

# Optimization of linear induction machines based on a novel adaptive genetic algorithm

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**Abstract:** In order to improve the thrust-power ratio index of the linear induction motor(LIM), a novel adaptive genetic algorithm (NAGA) is proposed for the design optimization of the LIM. A good-point set theory that helps to produce a uniform initial population is used to enhance the optimization efficiency of the genetic algorithm. The crossover and mutation probabilities are improved by using the function of sigmoid and they can be adjusted nonlinearly between average fitness and maximal fitness with individual fitness. Based on the analyses of different structures between the LIM and the rotary induction motor (RIM) and referring to the analysis method of the RIM, the steady-state characteristics of the LIM that considers the end effects of the LIM is calculated and the optimal design model of the thrust-power ratio index is also presented. Through the comparison between the optimal scheme and the old scheme, the thrust-power ratio index of the LIM is obviously increased and the validity of the NAGA is proved.

**Key words:** adaptive genetic algorithm; linear induction machine; uniform design

Linear electric motors including linear synchronous, induction and direct current motors have many advantages over rotational ones in efficiency, dynamic performance, and reliability due to the absence of mechanical gears and flat transmission systems. Among various types of linear motors, the linear induction motor(LIM) is especially attractive due to its simple structure and low cost. Different types of LIMs have been presented. Flat and tubular constructions are the most applicable topologies of LIMs. Some topologies of LIMs employ aluminum cages in their secondary. However, the use of an aluminum sheet instead of aluminum cages makes the LIM structure simpler.

Proper performance of the LIM requires optimization of its machining dimensions. So far, design optimization of the LIM has been considered in many researches, in which many different algorithms have been adopted such as the improved adaptive genetic algorithms(IAGA), the simulated annealing algorithm and the particle swarm optimization. However, the mode of LIMs is so complicated that the efficiency of optimization is low. In this paper, a high efficiency algorithm is presented.

The genetic algorithm(GA) is a popular stochastic optimization method, and it uses the concept of natural evolution and natural genetics. It has shown good performance regarding its ability to find globally optimal solutions. There

are operators called selection, crossover, and mutation, which enable the genetic algorithm to search globally optimal solutions over a wide region. According to global search ability, many scholars have applied the GA to the optimization of the LIM<sup>[1]</sup>. However, for the proper tradeoff balance, adjusting parameters, such as crossover probability and mutation probability, are necessary for the GA.

The adaptive genetic algorithm proposed by Srinivas et al.<sup>[2]</sup> is implemented to optimize the design of the LIM and the IAGA<sup>[3]</sup> is also implemented to optimize power transformers. In the IAGA, the individual crossover and mutation probabilities have a linear relationship with the fitness value,

$$P_c = \begin{cases} P_{c1} - \frac{(P_{c1} - P_{c2})(f' - f_{avg})}{f_{max} - f_{avg}} & f' \geq f_{avg} \\ P_{c2} - \frac{(P_{c2} - P_{c3})(f' - f_{min})}{f_{avg} - f_{min}} & f' < f_{avg} \end{cases} \quad (1)$$

$$P_m = \begin{cases} P_{m1} - \frac{(P_{m1} - P_{m2})(f - f_{avg})}{f_{max} - f_{avg}} & f \geq f_{avg} \\ P_{m2} - \frac{(P_{m2} - P_{m3})(f - f_{min})}{f_{avg} - f_{min}} & f < f_{avg} \end{cases} \quad (2)$$

where  $f_{max}$  is the maximal fitness of the population;  $f_{avg}$  is the average fitness of the population;  $f_{min}$  is the minimal fitness of the population;  $f'$  is the larger fitness between two individuals in a crossover operation;  $f$  is the individual fitness in a crossover operation. Local elitisms are not easily evolved in the IAGA and thus its global search ability is limited.

To enhance the performance of linear induction motors, the IAGA is exploited to optimize the multimodal function of variables, such as dimensions and shapes. However, the IAGA is not readily applicable and a novel adaptive genetic algorithm, which includes dynamic adjustments for the crossover and mutation rates together with the uniform design for the initial population, is proposed to improve the global search ability of the GA. The proposed method is validated by applying it to optimize the design of the LIM.

## 1 Novel Adaptive Genetic Algorithm(NAGA)

The NAGA, which has improved both the design of the initial population and the design of the genetic operation, is proposed based on the IAGA. In the following, the flow of the NAGA and the innovation are introduced.

### 1.1 Encoding

Instead of binary coding, the NAGA uses the real code to represent a chromosome. The real code is a way that expresses the solution by a real number, which does not have influ-

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ence on precision and storage. In addition, it helps to bring factual information to the algorithm, and gives clear physical meaning to the code. Therefore, the real code is widely applied to complicate and high dimensional problems.

We randomly select a distinct point for each gene of the problem from the search space. The range of each variable depends on a given problem. The chromosome  $X$  is shown as follows:

$$X = x_1, x_2, \dots, x_n$$

If an invalid gene is formed, which does not satisfy a constraint condition of a given problem, we ignore the whole chromosome and generate another new chromosome with valid genes. Thus, no repairing algorithm is used in the NAGA.

## 1.2 Selection

According to a certain rule such as the turntable set, individuals of the old population are selected and put into new ones. For a stochastic sample, the better individuals can be selected while the worse ones can be excluded. For a deterministic sample, the better individuals are certainly selected and the worse ones are excluded.

In this case, the turntable set is adopted. It is a familiar stochastic sample. It is similar to roulette gambling in betting games. The basic idea of the turntable set is

$$p_i = f_i / \sum_{j=1}^N f_j = f_i / f_{\text{sum}}$$

where  $p_i$  is the choice probability of individual  $i$ ;  $f_i$  is the fitness of individual  $i$ ;  $f_{\text{sum}}$  is the sum fitness of the population.

## 1.3 Uniform design for the initial population

By analyzing the genetic algorithm, it can be found that the distribution of the initial population directly concerns the global convergence and search efficiency of the genetic algorithm. The reasonable setting of an initial population is an important problem in the application of the genetic algorithm to perform optimization calculations. On the basis of the good-point set theory, a new method is proposed to establish an initial population with good diversity by the uniform design. The new method has advantages in simplicity, diversity, and multi-dimensions; therefore, it can effectively improve global convergence and speed.

Suppose that the chromosome of the initial population set is<sup>[4]</sup>

$$S_N^i = \{s_1^i, s_2^i, \dots, s_a^i\} \quad i = 1, 2, \dots, N \quad (3)$$

A good-point set in the space  $H$  is selected as

$$P_n(i) = \{\{r_1 i\}, \{r_2 i\}, \dots, \{r_a i\}, i = 1, 2, \dots, N\} \quad (4)$$

where  $r_k = e^k, 1 \leq k \leq a$ .

If the real code is used,  $s_k^i = \alpha_k + \{r_k i\}(\alpha_k - \beta_k)$ . The method of a good-point set that helps to produce a uniform initial population is used to enhance the optimization efficiency of the GA (see Fig. 1 and Fig. 2).

## 1.4 Design of genetic operation

Eqs. (1) and (2) show that crossover and mutation probabilities can be adjusted between average fitness and maximal

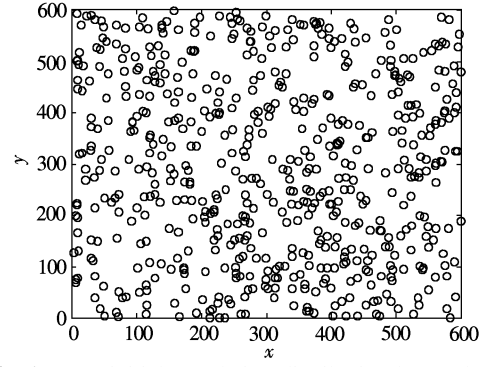


Fig. 1 2-D initial population distribution by randomness

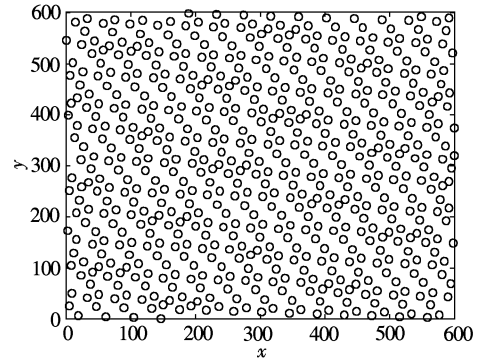


Fig. 2 2-D initial population distribution by a good-point set

fitness with individual fitness. Improvement can be further made on improving convergence speed, avoiding premature convergence and reducing redundant iterative operations in the later operating process of the algorithm. The NAGA proposed in this paper, which makes the adaptive adjusting curves of crossover and mutation probabilities change slowly by  $f_{\text{avg}}$ , can increase the crossover and mutation probabilities of individuals whose fitness approaches the average fitness of the population greatly.

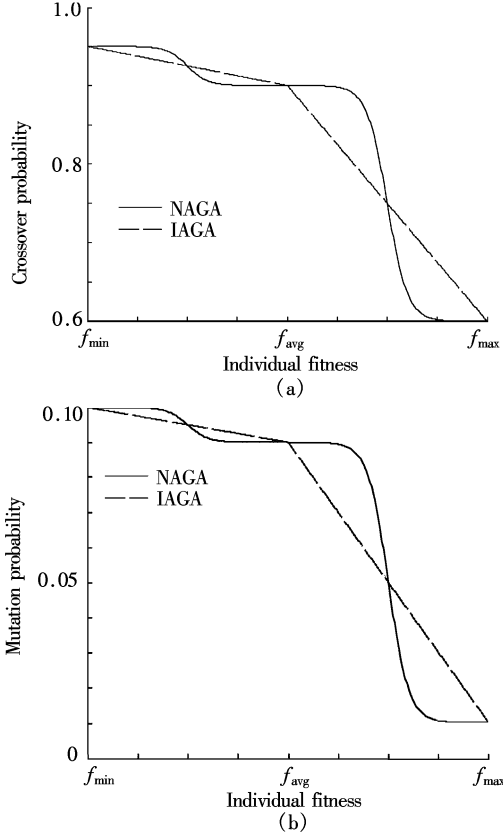
In the proposed algorithm,  $P_c$  and  $P_m$  can be adjusted according to the individual fitness using the following method<sup>[5]</sup>:

$$P_c = \begin{cases} P_{c1} - \frac{P_{c1} - P_{c2}}{1 + \exp\left(-A \left(\frac{2(f' - f_{\min})}{f_{\text{avg}} - f_{\min}} - 1\right)\right)} & f' < f_{\text{avg}} \\ P_{c2} - \frac{P_{c2} - P_{c3}}{1 + \exp\left(-A \left(\frac{2(f' - f_{\text{avg}})}{f_{\max} - f_{\text{avg}}} - 1\right)\right)} & f' \geq f_{\text{avg}} \end{cases} \quad (5)$$

$$P_m = \begin{cases} P_{m1} - \frac{P_{m1} - P_{m2}}{1 + \exp\left(-A \left(\frac{2(f - f_{\min})}{f_{\text{avg}} - f_{\min}} - 1\right)\right)} & f < f_{\text{avg}} \\ P_{m2} - \frac{P_{m2} - P_{m3}}{1 + \exp\left(-A \left(\frac{2(f - f_{\text{avg}})}{f_{\max} - f_{\text{avg}}} - 1\right)\right)} & f \geq f_{\text{avg}} \end{cases} \quad (6)$$

The improved  $P_c$  and  $P_m$  can preserve the elitist and enhance mutation probability of the deteriorating individuals; therefore, premature convergence is solved and the global search ability is improved greatly. The  $P_c$  and  $P_m$  curves of

the NAGA and the IAGA are shown in Fig. 3.



**Fig. 3**  $P_c$  and  $P_m$  curves of IAGA and NAGA. (a)  $P_c$  curve; (b)  $P_m$  curve

### 1.5 Crossover operator

The crossover operation is a process where a new offspring is generated from parents during reproduction. The gene in the chromosome of two parents is crossly selected one by one as the gene of the offspring with a probability of  $P_c$ .

In the proposed algorithm, we use the arithmetic crossover which carries out a simple linear combination between two parents by generating a random value,  $\alpha \in (0, 1)$ .

We obtain two children defined as

$$X' = \alpha X + (1 - \alpha) Y, \quad Y' = (1 - \alpha) X + \alpha Y \quad (7)$$

### 1.6 Mutation operator

The mutation operator plays an important role in introducing new genes to the chromosomes with a probability of  $P_m$ . The mutation operator diversifies during the search and prevents the premature convergence from leading to nearly the same individuals within a population after several generations. The mutation probability must be sufficiently small to ensure that the crossover is the primary means of new offspring. In our algorithm we use uniform mutation. With this method. The next population is changed, according to a certain probability, into a drawn random number in a uniform distribution on the interval  $[X_{\min}, X_{\max}]$ . The new individual is

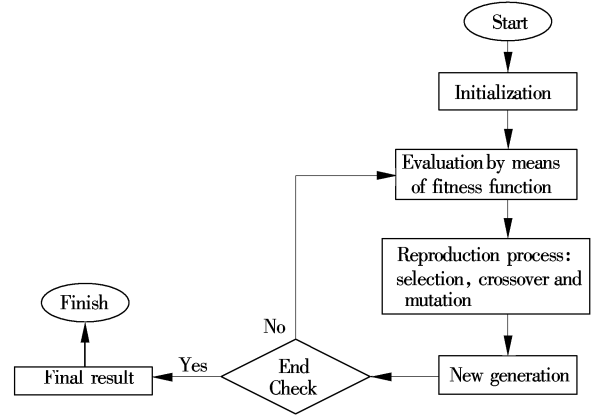
$$Y = X_{\min} + r(X_{\max} - X_{\min}) \quad (8)$$

where  $r \in (0, 1)$  is a random variable.

### 1.7 Flow of genetic algorithm

The main steps of the genetic algorithm are reported as follows:

- 1) Build an aptness function from the objective function.
- 2) A population of  $N$  individuals is generated through uniform design, each of which is characterized by a string of floating point numbers.
- 3) All the individuals of the population are evaluated by means of the fitness function. The best fitness is calculated. The average fitness of the population as well as the global fitness is valued meantime.
- 4) The rules of the genetic algorithm are applied in order to generate a new population of  $N$  individuals. The reproduction process is composed of the following three steps: selection, crossover, and mutation.
- 5) A new population is achieved. All the individuals are evaluated as described in step 3) and the subsequent steps are repeated. The procedure ends after a prefixed number of generations or when the best or the average fitness values reach a satisfactory level. The flowchart is shown in Fig. 4.



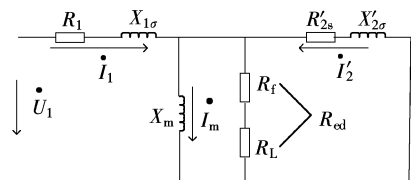
**Fig. 4** Flowchart of genetic algorithm

## 2 Application to Linear Induction Machines

The design of the LIM belongs to a nonlinear optimization problem. The optimizing processes are as follows.

### 2.1 Performance analysis

A simple equivalent circuit for the LIM is shown in Fig. 5. According to Ref. [6], parameter values of the circuit are obtained.



**Fig. 5** Equivalent circuit for LIM

Equivalent impedance

$$Z_e = \frac{1}{\frac{1}{jX_m} + \frac{1}{R_{cd}} + \frac{1}{R'_{2s} + jX'_{2s}}} = R_e + jX_e \quad (9)$$

Phase current

$$I_1 = \frac{U_1}{\sqrt{(R_1 + R_e)^2 + (X_1 + X_e)^2}} \quad (10)$$

Power factor

$$\cos\varphi = \frac{R_1 + R_e}{\sqrt{(R_1 + R_e)^2 + (X_1 + X_e)^2}} \quad (11)$$

Induced voltage

$$E_1 = I_1 \sqrt{R_e^2 + X_e^2} \quad (12)$$

Secondary current

$$I'_2 = \frac{E_1}{Z'_{2s}} \quad (13)$$

Propulsion force

$$F_e = \frac{m_1}{v_s} \left( I_1'^2 R'_{2s} + \frac{sE_1^2}{R_{edf}} \right) \quad (14)$$

Therefore, the performance between propulsion force and slip ratio can be plotted, as shown in Fig. 6.

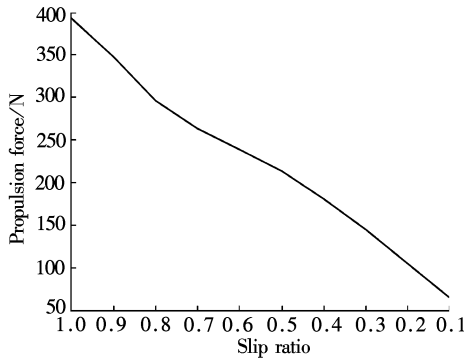


Fig. 6 Curve for propulsion force

## 2.2 Selection of objective function

In the LIM optimization problem, there are a few alternatives for choosing the objective function to be minimized or maximized. In general, cost or weight of the motor is defined as the objective function that will be minimized. However, other quantities can be chosen as the objective functions such as minimizing the losses or maximizing the propulsion force of the linear motor. Here, the propulsion force of the LIM is selected as the objective function. The objective function is

$$\max f(x) = F_e \quad (15)$$

## 2.3 Selection of variables

In this case, seven LIM parameters are chosen as variables. These seven parameters listed in Tab. 1 have the most significant effects on LIM performance. The other parameters may also play an important role in the LIM. However, they are not chosen due to the computation cost. To obtain an applicable design, the design parameters need to be con-

strained between upper and lower limit values<sup>[7]</sup>.

Tab. 1 Design parameters and their limit values

Design parameter	Lower limit	Upper limit
Number of turns per phase	40	70
Primary iron width/mm	60	100
Air-gap/mm	2	4
Primary slot width/mm	5	10
Primary slot height/mm	40	60
Secondary iron height/mm	2	5
Secondary iron width/mm	80	130

## 2.4 Selection of constrained conditions

The constraints consist of the permissible upper limits or lower limits. For instance, high values for the power factor are desired for good performance in the LIM, and the primary current density cannot exceed certain values because of the permissible machine operating temperatures<sup>[8]</sup>.

The constraints are somewhat flexible; thus, the final solution allows for slight constraint violations. It means that the final solution of the optimization may be slightly beyond the feasible space. Some of the constraints are sometimes ignored in order to gain significant improvements in the values of the objective function. Seven nonlinear inequality constraints selected here are shown in Tab. 2.

Tab. 2 Inequality constraints

Constrained parameter	Value
Efficiency	> 0.4
Power factor	> 0.13
Primary tooth flux density/T	< 1.6
Primary yoke flux density/T	< 1.2
Primary current density/(A·m <sup>-2</sup> )	< 10 <sup>7</sup>
Primary slot filling factor	< 0.75
Electric loading/(A·m <sup>-1</sup> )	< 10 <sup>5</sup>

## 2.5 Penalty function

Genetic algorithms are generally used to solve non-constrained problems. In order to use them to constrained problems, penalty and augmented objective functions are introduced,

$$\min/\max f(X, \sigma) = f(X) + P(X, \sigma) \quad (16)$$

where  $\sigma$  is penalty factor<sup>[9]</sup>,

$$P(X, \sigma) = \sigma \left[ \sum_{i=1}^n |\min\{0, g_i(X)\}| + \sum_{j=1}^m |h_j(X)| \right] \quad (17)$$

## 2.6 Result

The proposed algorithm has been used to solve LIM optimization problems and the results are compared with those obtained by the IAGA. It can be seen from Fig. 7 that the solutions of the maximum propulsion force have been improved and also the solutions have faster converge as well. And the obtained optimized results are shown in Tab. 3 and Tab. 4.

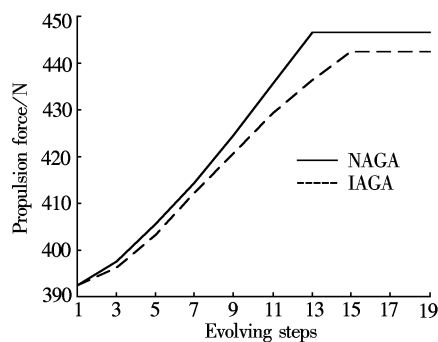


Fig. 7 LIM evolving process

Tab.3 Design parameter values obtained after cost optimization

Design parameter	Initial motor	Optimized motor
Number of turns per phase	59	52
Primary iron width/mm	80	85
Air-gap/mm	3	2
Primary slot width/mm	7	5.6
Primary slot height/mm	50	49.3
Secondary iron height/mm	3	2.6
Secondary iron width/mm	109	91

Tab.4 Constraint values obtained after cost optimization

Constraint parameter	Initial motor	Optimized motor
Efficiency	0.57	0.68
Power factor	0.18	0.19
Primary tooth flux density/T	1.59	1.35
Primary yoke flux density/T	0.87	0.86
Primary current density/(A·m <sup>-2</sup> )	9.3×10 <sup>6</sup>	9.9×10 <sup>6</sup>
Primary slot filling factor	0.74	0.73
Electric loading/(A·m <sup>-1</sup> )	97 371	91 610
Propulsion force/N	392.4	446.5

applied to the design of the linear induction motor. The proposed method can optimize the linear induction motor, and evaluate the propulsion force and performance of the design. The computational results show the validity of the proposed method.

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3 Conclusion

The proposed NAGA is compared with the IAGA. An optimization technique based on the NAGA is developed and

基于新型自适应遗传算法的直线感应电机的优化设计

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摘要: 为了提高直线感应电机的力能指标, 提出一种新型自适应遗传算法, 并对直线感应电机进行了优化设计. 采用佳点集理论对遗传算法的初始化种群进行均匀设计, 提高了遗传算法的优化效率. 同时利用 sigmoid 函数改进了交叉概率和变异概率, 使交叉率和变异率按照个体的适应度在平均适应度和最大适应度之间随 sigmoid 曲线进行非线性调整. 在分析直线感应电机与旋转电机物理结构差异的基础上, 得到考虑边端效应的直线感应电机的稳态性能, 并给出直线感应电机力能指标的优化模型. 通过对优化后的设计方案与原设计方案的比较发现: 直线感应电机的力能指标显著提高, 验证了方法的有效性.

关键词: 自适应遗传算法; 直线感应电机; 均匀设计

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