OPTIMIZATION FOR INDUCTION MOTOR DESIGN BY IMPROVED GENETIC ALGORITHM

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Abstract

Optimization for induction motor design is one of the interested subjects by electrical engineers. This paper proposes an Improved Genetic Algorithm (IGA) for optimization of 3-phase induction motor design. The proposed IGA possesses the characteristics of real number encoding, stochastic crossover operator, self-adaptable mutation operator and annealing penalty function, and multi-turns evolution strategy for solving nonlinear constrained multivariable optimization problems. A model for optimization of 3-phase induction motor design based on magnetic circuit analysis is established and discussed. The IGA, which was tested by a mathematical example, is applied to the optimization of the *Y-series* 3-phase induction motor design. The results are compared with the data of manufacturers and it is shown that the algorithm can reduce the active material costs and/or improve the efficiencies of the motors.

1. INTRODUCTION

Induction motors have always played and will continue to play an important role in the industry due to their simple structure, ruggedness and high reliability. It is much desired by both the users and the manufacturers to optimise the design to improve the efficiency and reduce the active material cost of the induction motors.

Because the optimization of induction motors design is a highly nonlinear mix-discrete constrained multi-variable problem, the conventional optimization methods, such as the enumerated approach, are not effective. As a modern intelligent approach, the genetic algorithms have shown promising effect [1] and are being widely used for solving the optimization problems for electrical machines and other electromagnetic devices [2,3,4]. However, the conventional generic algorithms (CGA) have some shortcomings such as prematurity, local optimal trap and long time-consuming.

In order to enhance the capability of searching for the global optimum or quasi-optimums of induction motor design within a reasonable computation time, an improved genetic algorithm (IGA), which can overcome the aforementioned shortcomings of CGA to some extent, is proposed in this paper. Some interrelated key techniques, such as the encoding method, the genetic operators, and the constraining conditions are further investigated, improved and verified by a mathematical test.

Based on the magnetic circuit analysis, a model for 3-phase induction motor design is established. The IGA is then applied to this model to search for the optimum designs. The results are compared with the data of manufacturers and it is shown that the algorithm may reduce the active material costs and/or improve the efficiencies of 3-phase induction motors.

2. IMPROVED GENETIC ALGORITHM

2.1 Overview of CGA

The CGA emulate biological evolutionary theories to solve optimization problems [1]. They provide solutions by generating a set of chromosomes referred to as a generation. Each string (chromosome) has its own fitness measure that reflects how well a creature can survive under the surrounding environment. The new generation of the strings is created through three major genetic operations – *selection*, *crossover* and *mutation*, which provide a powerful global search mechanism. Selection is a process in which individual strings are copied into a mating pool according to their fitness values. Crossover is a structured recombination operation. In the classical one-point crossover, a random position in a string is chosen and all characters to the right of this position are swapped. Mutation is an occasional random alteration of the value of a string position.

2.2 Encoding Scheme

Each string (chromosome) of the CGA is expressed by the binary code of the corresponding objective variables. Frequent encoding and decoding in the process of optimization cause long execution time and slow converging speed. To improve the convergent capability, real number code is used to encode and decode for the IGA implementation in this paper.

2.3 Crossover Operator

To increase the solution space and speed up the convergence of optimization, the IGA uses the stochastic crossover method incorporating the arithmetic crossover technique and the uniform crossover scheme. The stochastic crossover strategy is a kind of new crossover operator with parents to bring four offspring. Two offspring are produced by the arithmetical crossover operator [3], and the other two by the uniform crossover operator, which is a standard crossover method of the CGA.

2.4 Mutation Operator

The CGA′s mutation rate is usually constant and the mutation operator is independent of the number of iterations. The capability of searching the optimization results will become more and more inefficient with the development of optimum process. To overcome the aforementioned problems and improve the capability of global search of the CGA to some extent, a self-adaptive mutation operator is developed as the following

$$x_i' = \begin{cases} x_i + \Delta(t, u_i - x_i) & if \quad rd = 0 \\ x_i - \Delta(t, x_i - l_i) & if \quad rd = 1 \end{cases} \qquad (1)$$

where $\Delta(t, y) = y(1 - r^{t^2})$, r is a stochastic number within (0, 1), $t=1-Fitness(X)/fit_{max}$, $Fitness(X)$ is the fitness value of the current individual, fit_{max} the maximal fitness value of current population, x_i' the *i-th* weight of the new generation individual X', x_i the *i-th* weight of the former generation individual X, u_i and l_i are the upper and lower bounds of x_i, and rd is a random value of either "0" or "1".

The IGA can adaptively search the solution areas according to the quality of the solution by this self-adaptive mutation operator.

2.5 Other Improvements

Selection operator is performed by using the tournament scheme. An elitist strategy is also used and the best individual of the previous generation guarantees the best individual of the population to be present in the next. In addition, during the optimization process the crossover is implemented by using an exponentially decreasing rate, which starts at a specified maximum and decreases exponentially until it reaches a given minimum. Contrary to the crossover method, the mutation is implemented by using an exponentially increasing rate. Moreover, it is important to create an initial population of strings throughout the whole solution space. This paper adopted an artificial initial population by considering some experience constraints.

2.6 Mathematical Testing Example

For the sake of verifying the capability of the IGA′s global search, the *Camel* function [4]

$$f(x,y) = (4 - 2.1x^2 + x^4/3)x^2 + xy + (-4 + 4y^2)y^2 \qquad (2)$$

is tested. It has several local minimums and the global minimum is -1.031628. The parameters for the IGA implementation are selected through simulation as shown in Table I. The optimization results of the IGA in comparison with those of the CGA [4] are listed in Table II, and it is shown that the IGA′s performance is far better than that of the CGA.

TABLE I

IGA PARAMETERS FOR *CAMEL* FUNCTION OPTIMIZATION

IGA Parameters	Values
Population size	60
Initial crossover rate	0.85
Initial mutation rate	0.008
Final crossover rate	0.6
Final mutation rate	0.01
Maximum number of generations	50

TABLE II

OPTIMIZATION RESULTS OF CGA AND IGA FOR *CAMEL* FUNCTION

Algorithms	Times	*x*	*y*	*f(x ,y)*
CGA	—	-0.08789	0.71286	-1.031613
IGA	1	0.09016	-0.71282	-1.031628
	2	-0.08975	0.71282	-1.031628
	3	0.08938	-0.71259	-1.031628
	4	-0.08982	0.71268	-1.031628

3. MODEL FOR OPTIMIZATION OF 3-PHASE INDUCTION MOTOR DESIGN

The optimization problem for 3-phase induction motor design can be formulated as

$$\begin{cases} \min \quad f(X) \\ s.t. \quad g_i(X) \geq 0, \; i = 1,2,\cdots,m \\ \qquad\; h_i(X) = 0, \; i = 1,2,\cdots,n \end{cases} \qquad (3)$$

where *f(X)* is the objective function of optimization, $g_i(X)$ and $h_i(X)$ are constraining functions, and X is the design variable set. The highly nonlinear constrained multivariable optimization problem is very difficult to be solved by the conventional methods.

3.1 Objective Functions

In order to reduce the active (main) material cost and improve the efficiency of 3-phase induction motors, two different objective functions of optimization are defined separately as

$$\begin{cases} f_1(X) = k_{Fe}W_{Fe} + k_{Cu}W_{Cu} + k_{Al}W_{Al}, \ or \\ f_2(X) = 1/\eta \end{cases} \tag{4}$$

where k_{Fe}, k_{Cu}, and k_{Al} are the unit prices of magnetic material, copper wire and aluminium conductive bars, respectively, W_{Fe}, W_{Cu}, and W_{Al} are the masses of the corresponding materials, and η is the motor efficiency.

3.2 Optimization Design Variables

There are hundreds of design variables in 3-phase induction motor design and it is crucial to choose suitable parameters as the optimization design variables. In (3), the model of optimization for 3-phase induction motor design, ten independent optimization design variables were selected carefully as the following

$$X=[x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_8, x_9, x_{10}]$$

$$=[L, D_{i1}, \delta, Z_0, R, b_{s1}, h_{s2}, b_{r1}, b_{r2}, h_{r2}] \tag{5}$$

where L is the axial length of the core, D_{i1} the inner diameter of the stator, δ the length of the air-gap, Z_0 the number of turns of the stator winding, and R, b_{s1}, h_{s2}, b_{r1}, b_{r2} and h_{r2} are the geometric dimensions of the stator and rotor slots, as shown in Fig. 1.

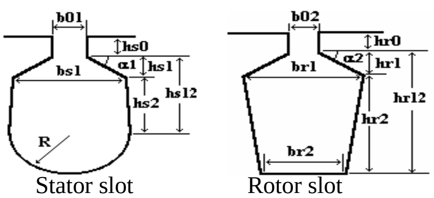

Fig.1 Slot Dimensions

3.3 Constraining Functions

The CGA usually adopts the sequential unconstrained minimization technique (SUMT) to solve the problems defined by (3). Experiences and simulations have shown that if the penalty factor is selected too large, the CGA may cause premature convergence. On the other hand, if the penalty factor is selected too small, the CGA may yield a highly computational burden. To solve this problem, a new annealing penalty function, which adopts self-adaptive annealing penalty factors, is developed for the IGA:

$$\begin{cases} F(X,\sigma) = f(X) + P(X,\sigma) \\ P(X,\sigma) = \sigma[\sum_{i=1}^{m} |\min(0, g_i(X)| + \sum_{i=1}^{n} |h_i(X)|] \end{cases} \tag{6}$$

where σ is the penalty factor ($\sigma=1/T$, $T_{i+1}=T_i\alpha$, T the value of the control temperature, α the cooling coefficient within the range of 0-1 [5]), $P(X,\sigma)$ the penalty function, and $F(X,\sigma)$ the generalized objective function defined by the IGA.

To reflect the changing feature of the nature and emulate the surrounding environment becoming more rigour with the development of the generations, the fitness value of a string is defined as

$$fit = F_m - F(X,\sigma) \tag{7}$$

where F_m is a maximum objective function in a generation.

To avoid prematurity, another technique known as the multi-turn evolution strategy was used in this paper. It can reduce the genetic generations, redefine the penalty factor in each genetic turn, and increase the genetic turns to ensure the capability of searching for the global optimum.

4. APPLICATION OF IGA TO OPTIMIZATION OF 3-PHASE INDUCTION MOTOR DESIGN

The IGA are applied for design optimization of the *Y-series* 3-phase induction motors. In the process of optimization, the constraining functions in (3) are implemented as the following

$$\begin{cases} g_1(x) = \eta - \eta' \geq 0 \\ g_2(x) = \cos\varphi - \cos\varphi' \geq 0 \\ g_3(x) = T_m - T'_m \geq 0 \\ g_4(x) = T_{st} - T'_{st} \geq 0 \\ g_5(x) = I'_{st} - I_{st} \geq 0 \\ g_6(x) = AJ_0 - AJ \geq 0 \\ g_7(x) = 80\% - S_f \geq 0 \\ g_8(x) = S_f - 70\% \geq 0 \end{cases} \tag{8}$$

where η, $cos\varphi$, T_m, T_{st} and I_{st} are the motor efficiency, power factor, maximum torque, starting torque and starting current respectively (the corresponding apostrophic quantities are the Chinese national standard), AJ and AJ_0 are the designed and requested values of the heat load, and S_f is the stator slot fill factor.

Based on the algorithm mentioned above, a software for 3-phase induction motor design was developed under the platform of Microsoft Visual Basic. The optimization results of 11 motors are listed in Table III by the design software. It is shown that the average reduction of active material costs is 11.86% by defining $f_1(X)$ as the objective function and the average increase of efficiencies is 1.65% by defining $f_2(X)$ as the objective function in (4). The more detail information about the optimization design of a motor (Y90S-2) is given in Table IV.

TABLE III Optimization Results of the *Y-series* 3-phase Induction Motors by IGA

No.	Motor type	Power *(kW)*	Data of manufacturer		Optimization of Cost*		Optimization of Efficiency	
			Cost (CNY)*	η	*Cost**	*Decrease of Cost**	η	*Increase of* η
1	Y802-2	1.1	77.78	0.7818	72.25	7.11%	0.7988	2.17%
2	Y90S-2	1.5	96.38	0.7989	88.64	8.03%	0.8160	2.14%
3	Y100L2-4	3	189.17	0.8367	143.7	24.04%	0.8684	3.79%
4	Y112M-6	2.2	187.65	0.8080	179.27	4.47%	0.8249	2.09%
5	Y132M-8	3	320.56	0.8238	288.22	10.09%	0.8441	2.46%
6	Y160L-6	11	665.80	0.8865	578.71	13.08%	0.8956	1.03%
7	Y180L-8	11	829.50	0.8830	740.24	10.76%	0.8932	1.16%
8	Y200L-8	15	986.27	0.8858	895.09	9.24%	0.8970	1.26%
9	Y225M-8	22	1484.93	0.9081	1358.77	8.50%	0.9166	0.94%
10	Y250M-8	30	2036.11	0.9110	1696.91	16.66%	0.9190	0.88%
11	Y280M-8	45	2917.66	0.9267	2378.38	18.48%	0.9291	0.26%
		Average				11.86%		1.65%

* Represents the active material costs in CNY (Yuan Renminbi)

TABLE IV Optimization Results of the *Y90S-2* Motors by IGA

Motor Type	Y90S-2	Data of manufacturer	Optimization of cost	Optimization of efficiency
Design variables	Length of the core: L (mm)	85	75	110
	Inner diameter of the stator : D_{i1} (mm)	72	70	70
	Length of the air-gap : δ (mm)	0.35	0.3	0.3
	Number of turns of stator winding: Z_0	74	77	69
	Dimension of the stator slot: R (mm)	0.485	0.4767	0.4626
	Dimension of the stator slot: b_{s1} (mm)	0.77	0.7246	0.8403
	Dimension of the stator slot: h_{s2} (mm)	0.6	0.5475	0.4521
	Dimension of the rotor slot: b_{r1} (mm)	0.69	0.495	0.8272
	Dimension of the rotor slot: b_{r2} (mm)	0.29	0.195	0.3171
	Dimension of the rotor slot: h_{r2} (mm)	1.03	0.75	1.1717
Constraining conditions	Efficiency: $\eta \geqslant 0.78$	0.7989	0.7817	0.8160
	Power factor: $cos\varphi \geqslant 0.85$	0.8306	0.8538	0.8501
	Per-unit of maximum torque: $T_m \geqslant 2.2$	2.8508	2.7703	2.8957
	Per-unit of starting torque: $T_{st} \geqslant 2.2$	2.8441	3.3609	2.9632
	Per-unit of starting current: $I_{st} \leqslant 7.0$	6.0214	5.4163	6.8708
	Stator slot fill factor: $70\% \leqslant S_f \leqslant 80\%$	70.01%	79.47%	78.01%
	Heat load: $AJ \leqslant 1500$ ($10^8 \cdot A^2/m^3$)	1223.98	1294.82	1074.21
Active material costs (CNY)		96.38	88.64	112.16

5. CONCLUSION

An improved genetic algorithm for optimization of 3-phase induction motor design has been developed. The proposed IGA includes several improvements such as the encoding scheme, the stochastic crossover technique, the self-adaptive mutation operator, the annealing penalty function, and the multi-turn evolution strategy. As demonstrated by optimizing the *Camel* function, the IGA can provide a better global optimum or quasi-optimums than the CGA.

Moreover, a model for the optimization of 3-phase induction motor design based on magnetic circuit analysis is established and discussed. The IGA was applied to the optimization of the *Y-series* 3-phase induction motor design and the optimization results of 11 motors show that the average active material costs of the motors can be reduced by 11.86% and the average efficiencies can be increased by 1.65%.

6. REFERENCES

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