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Parameter Identification of induction motor based on intelligent optimization algorithm

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Abstract

During the operation of induction motors, due to skin effect, temperature changes, magnetic circuit saturation and other factors, their inductance and resistance will change. If the parameters are not adjusted during the operation of the motor, the speed will be estimated the accuracy of the results affects. Therefore, this article is based on the intelligent optimization algorithm to identify the parameters of the induction motor. In the flux observer and MRAS algorithm in the simulation system established in the article, current model and voltage model are used. Among them, the current model is susceptible to changes in the rotor time constant, and the voltage model is susceptible to changes in the stator resistance and stator inductance. The simulation result of the optimization algorithm shows a good parameter identification effect.

Keywords

Intelligent optimization algorithm; extinguishing algorithm; in your paper.

1. Introduction

Considering the working conditions of the induction motor change during the actual working process, the parameters of the induction motor will also dynamically change. Generally, the main reasons for the change of induction motor parameters during the operation of induction motors are as follows: temperature changes, frequency changes and magnetic circuit saturation. Previous research reports have shown that the above three factors can make the resistance most susceptible to environmental influences and have large changes. On the contrary, the inductance change in the motor is relatively small [1].

In the speed sensor-less application, the stator and rotor resistance are the key parameters that affect the speed estimation. During the operation of an induction motor, its parameter changes are unavoidable, and the parameter changes will inevitably cause errors in rotor flux observation and speed estimation. In a speed sensor-less control system based on field orientation, the flux observation and speed estimation are Inaccuracy will inevitably affect the entire speed control system. In a stable induction motor system, the rotor time constant and the stator resistance change will have a significant impact on the field-oriented induction motor vector control system, and the effect of the stator resistance change will be more significant. In order to make the designed induction motor control strategy adapt to the change of the time constant and stator resistance during the operation of the induction motor, it is necessary to study the parameter identification technology of the induction motor. In order to reduce the complexity of the algorithm and improve its efficiency, this paper mainly discusses the parameter identification research of rotor time constant and stator resistance.

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2. Principle of parameter identification based on intelligent optimization algorithm

At present, the meta-heuristic search algorithms inspired by the laws of biological evolution mainly include: genetic algorithm, particle swarm optimization algorithm, ant colony optimization algorithm, differential evolution and other traditional algorithms and some new intelligent optimization algorithms. Compared with traditional optimization algorithms, these intelligent algorithms have the advantage that they do not require continuous or differentiable objective functions, and they also have the characteristics of global search and robustness.

Global search refers to the parallel search in the search feasible space, which means that it does not depend on the characteristics of the problem itself and has universality for solving the problem. The robustness means that the algorithm is not sensitive to the initial value and has good fault tolerance. The intelligent optimization algorithm can not only effectively construct the model to identify the model structure, but also obtain the system model parameter results. For an induction motor, such as an asynchronous motor model, its structure is known, and only parameter identification is required.

For parameter identification by means of intelligent optimization algorithms, the first key issue to be solved is how to evaluate the obtained parameters, the essence of which is to determine the fitness function of the intelligent optimization algorithm. System identification is carried out on the basis of measuring the input and output of the identified system. Given an equivalent tracking model with the same structure as the identified system but with undetermined parameters, evaluating the pros and cons of a set of system parameters is to look at this set of parameters under the same input conditions to make the output of the equivalent tracking model and the identified system the proximity of the output.

This type of identification method can be applied to problems where system parameters can be derived from input and output. The task of the intelligent optimization algorithm is to find the parameter value that makes the two system errors the closest. Suppose the dynamic mathematical model of the reference model is:

$$\begin{cases} \dot{x} = f(\theta, x, u) \\ y = Cx \end{cases} \tag{1}$$

Among them, x is the state vector, u is the input vector, is the parameter vector to be identified, y is the measurable vector, and C is the constant matrix of suitable order

Therefore, an equivalent model corresponding to the identified system is established:

$$\begin{cases} \dot{\hat{x}} = f(\hat{\theta}, \hat{x}, u) \\ \hat{y} = C\hat{x} \end{cases} \tag{2}$$

Among them, is the state vector of the equivalent tracking model, is the estimated value of, and is the estimated value of y.

Define the output error as:

$$\mathrm{e} = y - \hat{y} \tag{3}$$

From t_0 to t_1, the degree of difference between the output of the equivalent tracking model and the output of the identified system can be defined by:

$$H(\theta) = \int_{t0}^{t1} e^T e \tag{4}$$

Then the fitness function of the system containing the parameters to be identified is defined as :

$$H(\theta) = \sum_{k=0}^{N-1} [e^T(k) e(k)] = \sum_{k=0}^{N-1} \{[y(k) - \hat{y}(k)]^T [y(k) - \hat{y}(k)]\} \tag{5}$$

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After the fitness function is defined, the minimum value of the fitness function can be found through the intelligent optimization algorithm. When the minimum value of the fitness function is found, the parameter corresponding to the minimum fitness function is found. Meanwhile, the parameter is completed the task of identification. According to formulas (1) to (5), the parameter identification problem is converted to the problem of finding the minimum error. When the fitness function adjusts the parameters so that the output error between the electrical model and the actual model approaches zero, then the system can be considered as true the value is equal to the parameter value.

3. Improved moth extinguishing algorithm

For any generalized optimization algorithm, global exploration and local development capabilities are two main aspects. The global exploration capability refers to searching the entire search space, and the local development capability refers to the local search of searching a small area in a large search space. Both of these phenomena help the algorithm avoid the local minimum stagnation problem (global development) and provide better convergence and diversified solutions (local exploration). Another important feature is the balance between these two phenomena. Any algorithm that can achieve these three characteristics can be considered a member of the most advanced algorithm family. The MFO algorithm is a new algorithm, and it can be seen from the research of Muangkote et al. that it has the problem of poor global exploration ability [51]. Therefore, it can be said that the overall exploration capabilities of MFO need to be strengthened to adapt to high-end issues.

4. Algorithm test

Before formally using the intelligent optimization algorithm for parameter identification of induction motors, it is necessary to verify whether the algorithm has converged. It is difficult to prove whether the evolutionary algorithm has converged from a theoretical point of view. At present, the commonly used method is to use the standard test function to verify the convergence and convergence of the algorithm. Accuracy. This article first implements GA, MFO and IMFO algorithms in MATLAB using M language. With reference to the CEC2013 evaluation standard, four minimization standard test functions including unimodal function and basic multimodal function are selected, and four commonly used standard test functions are used as the fitness function of the algorithm, and the optimization is performed to verify the adopted The effectiveness and convergence of the IMFO algorithm, and the results are compared with other several algorithms [54]. The four typical functions are as follows

Table 1 Test functions

Function	Test Functions	Dimensi-onality	Domian	Maximum or Minimum
Sphere	$f_1(x)=\sum_{i=1}^{n} x_i^2$	10	[-100, 100]	0
Rosenbrock	$f_2(x)=\sum_{i=1}^{n-1}[100(x_{i+1}-x_i^2)^2+(x_i-1)^2]$	10	[-100, 100]	0
Rastrigin's	$f_3(x)=\sum_{i=1}^{n}[x_i^2-10\cos(2\pi x_i)+10]$	10	[-100, 100]	0
Griewank	$f_4(x)=\frac{1}{4000}\sum_{i=1}^{n} x_i^2-\prod_{i=1}^{n}\cos(\frac{x_i}{\sqrt{i}})+1$	10	[-600, 600]	0

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In order to have an intuitive understanding of these 4 kinds of functions, draw their graphs in two-dimensional form respectively.

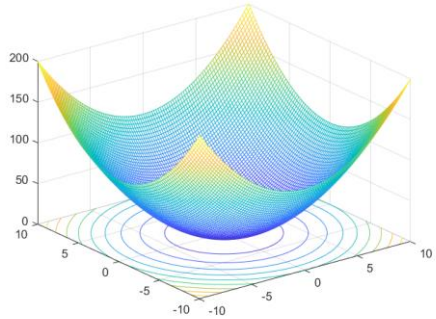

Fig. 1 Sphere function

The Sphere function is shown in Figure 1. It has only one extreme point globally, so it can be used to test the optimization performance of the algorithm.

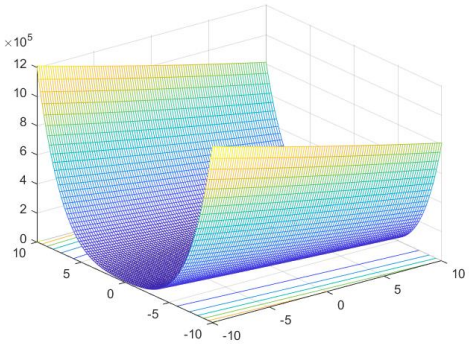

Fig. 2 Rosenbrock

The two-dimensional form of the Rosenbrock function is shown in Figure 2. It is a non-convex function used to test the performance of the optimization algorithm. Its characteristic is that the global maximum value does not change much, so it is not easy to find the optimal value.

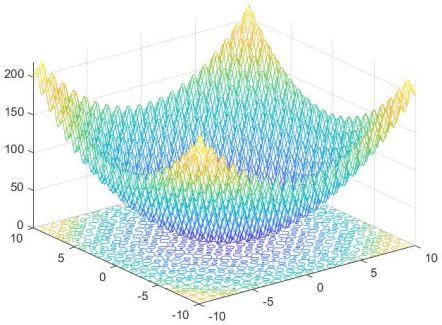

Fig. 3 Rastrigin's function

Figure 3 is a two-dimensional graph of Rastrigin's function. Its characteristic is that there is a local extreme point in the entire function space but there is only one optimal value in the global, and the function value at this position is 0. Therefore, it is suitable for the optimization ability of the detection algorithm.

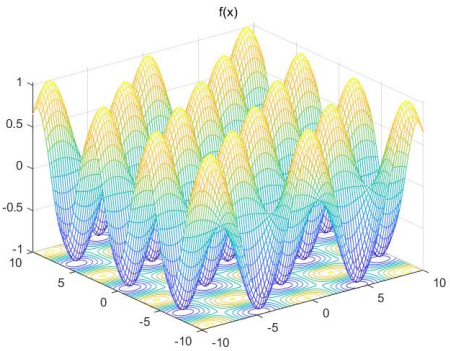

Fig. 4 Griewank function

Figure 4 shows the Griewank function. This function has many local minima and is related to the dimension of the problem. The global minimum value 0 is at (0, 0). Griewank is a typical nonlinear multimodal problem with a wide range of the search space is usually considered to be a complex multi-modal problem that is difficult to handle with optimization algorithms

Among the above four test functions, only F1 is a relatively simple unimodal function. F2, F3, and F4 are all multimodal functions with a large number of local extreme points in the optimization space. Therefore, the latter three are different for the optimization algorithm. Language is a function that is difficult to optimize. Among them, F2 and F3 each have a global minimum point with a function value of 0, and F has a global maximum point with a function value of 1. Among them, F1 and F2 are mainly used to test the optimization speed and convergence accuracy of the algorithm, and F3 and F4 are mainly used to test the global search ability of the algorithm. The dimensions of the test functions F1, F2, F3, and F4 are all 10 dimensions, the domain of F1, F2, F3 is [-100, 100], and the domain of F4 is [-600, 600], and other parameters are the same. The following four functions are used to test the above-mentioned algorithm, and run randomly for 50 consecutive times. The results are shown in Table 2 and Table 3. There are two types of average minimum value and variance data, and minimum minimum value and maximum minimum value. Among them, the former can reflect the performance and stability of the algorithm, while the latter is used to test the best convergence accuracy that the algorithm can achieve and verify whether the algorithm has premature phenomena.

Table 2 Test results repeated 50 times

Function	Mean			Variance		
	MFO	IMFO	PSO	MFO	IMFO	PSO
F1	2.2540	4.7539e-10	2.2154e+03	1.4809	3.8485e-10	580.0491
F2	2.5380e+03	8.3458	7.2860e+07	2.9500e+03	0.1364	4.4898e+07
F3	54.0698	3.2049e-04	2.5289e+03	8.5244e-04	0	660.4513
F4	0.7368	0.0049	1.5975	0.1396	0.0214	0.1656

Table 2 shows the statistical characteristics of the test results. The mean and variance of the minimum values of different algorithms when tested with different test functions can be obtained. For the F1 function, the IMFO algorithm performs the best, with an average minimum value of 4.7539e-10 and a variance of 3.8485e-10, which reflects the powerful development capabilities of the IMFO algorithm. For the F2 function, the IMFO algorithm still performs best. For the F3 and F4 functions, the performance of the IMFO algorithm far exceeds the MFO algorithm and the PSO algorithm, reflecting the exploration ability of IMFO.

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Table 3 Test results repeated 50 times

Function	Max minimum			Min minimum		
	MFO	IMFO	PSO	MFO	IMFO	PSO
F1	6.4026	1.8087e-09	3.3231e+03	1.7169e-28	3.5100e-11	890.1265
F2	1.1784e+04	8.5521	1.6843e+08	156.2533	8.1231	8.9020e+06
F3	79.2501	0.0049	4.0295e+03	23.2734	2.7452e-07	1.1442e+03
F4	0.9870	0.1336	1.8645	0.3845	2.1689e-09	1.1373

Table 3 shows the max minimum value and min minimum value reached by different algorithms when testing with different test functions. For functions F1 and F2, it can be seen that both the MFO algorithm and the PSO algorithm have premature phenomena, and the maximum minimum and min minimum values of the IMFO algorithm are very close to the actual minimum, so the IMFO algorithm can be obtained The improvement of development ability is a valid conclusion. For functions F3 and F4, the performance of the IMFO algorithm also greatly exceeds the MFO algorithm and the IMFO algorithm, but the IMFO algorithm also has a certain premature phenomenon in the F4 function, indicating that it still has room for improvement, but it is used for induction motor parameter identification The question is enough.

In summary, it can be clearly seen that one of the traditional intelligent optimization algorithms, that is, the performance of the PSO algorithm is poorer than that of the MFO algorithm, and the MFO algorithm is a bit worse than the IMFO algorithm. Therefore, this article considers the parameter identification of induction motors based on the IMFO algorithm, and in order to more clearly reflect the superiority of the improved MFO algorithm compared to the original MFO algorithm, its utilization is shown in Figure 5 to Figure 8. Comparison of the convergence curves of fitness functions for different test functions for performance testing.

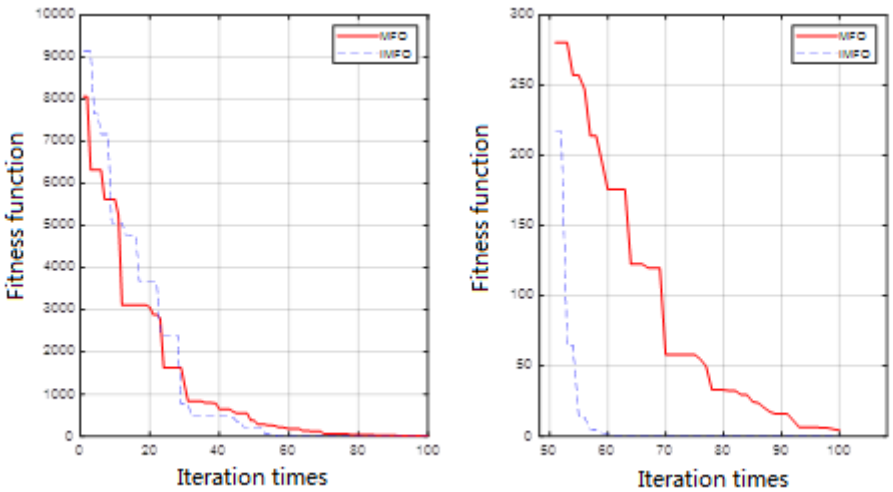

Fig. 5 Convergence curve of fitness function for different algorithms of Sphere function

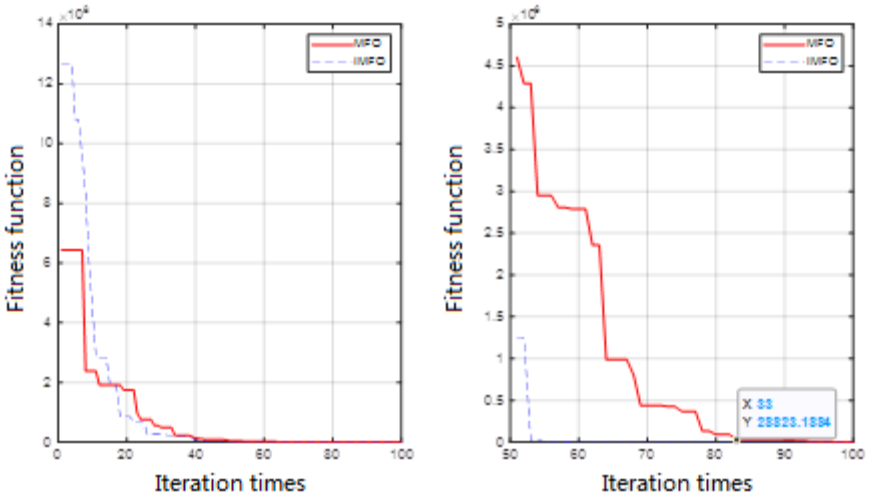

Fig. 6 Convergence curve of fitness function for different algorithms of Rosenbrock function

From Figure 5 to Figure 8, it can be seen that the IMFO algorithm and the MFO algorithm have little difference in the first half of the iterative process. This is because the IMFO algorithm mainly introduces chaos theory and Ke Western function enhances the algorithm's exploration ability, making it not easy to fall into the local optimal solution. In the latter half of the iteration, the extreme value of the fitness function it finds is much more accurate than the MFO algorithm. This is because by introducing adaptive weights, all moths are affected by the current optimal flame, thus strengthening their local optimization capabilities。

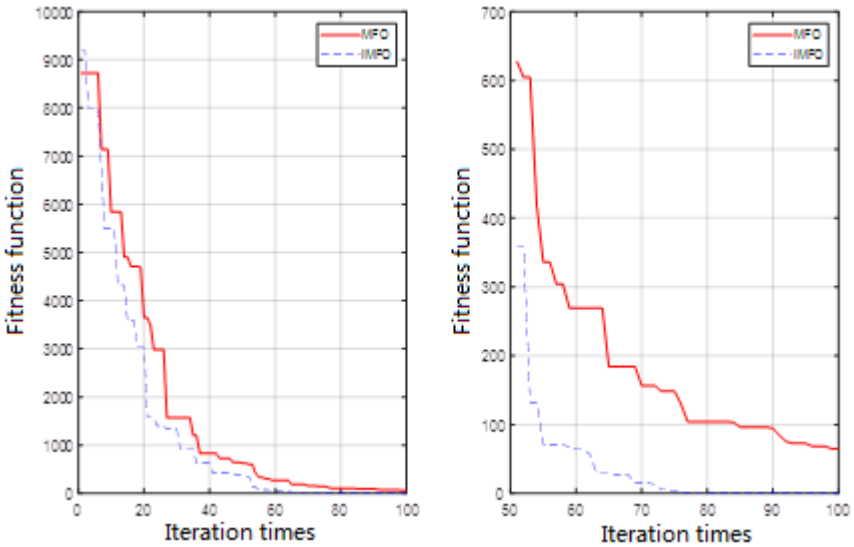

Fig. 7 The convergence curve of the fitness function of different algorithms of Rastrigin's function

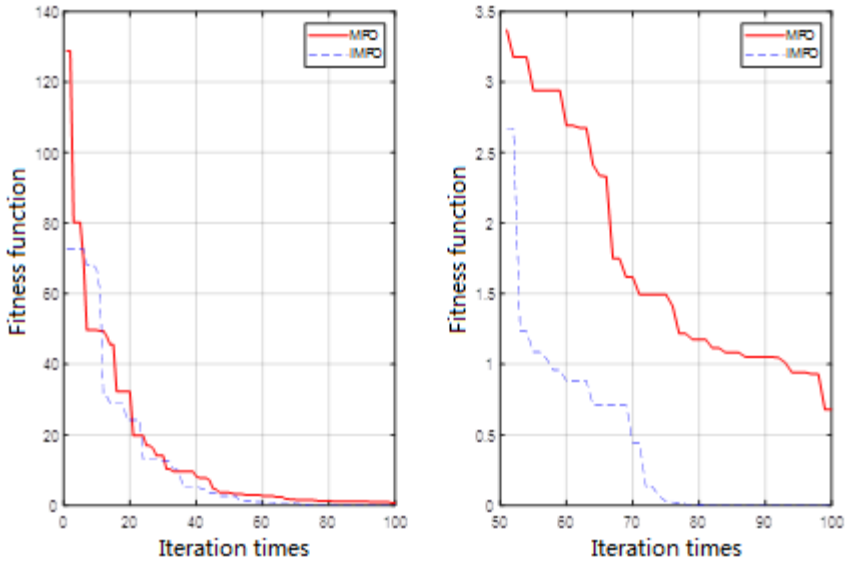

Fig. 8 Convergence curve of fitness function for different algorithms of Griewank function

5. Summary

In this paper, the sensitivity analysis of induction motor parameters is carried out, and simulation experiments are carried out on the influence of different parameter changes on the speed control performance of induction motors. It is concluded that the rotor time constant and stator resistance need to be identified during the operation of the induction motor. . Then the moth fire suppression algorithm is introduced and improved, and then the standard test function is used to test the performance of the improved moth fire suppression algorithm and the improved moth fire suppression algorithm. It is concluded that the global optimization ability of the improved moth fire suppression algorithm is better than the original moth fire suppression algorithm, and it is feasible for motor parameter identification. It laid the foundation for the next step to use the improved moth fire suppression algorithm to identify the parameters of induction motors.

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