P_{out}}{P_{in}} = \frac{P_{in} - P_{loss}}{P_{in}} \quad (3)$$

$$P_{in} = V_{dc} I_{dc} \quad (4)$$

Where P_{in} is the input power, P_{out} output power, V_{dc} and I_{dc} are the voltage and current values applied to the motor by the inverter respectively. Losses of the motor can be obtained with the following equation.

$$P_{loss} = P_{cu} + P_{ir} + P_{me} \quad (5)$$

Where P_{loss} total loss, P_{cu} , P_{ir} and P_{me} represent copper, iron and mechanical losses respectively [39].

$$P_{cu} = 3/2R(I_d^2 + I_q^2) \quad (6)$$

In this equation, R represents the winding resistance, and I_d and I_q represent stator currents of d - q axes [40].

$$P_{ir} = k_{hd}(\psi_d^2 + \psi_q^2) + k_{ep}(\psi_d^{1.5} + \psi_q^{1.5}) \quad (7)$$

$$k_{hd} = \beta_1 f + \beta_2 f^2 ; k_{ep} = \beta_3 f^{1.5} \quad (8)$$

In this equation, k_{hd} is the coefficient of equivalent hysteresis and eddy current losses k_{ep} is the coefficient of equivalent excess losses, ψ_d and ψ_q flux linkages of d - q axis, and $\beta_1 - \beta_3$ are machine design constants. Mechanical losses (P_{me}) are neglected in this study as they have a relatively low value among total losses [41].

RESULTS AND DISCUSSION

Efficiency optimization operations applied to PMSM, features given in Table 1, using four different optimization algorithms, two random searches and two gradient-based ones. Optimization processes were performed on a computer with an Intel Core i7-8700 3.2 GHz processor, 16 GB RAM Memory and GeForce GT-710 2GB graphics card without any other simultaneous processing. The time to reach the result of algorithms, all planned to be completed in a maximum of 300 iterations, is also recorded.

Before the optimization process to increase the efficiency of PMSM, 8 of the machine's geometric design parameters that affect the efficiency value were selected [42]. Selected variables are given in Table 2 with their minimum, maximum value range and reference values.

Objective function is set as the maximum efficiency in the optimization process, and PMSM diameter should not change much. Parameters $hs0$, $hs1$, rs , $airgap$ and

Table 2. Optimized PMSM parameters

Parameter	Description	Reference Value (mm)	Search Range
hs0	Stator tooth tip thickness	0.52	0.52-0.5201
hs1	Stator in-groove tooth tip thickness	0.455	0.455–0.45501
hs2	Stator in-groove height	6.6	6.0-8.0
airgap	Air gap	0.5	0.5-0.801
rs	Radius value under slot	1,96	1.96–1.9601
magnet_tickness	Magnet thickness	3.25	2.75–3.5
stator_yoke_thick	Stator yoke thickness	3.6	3.0–5.0
rotor_yoke_thick	Rotor yoke thickness	6,7	6.70-6.701

rotor_yoke_thick have a lower efficiency calculation effect than others and were defined to undergo minimum change. Optimization processes were carried out using Ansys Maxwell software.

Gradient-Based Algorithm Results

Sequential Nonlinear Programming optimizer, one of the gradient-based techniques, 300 iterations performed at 3205 seconds. In calculations, an efficiency value minimum of 89.87% and a maximum of 91.45% was obtained. As seen from the graph in Figure 7, there is no increasing efficiency curve from the beginning to the end of process.

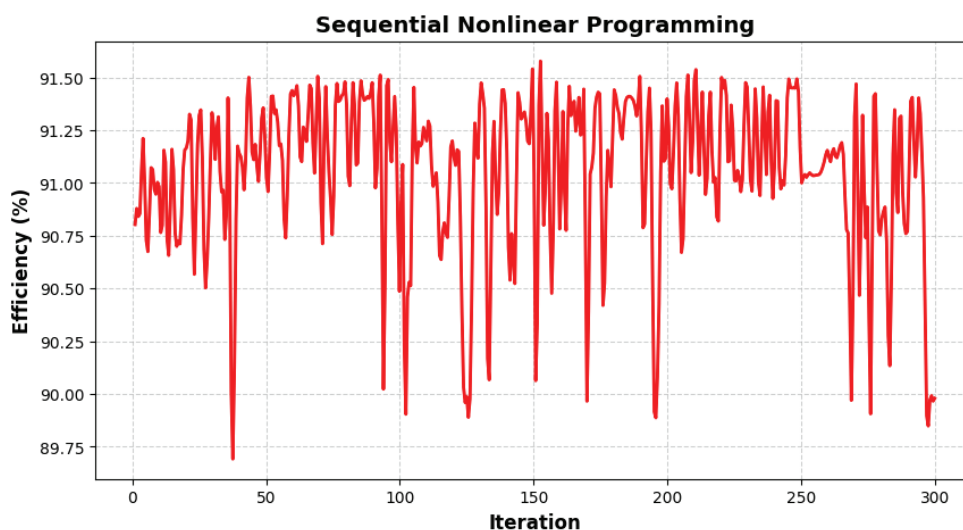
Another gradient-based technique, Adaptive Single Optimization algorithm, achieved efficiency values between 90.10% and 91.53% in the optimization process completed in 6679 seconds. Graph in Figure 8 shows the increasing convergence trend compared to Sequential Nonlinear Programming algorithm.

Random Search Algorithm Results

Genetic Algorithm, one of the random search-based techniques, obtained efficiency results ranging between 90.20% and 91.40% from 300 trials lasting 1228 seconds. Although the efficiency graph resulting from processes is not stable, gradually increasing values can be seen in the graph in Figure 9.

Another random search-based optimizer, adaptive multiple-objective, solved 300 trials in 543 seconds, less than the previous 3 algorithms. As a result, it produced efficiency values ranging from 90.10% to 91.51%. Graph in Figure 10 shows a stable efficiency value after half of the search operations.

Analytical design values and values obtained by optimization algorithms are shown in Table 3. Among 8 design parameters of PMSM, the efficiency value increased by more than 5% because of optimization processes that predict the variations of groove height (*hs2*), magnet thickness (*magnet_tickness*) and stator yoke thickness (*stator_yoke_tick*)

**Figure 7.** Results of Sequential Nonlinear Programming Algorithm.

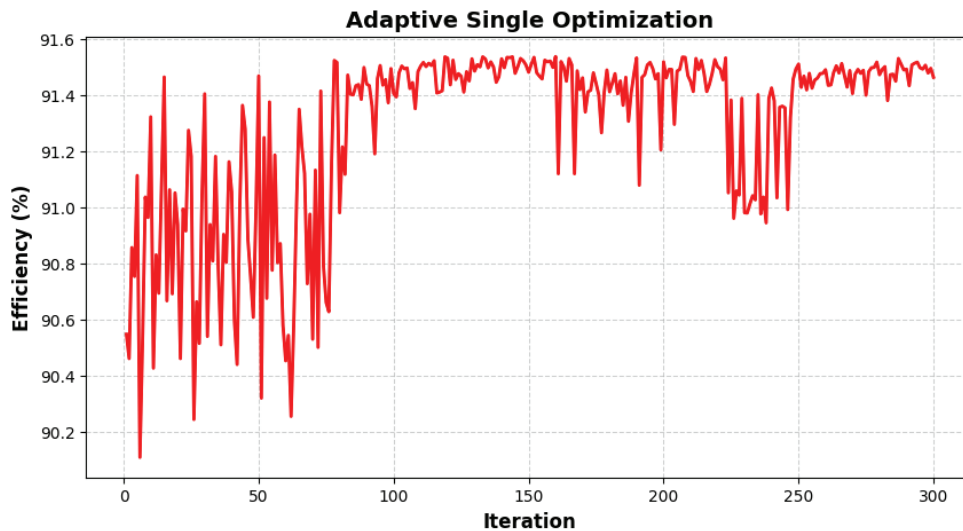


Figure 8. Results of Adaptive Single Optimization algorithm.

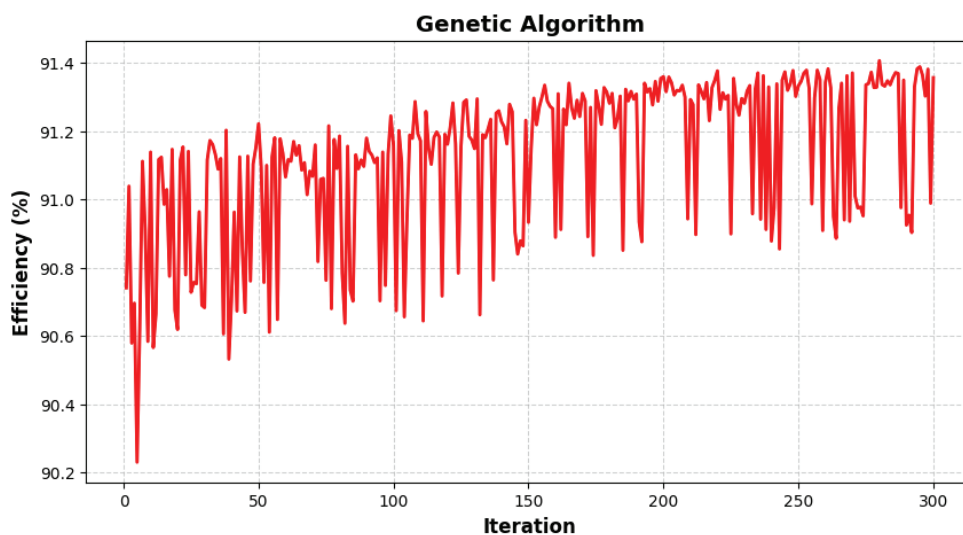


Figure 9. Results of genetic algorithm.

values within the range specified in Table 2. Although the optimum efficiency values obtained are close to each other, it has been found that gradient-based methods have longer convergence times than random search algorithms.

Regarding processing time, it can be said that algorithms adopting random search techniques have a significant advantage over gradient-based algorithms.

In order to avoid settling problems where PMSM will be used, ways to increase efficiency without increasing the diameter are being sought. Therefore, when the efficiency results obtained based on a maximum 5% variation of stator outer and stator inner diameter values specified in

Equations 1 and 2 are reconsidered, results in Table 4 are obtained.

While it is always desirable for optimization algorithms to produce high objective function values and complete the process quickly, it is equally valuable that the results obtained are feasible. Efficiency values obtained according to stator inner and outer diameter limits are shown in Figure 11.

As seen in the graph, both gradient based techniques (SNP and ASO) calculating the stator inner and outer diameter dimensions within 5% tolerance achieved an efficiency value of 91.44%.

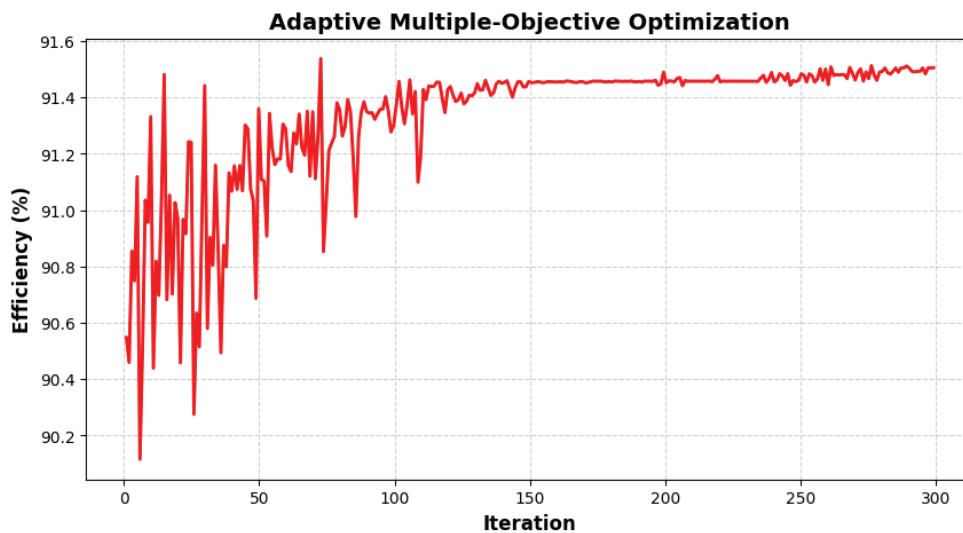


Figure 10. Results of adaptive multiple-objective algorithm.

Table 3. General results of optimization processes

Parameter	Analytical Design (mm)	SNP	ASO	GA	AMO
hs0	0,52	0,52	0,52	0,52	0,52
hs1	0,455	0,455	0,455	0,455	0,455
hs2	6.6	7.616	7.63	7.58	7.73
airgap	0.50	0.80	0.801	0.80	0.801
rs	1.96	1.96	1.96	1.96	1.96
magnet_tickness	3.25	2.75	2.75	2.88	2.76
stator_yoke_thick	3.6	4.44	5.00	4.55	4.95
rotor_yoke_thick	6.70	6.70	6.70	6.70	6.70
Efficiency (%)	86.67	91.45	91.53	91.40	91.51
Efficiency difference (%)	-	5.52	5.612	5.462	5.589
Optimization Time (sec)	-	3205	6679	1228	543
Iteration Number	-	190	119	279	277

Table 4. Optimization results according to stator inner and outer diameter variation

Parameter	Analytical Design	SNP	ASO	GA	AMO
Stator inner diameter (mm)	45.9	45.54	45.58	45.72	45.73
Stator outer diameter (mm)	72.17	75.48	75.61	75.50	75.67
Efficiency (%)	86.67	91.44	91.44	91.38	91.35
Efficiency difference (%)	-	5.508	5.508	5.439	5.404
Iteration Number	-	245	138	296	95

Optimization of efficiency on electrical machines is a topic frequently addressed by researchers. Table 5 shows the techniques used for optimizing efficiency of an electrical machine and efficiency increases achieved.

As shown in Table 5, numerous optimization studies have been conducted to increase efficiency of electrical machines. In most studies, an algorithm was used to perform optimization process and methods such as FEM were preferred to verify results. Of course, there are studies that

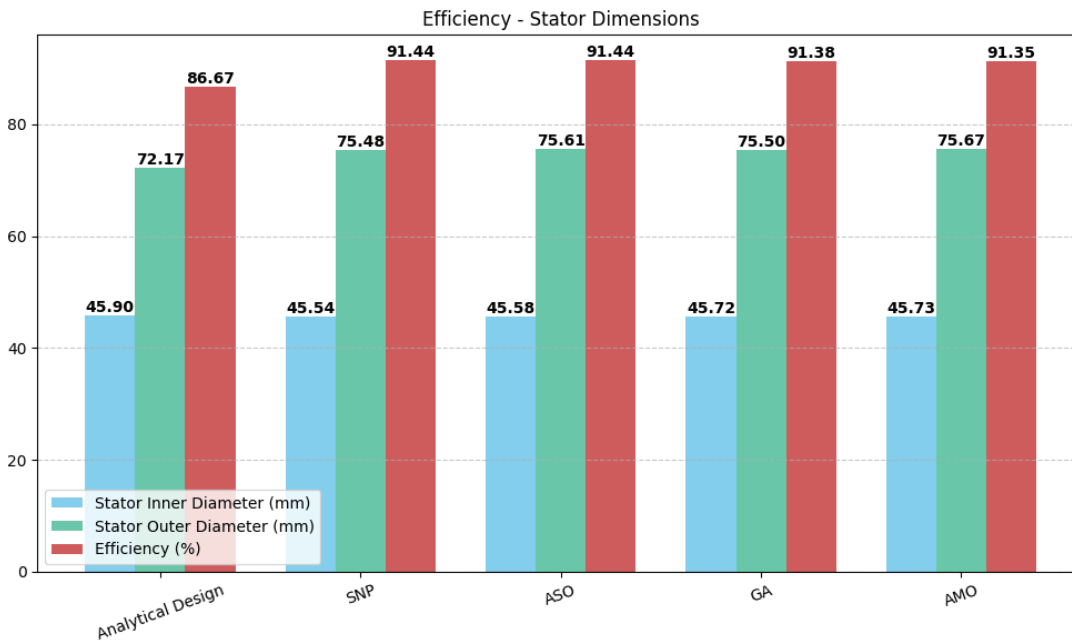


Figure 11. Stator size limits and efficiency results.

Table 5. Comparison with other studies in literature

Reference	Machine	Technique Used	Efficiency Increase
Xing Jin, Yong, et al.[43] 2018	PMSM	Improved Particle Swarm Optimization (PSO)	%2.64
Cui[5], 2023	PMSM	Design of Experiments (DOE) & Gray Wolf Optimization (GWO)	%0.31
Mutluer[44], 2021	PMSM	GWO and PSO	%2.33 by GWO %2.29 by PSO
Sarac[45], 2019	PMSM	GA and FEM	%0.112
Gundogdu & Komurgoz, [46] 2021	IPM	GA and 2D FEM	%1.45
This study	PMSM	Random search & Gradient based algorithms, 2D FEM	%5.508

Table 6. Values that provide the highest efficiency in SNP algorithm

Parameter	Description	Value (mm)
hs0	Stator tooth tip thickness	0.52
hs1	Stator inside slot tooth tip thickness	0.455
hs2	Stator inside slot height	7.61
airgap	Airgap	0.80
rs	Radius value inside bottom of slot	1,96
magnet_tickness	Magnet thickness	2.78
stator_yoke_thick	Stator yoke thickness	4.423
rotor_yoke_thick	Rotor yoke thickness	6,70
Efficiency (%)	-	91.44

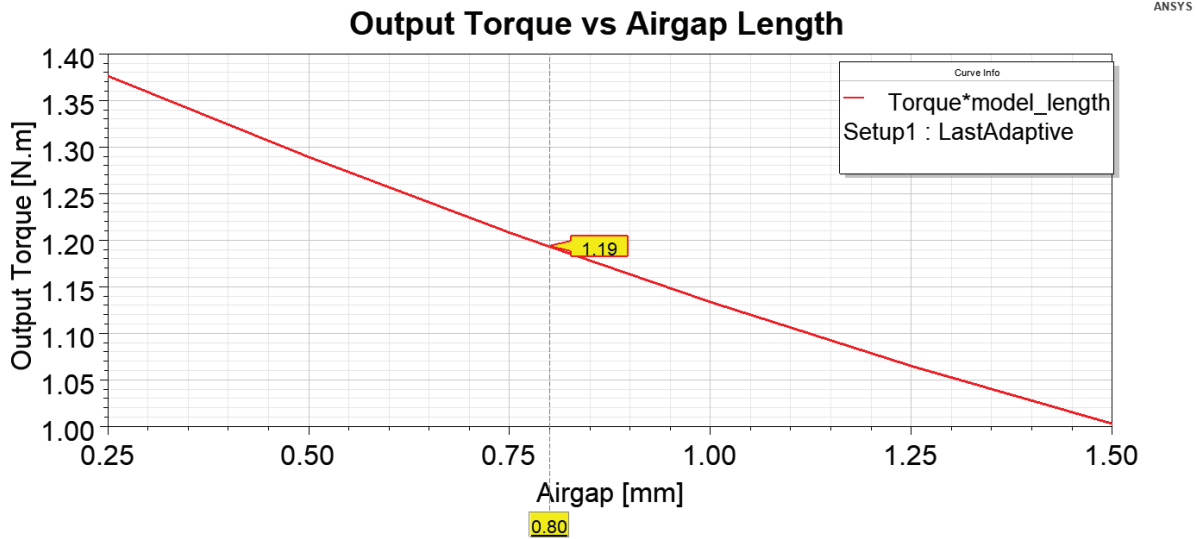


Figure 12. Airgap vs. output torque graph.

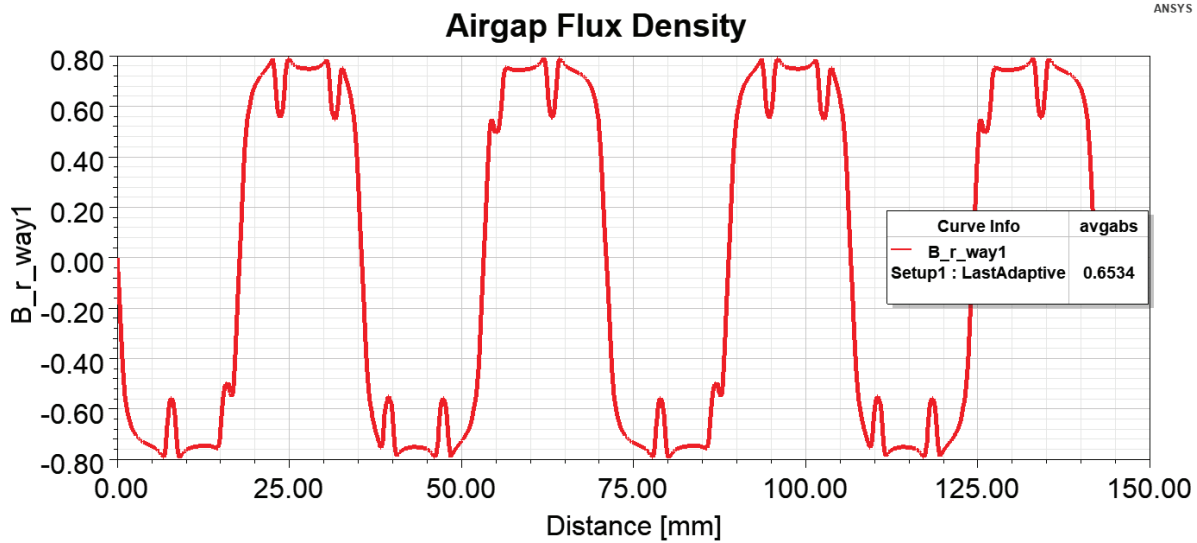


Figure 13. Airgap flux density.

cover various machines and include different performance values other than those seen in this table. According to studies in Table 5 that include PMSM efficiency optimization, the efficiency increase rate obtained in this study is remarkable.

Validation of Optimization with 2D FEA Results

Results obtained in the 245th iteration of the SNP algorithm, which produces the optimum efficiency values in accordance with the change constraint of stator inner and outer diameters, are shown in Table 6.

For the evaluation of study, air gap-output torque, airgap magnetic flux density and torque ripple graphs obtained

from 2D finite element analysis of designed motor according to the values in Table 5 are presented. Figure 12 shows change in output torque according to the airgap distance.

As seen in Figure 12, targeted output torque is approximately achieved with an airgap of 0.80 mm. As the air gap decreases, the output torque increases, but this can cause some mechanical problems, such as contact between the rotor and stator during operation. Figure 13 shows the change flux density in the air gap arc.

Sequential pattern in flux density graph in Figure 13 is due to shape of stator tooth structure and slot openings. Specific magnetic loading in airgap, was determined as 0.6534 Tesla according to 2D FEA analysis result. Flux density in airgap is

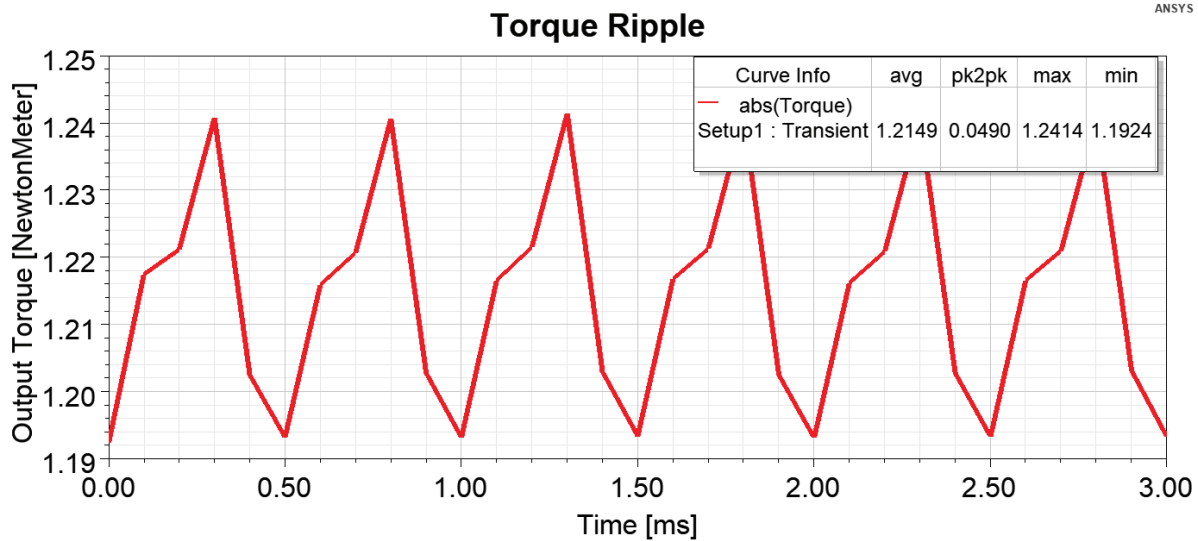


Figure 14. Dynamic torque graph showing torque ripple.

consistent according to obtained permanent magnet thickness and magnetic saturation limit of material used in stator. Dynamic torque graph is given in Figure 14.

It has been determined that the dynamic torque analysis in Figure 13 obtained with 2D FEA is compatible with the design results. In addition, it is seen in the graph that the torque ripple is 4%. For more sensitive servo applications, the torque ripple value can be reduced by using methods such as geometric optimization, shifting the permanent magnet placement, stator winding type and slot/pole number combination [47,48].

CONCLUSION

Optimization of permanent magnet synchronous motors requires a multifaceted effort encompassing various techniques and methodologies. In this study, some optimization algorithms in Ansys Maxwell interface were preferred to compare gradient-based techniques and random search-based algorithms in optimization process of electric motors. Results showed that both random search optimizers achieved high-efficiency values faster. It is evaluated that the reason why gradient-based techniques obtain higher efficiency values, even though their operations take longer to complete, may be the width of the search space and the preference of search ranges. However, when the criteria related to stator inner and outer diameter are taken into consideration, it is noteworthy that results obtained by gradient-based optimizers are more applicable. Algorithm's fast results and high objective function performance are expected results since they positively affect processing cost. However, since motor design phase is carried out in first place and in a robust manner directly affects the subsequent production process and product quality, long processing times are acceptable if necessary. Although gradient-based

algorithms are seen as disadvantageous in terms of optimization time, they are advantageous in terms of obtaining values that provide high efficiency.

Researchers can develop hybrid algorithms by integrating random search and gradient-based optimization methods. Thus, they can emerge full potential of PMSMs and design more energy-efficient, reliable and environmentally sustainable electric motor systems. This research aimed to illuminate principles inherent in PMSMs, challenges and opportunities in optimization process, in this way contributing to advancement of electric motor technology and broader pursuit of energy optimization and sustainability.

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AUTHORSHIP CONTRIBUTIONS

Authors equally contributed to this work.

DATA AVAILABILITY STATEMENT

The authors confirm that the data that supports the findings of this study are available within the article. Raw data that support the finding of this study are available from the corresponding author, upon reasonable request.

CONFLICT OF INTEREST

The author declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

ETHICS

There are no ethical issues with the publication of this manuscript.

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