Multi-objective Parameter Optimization of Permanent Magnet Synchronous Motor based on Improved Gray Wolf Algorithm

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Abstract

In today's critical fields such as industrial automation and electric vehicles, permanent magnet synchronous motors (PM synchronous motors) are favored for their excellent high efficiency, high power density, and outstanding control characteristics. However, with the continuous improvement of motor performance standards in industrial production, how to further improve the operating efficiency of PM synchronous motors and effectively suppress torque pulsation has become the core issue of motor performance optimization. In order to improve the operating efficiency of permanent magnet synchronous motors and suppress torque pulsations, this study proposes an improved gray wolf algorithm, which finely adjusts the convergence factor by exploiting the dynamic output of the chaotic mapping while updating the alpha wolf position in the gray wolf algorithm. In addition, the updating mechanism of X_2 is also improved. Finally, a comparative analysis between the initial design scheme and the optimized scheme was carried out by means of finite element analysis. The finite element analysis results show that the motor efficiency before optimization is 88.52% and the torque pulsation is 8.13%, while the motor efficiency after multi-objective optimization is 89.39% and the torque pulsation after multi-objective optimization is 4%. Obviously, the Amoy Gold Gray Wolf algorithm is superior to the Gray Wolf algorithm in the multi-objective optimization design of the motor, which can quickly achieve the optimal parameter configuration of the permanent magnet synchronous motor.

Keywords

Permanent Magnet Synchronous Motortorque Pulsation; Multi-objective Optimization; Gold Rush Gray Wolf Algorithm.

1. Introduction

In the contemporary industrial automation field, permanent magnet synchronous motors (PM synchronous motors) are widely used as core components in precision manufacturing and high-end equipment due to their excellent efficiency, precise control, and superior performance. With their compact structure and high energy conversion efficiency, permanent magnet synchronous motors (PMSMs) have a rotor-stator configuration that directly affects the overall efficiency of the system. However, the unstable factor of torque pulsation may lead to increased noise, intensified vibration, and reduced motion control accuracy, thus negatively affecting the overall performance of the drive system. Therefore, reducing the torque pulsation and improving the efficiency of permanent magnet synchronous motors is the key to improving the overall performance of motors [1-3].

In order to solve the motor multi-objective design problem, research scholars have proposed a variety of intelligent optimization algorithms, including ant colony algorithm (ACO), particle swarm algorithm (PSO) and various hybrid algorithms, etc. Zhang.L [4] et al. proposed a method of cogging torque group reduction based on particle swarm optimization algorithms, and through the comprehensive optimization of the stator slots opening width, the pole arc coefficient, and the number of pole segments of the permanent magnets in three different combinations, the method can reduce the cogging torque. Zhang.S [5] et al. proposed an optimized multi-objective artificial hummingbird algorithm and combined it with Taguchi's method with the aim of enhancing the torque smoothness of a permanent magnet synchronous motor while minimizing the fluctuation of its back electromotive force. Qu.C et al. in [6] proposed a new built-in permanent magnet synchronous motor with Taguchi's method for optimization of design parameters to significantly reduce cogging torque and torque pulsations. Perid.D et al [7] used Maxwell finite element analysis with moth flame algorithm optimization to enhance the motor magnetic density distribution and efficiency. Yang.M et al [8] and optimized the auxiliary slot design of 12-pole 36-slot motor by Taguchi's method, which effectively reduced the cogging torque. The above literature adopts the method of intelligent optimization algorithm to reduce the cogging torque, but it encounters the problems of slow convergence speed, easy to fall into local optimum, and unable to find the global optimum solution in terms of algorithm. Secondly, the above literature only focuses on a single optimization objective, and it is likely that when optimizing a certain performance, another performance will be degraded.

Compared with other current mainstream algorithms, the Gray Wolf Algorithm (GWO) shows unique advantages in motor multi-objective design optimization. By simulating the social hierarchy and hunting behavior of gray wolves, the gray wolf algorithm not only simplifies the complexity of the algorithm, but also improves the diversity of the population and the search efficiency. Moreover, this feature enables it to avoid premature convergence to local optimal solutions while maintaining the global search capability. In addition, the gray wolf algorithm effectively maintains the diversity of the population through the guidance of excellent individuals during the evolution process, thus improving the robustness of the algorithm.

In order to solve the problem that the gray wolf algorithm is prone to fall into local optimal solutions as well as slow convergence, this study proposes an improved gray wolf algorithm, which is enhanced by the introduction of a chaotic mapping mechanism in the algorithm. According to the dynamic output characteristics of the chaotic mapping, the convergence factor of the algorithm is dynamically adjusted, so that the algorithm can better balance the exploration (searching for new regions in the search space) and utilization (detailed search in the known better regions) in the search process, improve the global search ability and avoid premature convergence. Meanwhile a new update strategy is proposed to optimize the alpha wolf position in the grey wolf algorithm based on the behavioral pattern of gold prospectors migrating to gold mines. This update strategy simulates the migration process of prospectors to the gold mine, which enables the alpha wolf to guide the population more effectively towards the potential optimal solution region. In addition, the updating method of X_2 (i.e., beta wolf) in the gray wolf algorithm is improved. By simulating the collaborative behavior among the gold miners, the updating rules of X_2 are redesigned so that it can more effectively collaborate with the alpha wolf in the exploration of the solution space while maintaining the diversity of the population, thus improving the overall performance and solution quality of the algorithm. It provides a new technical path and theoretical support for the intelligent development in the field of motor design.

This paper firstly reviews the relevant research background of motor optimization algorithm. Secondly, it improves the gray wolf algorithm and designs an experimental scheme for the improved gray wolf algorithm. And the improved Gray Wolf algorithm is applied to optimize the motor model. Finally, the main research results of this paper and the future application prospects of the improved Gray Wolf algorithm in the field of multi-objective optimization design of electric machines are summarized.

2. Basic Model

2.1 The Gray Wolf Algorithm

The basic principle and process of the Gray Wolf algorithm are first introduced, and then innovative improvements to the Gray Wolf algorithm are described, as well as how these improvements can significantly enhance the application of the algorithm to multi-objective optimization problems in electric machines.

The Gray Wolf algorithm is a branch of simulation optimization methods and belongs to the stochastic global optimization technique. The basic concept of the algorithm is derived from the social hierarchy and hunting mechanism of gray wolf packs observed in nature. It has the advantages of simple structure, few parameters to be adjusted, and the existence of adaptively adjustable convergence factors. The process of the gray wolf algorithm [34] can be described as the following process: (1) Initialization: first, determine the search space of the problem to be solved and its parameters, including the upper and lower bounds of the search space. Then, a certain number of gray wolf individuals (i.e., candidate solutions) are randomly generated and initial positions are assigned to each gray wolf individual, which correspond to potential solutions of the optimization problem. (2) Evaluation: the fitness of each gray wolf individual is evaluated, which is usually done through an objective function. Based on these fitness values, gray wolves with alpha (best solution), beta (second best solution), and delta (third best solution) ranks in the population can be identified (3) Updating positions: for each individual gray wolf in the population (including alpha, beta, delta, and omega), its position is updated. Position updating simulates the process of gray wolves encircling, hunting and attacking their prey. (4) Iteration: the steps of evaluating and updating the position are repeated until the termination conditions are met, such as the maximum number of iterations is reached or the convergence of the solution reaches a preset threshold. (5) Termination: when the algorithm satisfies the termination condition, the iteration is stopped. Finally, the position of alpha wolf is output as the optimal solution.

The flow of the gray wolf algorithm is shown in Figure 1.

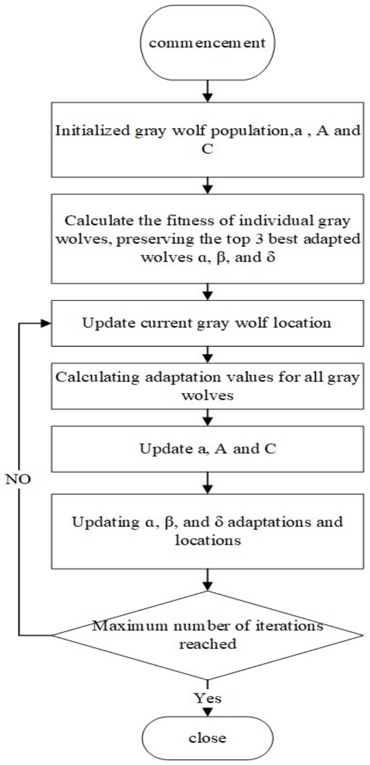

Figure 1. Flowchart of the gray wolf algorithm

First, the gray wolf population gradually approaches and surrounds the prey through equation (1):

$$\begin{gathered}\vec{D}=\left|\vec{C}\cdot\vec{X}_p(t)-\vec{X}(t)\right|\\ \vec{X}(t+1)=\vec{X}_P(t)-\vec{A}\cdot\vec{D}\end{gathered}\tag{1}$$

t represents the current number of iteration generations, A and C are denoted as coefficient vectors, and X_p and X_t represent the position vector of the prey and the position vector of the gray wolf, respectively.

$$\begin{gathered}\vec{A}=2\vec{a}\cdot\vec{r}_1-\vec{a}\\ \vec{C}=2\cdot\vec{r}_2\\ a=2-\frac{2t}{t_{max}}\end{gathered}\tag{2}$$

a is a convergence factor that decreases linearly from 2 to 0 with the number of iterations, and obeys a uniform distribution between [0, 1]. Second, the other gray wolf individuals Xi in the pack update their respective positions based on the positions Xα, Xβ, and Xδ of α, β, and δ:

$$\begin{gathered}\vec{D}_\alpha=\left|\vec{C}_1\cdot\vec{X}_\alpha-\vec{X}\right|\\ \vec{D}_\beta=\left|\vec{C}_2\cdot\vec{X}_\beta-\vec{X}\right|\\ \vec{D}_\delta=\left|\vec{C}_3\cdot\vec{X}_\delta-\vec{X}\right|\end{gathered}\tag{3}$$

D_α , D_β and D_δ denote the distances between a, β, and δ and other individuals, respectively and represent the current positions of ɑ , β, and δ, respectively; C_1, C_2, and C_3 are random vectors, and X is the current position of the gray wolf.

Finally, the position update formula of a gray wolf individual is as follows.

$$\begin{gathered}\vec{X}_1=\vec{X}_\alpha-A_1\cdot\left(\vec{D}_\alpha\right)\\ \vec{X}_2=\vec{X}_\beta-A_2\cdot\left(\vec{D}_\beta\right)\\ \vec{X}_3=\vec{X}_\delta-A_3\cdot\left(\vec{D}_\delta\right)\end{gathered}\tag{4}$$

The process of constructing a model for attacking prey causes a decrease in the value of a to cause the value of A to fluctuate as well, according to the formula in (4).

2.2 Improving the Gray Wolf Algorithm

The Gray Wolf algorithm is slow to converge when dealing with multi-objective optimization problems and is not efficient in solution set diversity search. In contrast, the Gold Panning Optimization Algorithm, as an emerging method, continuously explores different locations and strategies to find the best solution through the process of gold panners sifting through the riverbed for gold. The algorithm exhibits fast convergence and efficient search capability, as well as good robustness and adaptability. The use of the improved Grey Wolf algorithm based on the principle of

Gold Panning Optimization Algorithm, i.e., Gold Grey Wolf Optimizer (GGWO), can achieve better results in multi-objective optimization problems.

The specific improvement points of Gold Grey Wolf Optimizer compared with the original Grey Wolf Optimizer are as follows:

2.2.1 Convergence Factor Improvement

The linear decrease of the convergence factor a in the original gray wolf algorithm leads to the posibility that the algorithm may converge prematurely at the early stage of the search and cannot continue to explore other potential optimal solutions. In contrast, in this paper, through the dynamic output characteristics of chaotic mapping, the algorithm is able to better control the convergence speed and avoid premature convergence, thus exploring the solution space more comprehensively.

$$\alpha = 2^{*}\cos\left((t/\mathrm{maxiter})^{*}(\Pi/2)\right) \tag{5}$$

2.2.2 Migration Process Improvement

By simulating the migration process of gold miners to the gold mine in the gold panning optimization algorithm, the population can be effectively guided to move towards the potential optimal solution area. In this paper, by updating the position of alpha wolf, the population can be better guided to move toward the potential optimal solution area, improving the search efficiency and convergence speed.

$$\begin{gathered}
\vec{D}_1 = \vec{C}_1 \cdot \vec{X}_{(t)} - \vec{X}_{(t)} \\
\vec{X}_{newi}(t+1) = \vec{X}_i(t) + \vec{A}_1 \cdot \vec{D}_1 \\
\vec{A}_1 = 1 + l_1\left(\vec{r}_1 - \frac{1}{2}\right) \\
\vec{C}_1 = 2\vec{r}_2 \\
l_e = \left(\frac{\max_{iter} - iter}{\max_{iter} - 1}\right)^{e} \cdot \left(2 - \frac{1}{\max_{iter}}\right) + \frac{1}{\max_{iter}}
\end{gathered} \tag{6}$$

2.2.3 Improved Modalities of Cooperation

The updating formula of X_2 in the gray wolf algorithm may lead to a decrease in the diversity of the population, thus reducing the robustness of the algorithm. In this paper, by simulating the collaborative behavior among gold miners, the improved updating formula of X_2 can avoid the premature convergence of individuals to the local optimal solution while maintaining the diversity of the population.

$$X_2 = X_\beta^t + \mathrm{rand}^{*}\left(X_\beta^t - I^{*}X_i^t\right) \tag{7}$$

The optimization process of the Gold Rush Gray Wolf algorithm is shown in Figure 2.

The improvement of the gold prospecting algorithm is in the following three points: (1) This algorithm improves the convergence factor according to the output dynamics of the chaotic mapping. (2) Drawing on the migration formula of the gold prospector to the gold mine to update the alpha wolf of the gray wolf algorithm to simulate the migration way of the gold prospector to the gold mine. (3) Improve the updating method of X_2 by the idea of gold prospector cooperation.

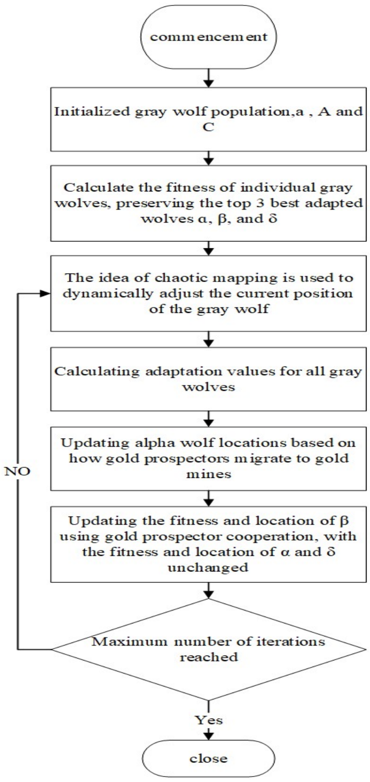

Figure 2. Flowchart of the Gold Rush Gray Wolf algorithm

3. Experiments and Analysis

3.1 Experimental Design

In order to evaluate the performance of the improved gray wolf algorithm, the CEC2005 series of test functions were used for testing. The test experiments were run for the traditional Gray Wolf algorithm, the improved Gray Wolf algorithm, and the Particle Swarm Algorithm (PSO), respectively, using computer equipment configured with an Intel(R) Core(TM) i7-3060H CPU @ 2.50GHz 16GB RAM. In order to ensure that the results of the experiments are fair and comparable, all the algorithms were initialized with the same settings, and the specific parameters are shown in Table 1.

Table 1. Initial parameter settings

name	population size	Number of iterations	Number of runs	test function
parameter value	30	300	20	CEC2005

When evaluating the performance of intelligent optimization algorithms, common indicators are mean, standard deviation, optimal value, worst value, and median indicators to judge, which can comprehensively reflect the efficiency and robustness of the algorithm in solving the problem. Figure 3 shows the results of the improved Gray Wolf Algorithm (GGWO) compared with the standard Gray Wolf Algorithm (GWO) and the Particle Swarm Optimization Algorithm (PSO) in terms of performance.

In terms of the minimum value metric, the Improved Gray Wolf Algorithm (GGWO) achieves a significantly lower minimum value than the Particle Swarm Optimization Algorithm (PSO) and the Gray Wolf Optimization Algorithm (GWO), which suggests that the GGWO is more efficient in finding the optimal solution. In terms of the standard deviation metric, GGWO presents a lower standard deviation, which means that the algorithm produces results with less dispersion over multiple runs, thus reflecting its higher algorithmic stability. In contrast, PSO and GGWO have higher standard deviations, showing that these algorithms have more significant fluctuations in their results in repeated experiments. In terms of the mean value metric, its average optimization results are significantly better than PSO and GWO, which indicates that the median metric further consolidates GGWO's advantage in multiple experiments, and its value is also lower than PSO and GWO, which suggests that in most experimental scenarios, GGWO is able to achieve better optimization results. As for the worst-case metrics, GGWO is able to maintain a high level of optimization even when faced with challenging conditions.

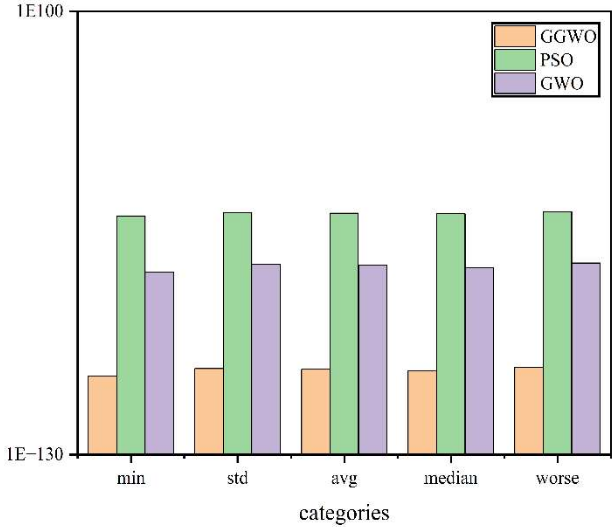

Figure 3. Algorithm performance comparison chart

The improved Gray Wolf algorithm was tested using the CEC2005 series of test functions, and the Gray Wolf algorithm, PSO algorithm and the improved Gray Wolf algorithm were used as comparison algorithms. It can be concluded that the improved gray wolf algorithm presents a significant improvement in the performance of the test function, which is characterized by fast convergence speed and good stability. The comprehensive analysis results show that the improved Gray Wolf algorithm has better convergence and stability during the test function iteration process.

3.2 Experimental Objects

Table 2. Basic parameters of permanent magnet synchronous motor

Parameter name	numerical value
Rated Voltage/V	220
Number of phases	3
Stator outer diameter/mm	5
Stator inner diameter/mm	33
Length of rotor core/mm	114
Thickness of permanent magnet/mm	3
Air Gap Length/mm	0.5
Number of turns per phase	30
Length of tooth width/mm	7

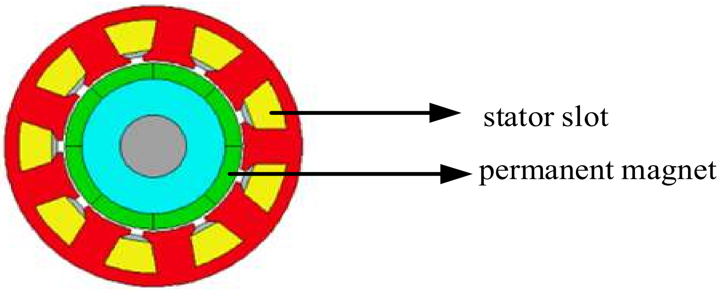

Figure 4. Model diagram of permanent magnet synchronous motor

In this paper, the 60CB series 8-pole, 9-slot permanent magnet synchronous motor is taken as the research objective, and the model of the permanent magnet synchronous motor is obtained according to the basic parameters in Table 2 as shown in Figure 4. Through finite element analysis, it is found that the torque pulsation of the motor reaches 8.13% and the efficiency is only 88.52%. The large torque pulsation leads to unstable output torque, which in turn affects the operation of the drive system. Especially in the case of precision control, it may reduce the machining accuracy and system response speed, and the long-term operation may also aggravate the degree of bearing wear and shorten the life of the motor. The results show that there is room for optimization of the motor in terms of stability and energy conversion.

3.3 Response Surface Modeling and Analysis

3.3.1 Response Surface Modeling

Response surface modeling is actually a mathematical model capable of predicting how the response variable will change as the input factors change. The model is characterized by its ability to reduce the number of experiments, save costs and improve the accuracy of experimental data. In response surface design, the commonly used methods include center composite design, BBD design, and uniform design. In particular, BBD design is favored for its lower number of experiments, high accuracy of model prediction, and ease of operation.

In BBD experimental method, it is necessary to determine the experimental test factors and levels of the experiment, and each factor is divided into three levels, which are the central value, upper limit, and lower limit of the optimization range of the design variables. It is proposed to use the BBD module in the design software to develop a response surface model for the two optimization objectives of motor efficiency and torque pulsation. Since three optimization variables are involved, FEA software is proposed to be used for simulation and analysis. The motor response surface test factors and levels are shown in Table 3. Where A is the stator slot opening width, B is the permanent magnet thickness and C is the permanent magnet arc length.

Table 3. Response surface experiment factors and levels

level	considerations		
	A/mm	B/mm	C/mm
-1	2	150	0
0	2.3	165	0.3
1	2.6	185	0.6

3.2.2 Model Significance Analysis

The results of the regression model analysis obtained by using response surface analysis are shown in Table 4, the size of the F-value determines the degree of influence of the influencing factors on the response value, while the larger the F-value represents the greater the degree of influence. And the size of P value represents whether the influencing factors are related to the response value motor efficiency regression model $R^2 = 0.9718$, motor torque pulsation regression model $R^2 = 0.9361$, both have R^2 close to 1, indicating that the model and its significant. The multiple correlation coefficient value R^2 reflects the similarity between the response surface model and the performance of the established motor model, the closer R^2 is to 1, indicating that the model established by the results of response surface analysis is more accurate. Therefore, the model can better reflect the relationship between factors and motor efficiency and torque pulsation during motor operation.

Table 4. Results of regression model analysis

Model	Source of variance	F-value	P-value	significance
Model 1	Model 1	13.02	0.0007	●●
	A	2.04	0.1909	
	B	39.20	0.0002	●●
	C	7.88	0.0229	●
	AB	1.02	0.3418	
	AC	1.33	0.2815	
	BC	18.34	0.0027	●●
	A^2	46.21	0.0001	●●
Model 2	Model 2	13.02	0.0007	●●
	A	22.50	0.0004	
	B	257.74	< 0.0001	●●
	C	132.10	< 0.0001	●●
	AB	0.0666	0.8004	
	AC	1.07	0.3209	
	BC	35.21	< 0.0001	●●

Note: ● is significant ($P<0.05$), ●● is highly significant ($P<0.01$), and the rest are not significant.

For model I, from the P-value in Table 4, B, BC and the secondary term A2 have a highly significant ($P<0.01$) effect on the motor torque pulsation, C has a significant ($P<0.05$) effect on the motor torque pulsation, and the rest are insignificant; from the F-value, the order of the three factors on affecting the motor torque pulsation in descending order is: B, C, and A, i.e., the arc length of permanent magnet has the greatest effect on motor torque pulsation, followed by the degree of cutback of the edge thickness of permanent magnet, and finally the stator slot opening width. has the greatest influence, followed by the extent of the permanent magnet edge thickness reduction, and finally the stator slot opening width.

For model II, from the P-value, the effect of A, C, B, and BC on the motor efficiency is highly significant ($P<0.01$), and the rest are not significant ($P>0.05$). From the F-value, it can be obtained that the effect of the three factors on the efficiency of the motor is in descending order of C, A, and B, i.e., the extent of reduction in the thickness of the edge of the permanent magnet, the width of the stator slot opening, and lastly, the arc length of the permanent magnet.

The analysis of variance (ANOVA) of the experimental effects of torque pulsation and motor efficiency of the motor gives two quadratic polynomial regression equations as

$$F(1)=6.24+0.21\cdot A+0.92\cdot B-0.4125\cdot C+0.21\cdot A\cdot B-0.24\cdot A\cdot C-0.89\cdot B\cdot C-1.3525\cdot A^2+0.1425\cdot B^2-0.0925\cdot C^2 \tag{8}$$

$$F(2)=89.02+0.065\cdot A-0.22\cdot B+0.1575\cdot C+0.005\cdot AB+0.02\cdot AB+0.115\cdot BC \tag{9}$$

Setting the structural constraints as

$$2\text{mm}\leqslant A\leqslant 2.6\text{mm}\quad 150\text{mm}\leqslant B\leqslant 180\text{mm}\quad 0\text{mm}\leqslant C\leqslant 0.6\text{mm} \tag{10}$$

3.4 Experimental Results

For the two optimization objectives of motor efficiency and torque pulsation, and the traditional gray wolf optimization algorithm is compared and analyzed with the improved gray wolf optimization algorithm. Figures 5 and 6 show the results of optimization of regression equations (8) and (9) obtained from the response surface method for the traditional gray wolf algorithm and the ameliorated gray wolf algorithm respectively.

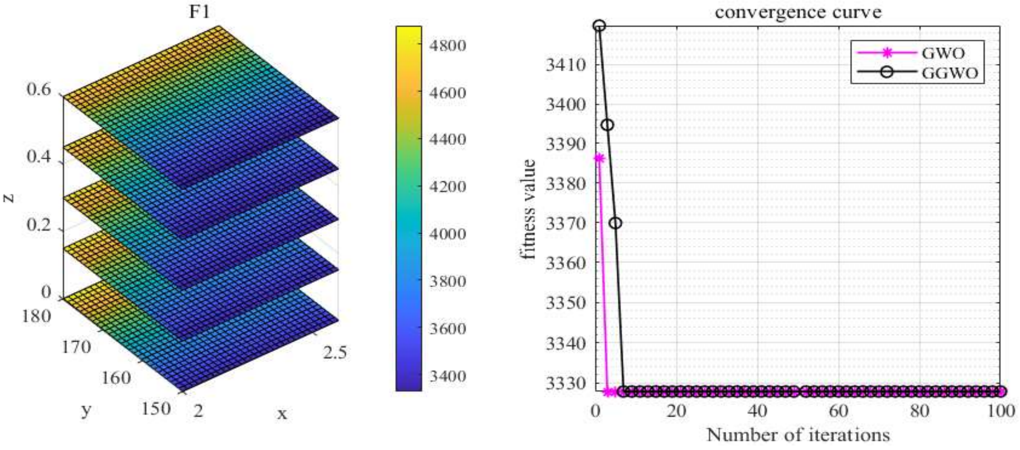

Figure 5. Tests of gray wolf algorithm on F1 function before and after improvement

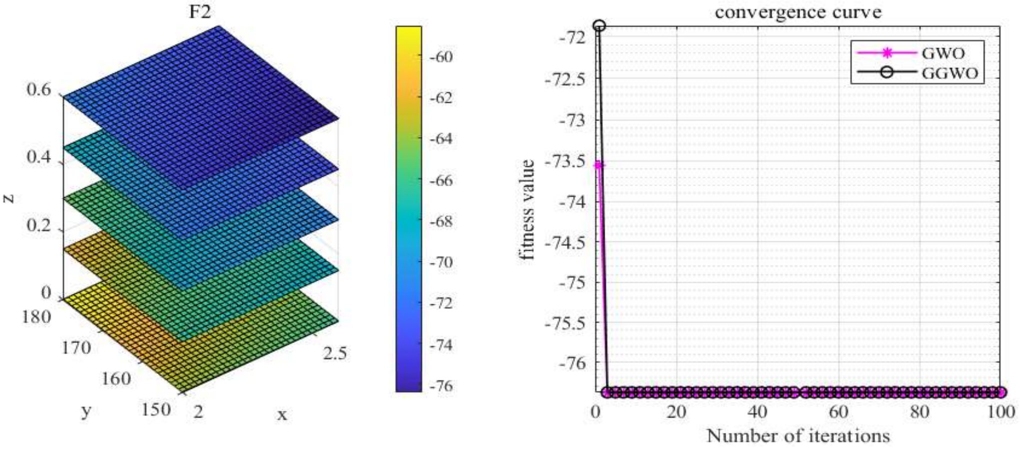

Figure 6. Test of gray wolf algorithm on F2 function before and after improvement

As can be seen in Figure 5, GGWO converges significantly faster than GWO on the test of the F1 function.GGWO reaches lower fitness values (i.e., better solutions) in fewer iterations. In terms of solution quality, GGWO eventually reaches lower fitness values than GWO, which means that GGWO finds better solutions. As can be seen in Figure 6, GGWO also exhibits faster convergence on the F2 function. It reaches lower adaptation values faster. In terms of solution quality, GGWO also reaches a lower final fitness value on the F2 function than GWO, indicating that it finds better solutions.

The whole optimization process is completed in a short period of time, the two optimization objectives are based on the set constraints and combined with the objectives of high motor efficiency and low torque pulsation, finally a set of optimal solutions are selected, this optimal solution has a motor efficiency value of 89.39% and a torque pulsation of 4%.

4. Finite Element Analysis Verification

The motor before and after optimization is analyzed and verified using finite element software. The motor loss before and after optimization is shown in Figure 7, the total loss of the motor after multi-objective optimization of the motor efficiency and torque pulsation using the Gold Rush Gray Wolf algorithm is the minimum of 44.19 W. The total loss of the motor with single-objective optimization is slightly larger than that of the motor with multi-objective optimization, and the simulation obtains the efficiency of the motor before optimization to be 88.52%, and that of the motor after multi-objective optimization to be 89.39%. It can be seen that both single-objective optimization and multi-objective optimization significantly reduce the torque pulsation of the motor compared to the pre-optimization, and the torque pulsation after multi-objective optimization is 4%, which is slightly smaller than that after single-objective optimization, with a torque pulsation of 4.19%. The waveforms of the motor cogging torque before optimization, single objective optimization and multi-objective optimization of the motor are shown in Figure 8. It can be seen that both single-objective optimization and multi-objective optimization reduce the torque pulsation compared to the pre-optimization and the torque pulsation after multi-objective optimization is slightly lower than the torque pulsation after single-objective optimization.

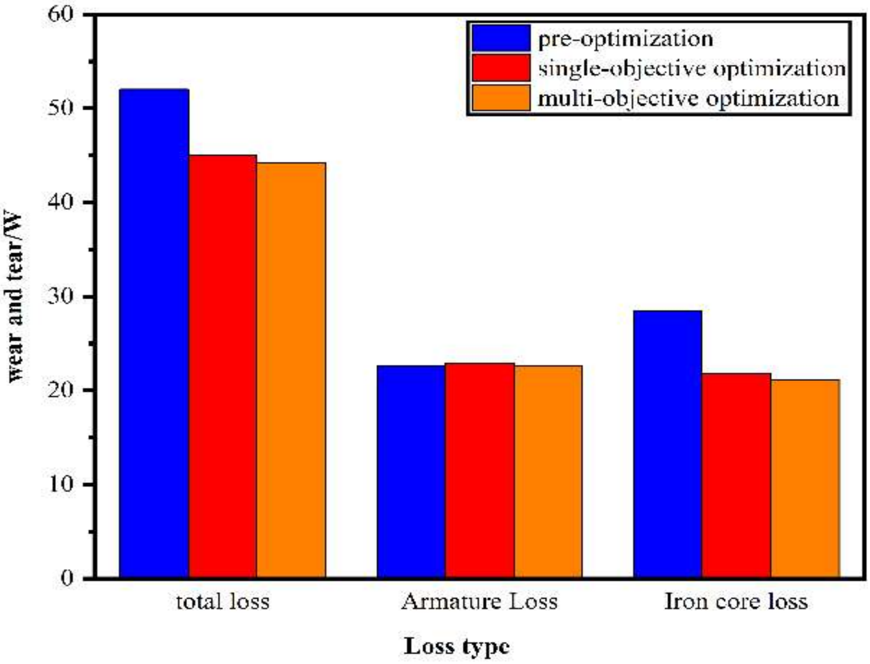

Figure 7. Comparison of losses before and after motor optimization

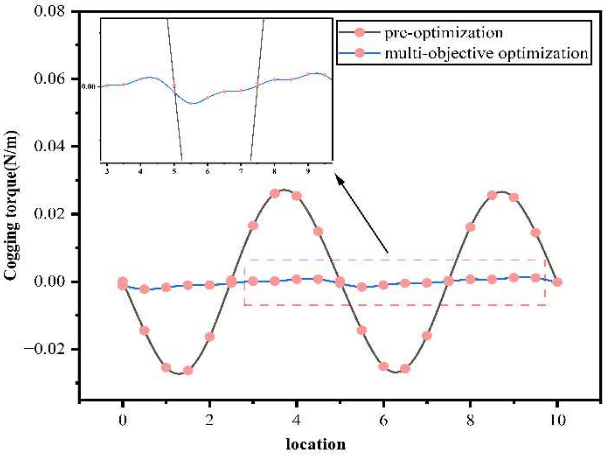

Figure 8. Comparison of cogging torque before and after motor optimization

Table 5. Comparison of motor simulation results before and after optimization

variable	Slot opening width /mm	Arc length of permanent magnet /mm	Permanent magnet edge thickness reduction /mm	efficiency /%	torque pulsation /%
Initial value	2.6	180	0	88.52	8.13
Multi-objective optimization value	2.6	150	0.6	89.39	4

The variables and simulation results before and after optimization are shown in Table 5. In Table 5, compared with the initial design, the single-objective optimization reduces the motor efficiency by 1.25% and the torque pulsation by 49%, while the multi-objective optimization improves the motor efficiency by 4% and the torque pulsation by 51%.

5. Conclusion

When applying optimization algorithms to optimize the multi-objective design problem of electric machines, it is difficult to obtain the optimal solution when facing the problems of slow convergence speed, easy to fall into the local optimum and conflict between objective functions. In order to solve these problems, this paper proposes an improved gray wolf algorithm, compared with the traditional gray wolf algorithm, the improved gray wolf algorithm has been significantly improved in terms of convergence speed and stability. The specific conclusions are as follows:

This algorithm fine-tunes the convergence factor by utilizing the dynamic output of chaotic mapping, while drawing on the principle of migration of gold prospectors to gold mines in order to update the alpha wolf position in the gray wolf algorithm, a strategy that simulates the intelligent migration process of prospectors to gold mines. In addition, the idea of gold prospector cooperation was adopted to improve the update mechanism of X_2.

With these improvements, GGWO is able to converge to the global optimal solution more quickly, saving computational time and resources. The model provides a practical path to accelerate the search for the optimal parameter combinations for the multi-objective design of electric machines. It effectively avoids the risk of premature convergence to the local optimal solution of the Gray Wolf algorithm, and shows better convergence performance and optimization potential. Future research will explore the application of GGWO in other types of motor optimization problems and investigate more effective improvement strategies to further enhance the performance of the algorithm.

The improved Gray Wolf algorithm proposed in this paper not only provides an efficient solution for the optimization of multi-objective design of electric motors, but also is of great significance in enhancing the application value of the algorithm in practical engineering problems.

References

[1] Ma Kongrong, Zhou Tuo, JI Jie, et al. Optimization analysis of cogging torque of permanent magnet synchronous motor [J]. Optimization of cogging torque of permanent magnet synchronous motor [J].

[2] Ren D J, Huang Q, Li J J, et al. Optimization analysis of cogging torque of built-in permanent magnet synchronous motor [J]. Explosion-proof Motor, 2019, 54(04): 4-7+43.

[3] Sun LZ, Zhao HR, Lu YP. Application of genetic algorithm in air gap magnetic field design of permanent magnet motor [J]. Journal of Harbin Institute of Technology, 2000, (01): 71-4+7.

[4] ZhangHang L, Tangang B, Tan S, et al. Cogging Torque Reduction of Permanent Magnet Motor Based on Particle Swarm Optimization Algorithm [J]. Journal of Physics: Conference Series, 2022, 2404(1): 012046.

[5] ZhangHang S, Yan H, Yang L, et al. Optimization Design of Permanent Magnet Synchronous Motor Based on Multi-Objective Artificial Hummingbird Algorithm [J]. Actuators, 2024, 13(7): 243.

[6] Qu C, Guo Z, Hu Y, et al. Multi-Objective Optimization Design of a New Permanent Magnet Synchronous Motor Based on the Taguchi Method [J]. Energies, 2022, 15(19): 7347.

[7] Perid D, Karaglan A D, YILMAZ K. Rotor design optimization of a 4000 rpm permanent magnet synchronous generator using moth flame optimization algorithm [J]. An International Journal of Optimization and Control, 2024, 14(2): 123-33.

[8] YangAng M, Xu Y, Cheng S. Optimal design of permanent magnet motor based on Taguchi algorithm [J]. Journal of Physics: Conference Series, 2022, 2383(1): 012019.

[9] Chun-yu H, Soe Min H, Guan han L, et al. Investigation of Design Performance in Outer Rotor BLDC Motor for Taguchi Method [Z]//CHUN-YU H, SOE MIN H, GUAN HAN L, et al. Piscataway; The Institute of Electrical and Electronics Engineers, Inc. (IEEE). 2023.

[10] Huang H, Wang X. Method for weakening cogging torque of built-in permanent magnet synchronous motor by auxiliary slot [J]. Journal of Physics: Conference Series, 2022, 2310(1): 012063.