Optimum Design of a Linear Induction Motor Using Genetic Algorithm, Niching GA and Neural Network

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Abstract - This paper presents the optimum design of a Linear Induction Motor (LIM) using Genetic algorithm, Niching Genetic algorithm and Neural Network. The design variables are optimized by different optimization methods and the results are discussed.

Keywords: optimum design, linear induction motor, genetic algorithm, niching genetic algorithm, neural network

1. Introduction

The linear induction motor (LIM) is used throughout various fields. K. Fujisaki proposed an application of the LIM in steel making plants [1]. He introduced that LIM can be used for transporting molten iron. Fig. 1 shows the system for this process. In the galvanizing process, the zinc ash adheres to the steel surface and deteriorates the quality of the steel. In this system, the LIM is anticipated for transferring molten zinc by electromagnetic force. The molten zinc is treated as the secondary part of the LIM. Since the LIM produces an electromagnetic force at the surface, the zinc ashes will flow with the molten metal. As the LIM must be installed within a limited region, optimum design is needed to produce maximum thrust. In this paper, genetic algorithm (GA), Niching Genetic algorithm (N-GA) and Neural Network (N-N) are used to optimize the variables of the LIM used in this system [2-4]. The calculated optimum designs are compared and discussed.

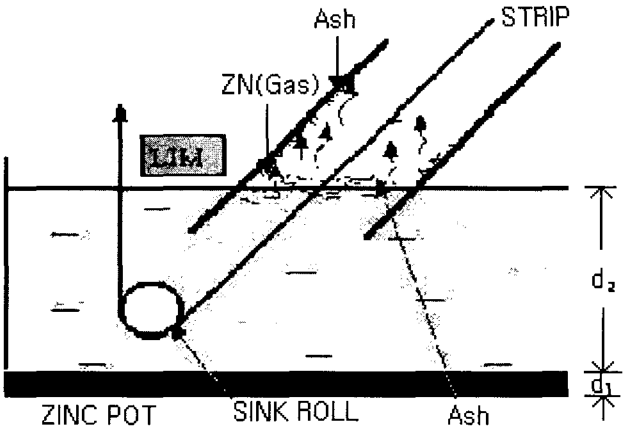

Fig. 1 Steel plating process

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2. The Characteristics of the LIM

Fig. 2 is the analysis model of the LIM. The molten metal is used as the secondary part of the LIM. Fig. 3 is the equivalent circuit.

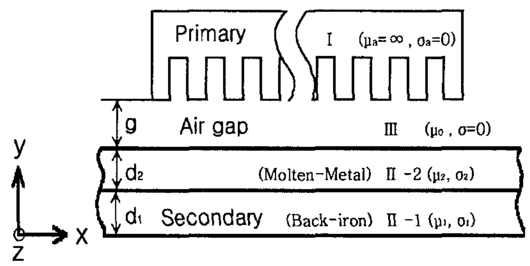


Fig. 2 LIM model

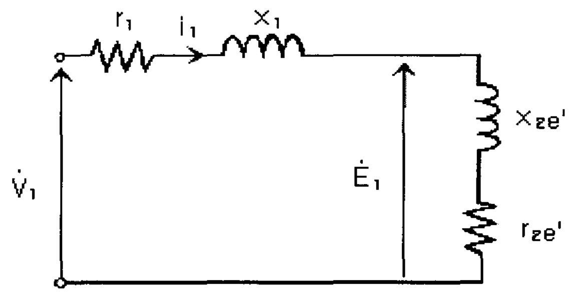


Fig. 3 Equivalent circuit

m - number of phase, V_1 - applied voltage[V]

r_1, x_1 - primary resistance and leakage reactance[Ω]

r_{2e}', x_{2e}' - secondary resistance and leakage reactance considering the end effect[Ω]

The produced thrust F_x is given as follows [5],

$$F_x = mV_1 r_{2e}' / V_S Z_1^2 [N] \tag{1}$$

where v_S is synchronous speed[m/s] and z_1 is equivalent circuit impedance[Ω].

3. Optimum Design of the LIM

3.1 Optimization method

The optimized design variables can be obtained by solving the problem.

$$\text{Find } \mathbf{X} \text{ which minimizes } f(\mathbf{X}), \quad \text{subject to } g_j(\mathbf{X}) \le 0 \ (j=1,2,\cdots,m) \tag{2}$$

where $\mathbf{X}=\{x_1,x_2,\cdots x_n\}$ are independent design parameters, n is the number of parameters and, j is the number of constraints.
In this paper SUMT is used [5] and, then the optimization problem is transformed as follows.

$$\text{Find } \mathbf{X} \text{ which minimize } \Phi_k$$

$$\Phi_k = \Phi(\mathbf{X}, r_k) = -f(\mathbf{X}) - r_k \sum_{j=1}^{n} [1/g_j(\mathbf{X})] \tag{3}$$

where r_k is penalty parameter $(k=1,2,\cdots)$.

The designed variables are selected using the optimization methods of genetic algorithm and neural network. These are combined with SUMT. The object functions are chosen as the thrust F_x and the weight of primary part W_g. Four design parameters and seven constraints are shown in Table 1.

Table 1 Design parameters and constraints

Design parameters	Constraints
X_1 : Zt (Teeth Width)	g1 : Primary current density $J_1 \le 5$ $[A/mm^2]$
X_2 : Ws (Slot Width)	g2 : Maximum flux density in teeth $B_{tm} \le 1.5$ [T]
X_3 : ds (Slot depth)	g3 : Maximum length of the LIM $L \le 530$ [mm]
X_4 : h (Stack height)	g4 : $5.0 \le Ws \le 12.5$ [mm]
	g5 : $2.5 \le Z_t \le 8$ [mm]
	\g6 : $30 \le ds \le 60$ [mm]
	g7 : $60 \le h \le 100$ [mm]

3.2 Optimization algorithm

GA Genetic algorithm is a search algorithm based on the mechanics of natural selction. GA can reduce the chance of searching local optima. In the proposed Sexual Reproduction model, individuals consist of the diploid of chromosomes, which are artificially coded as a binary string in computer programming. GA works from a rich database of point simultaneously (a population of strings), climbing many peaks in parallel and thus, the probability of locating the local optimum can be reduced [2].

Niching GA In this paper, Niching genetic algorithm is used. Niching methods have been developed to minimize the effect of genetic drift resulting from the selection operator in the traditional GA. A niche can be viewed as an organism task that permits species to survive in their environment. For each niche, the physical resources are finite and must be shared among the population of that niche. A niche is commonly referred to as an optimum of domain, the fitness representing the resources of that niche [3].

Neural Network In this paper, Hopfield neural network is used. A Hopfield net is a fully connected neural network. Each neuron has an internal activity and fires with over a grid of weights into every neuron. All information related to the problem to be solved is provided to the network in advance and expressed as a function [4]. In this paper an efficient algorithm is used, which combines the Hopfield network with the GA.

4. Results and Discussion

Table 2 shows the design parameters prior to optimization. The parameters are optimized using three optimization algorithms.

Table 2 Design parameters prior to optimization

	Design Parameters	Initial Value
Primary Voltage [V]	V_1	220
Frequency [Hz]	f_1	60
Primary Current [A]	I_1	8.1623
Primary Current Density [㎟]	J_1	5.1963
Primary Length [mm]	L_1	519.2
Number of Poles	p	4
Number of Slots	N_S	3
Pole Pitch [mm]	τ	108
Slot Depth [mm]	ds	47
Slot Width [mm]	W_S	8.8
Slot Pitch [mm]	t_S	12
Teeth Width [mm]	Z_t	3.2
Teeth Flux Density [T]	B_{tm}	0.3233
Primary Resistance [Ω]	r_1	3.3578
Primary Reactance [Ω]	x_1	8.1145
Back-iron Conductivity [1/Ωm]	σ_1	1.0×10^7

Molten Zinc Conductivity [1/Ωm]	σ_2	2.7x10^6
Stack Height [mm]	h	80
Air-gap [mm]	g	20
Back-iron Thickness [mm]	d_1	6
Molten Zinc Depth [mm]	d_2	300
Thrust [N]	Fx	11.5
Primary Core Weight [kg]	Wg	18.1
Thrust/Weight [N/Kg]	Fx/Wg	0.64

Fig. 4 shows the simulation results of the optimization when the object function is the thrust F_x. The thrusts of the optimized design rise to a greater extent than in the original: 156% for the N-N, and 162% for the GA and the N-GA. The design has the weight W_g [kg] as compared to the original: 104% for the GA, and 80% for the N-GA and the N-N. In this stage, the maximum thrust and maximum weight are obtained from the GA. This result is caused by one object function without any constraints on weight. Among the three optimization methods, the thrusts converge at almost equivalent values, and the maximum F_x/W_g is obtained from the N-GA method. Fig. 5 indicates the optimized design variables when the object function is the thrust F_x.

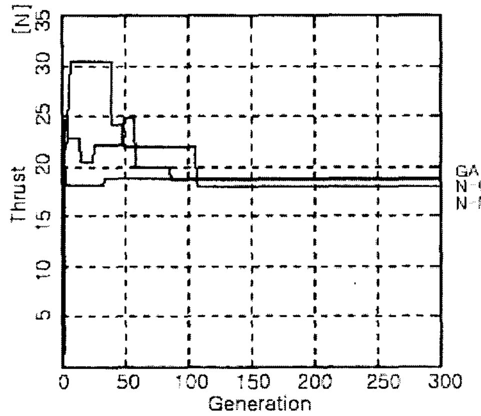
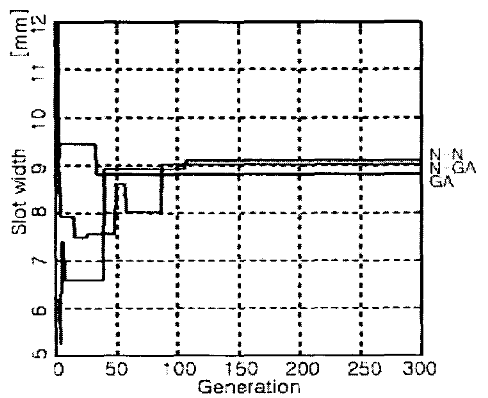
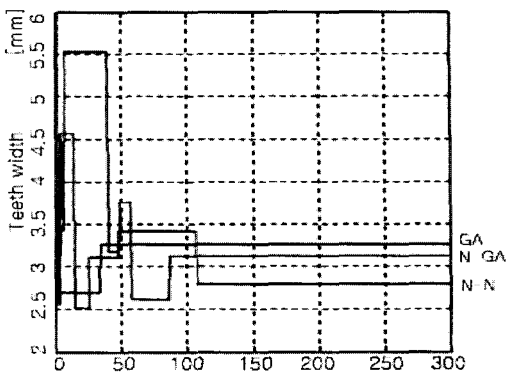


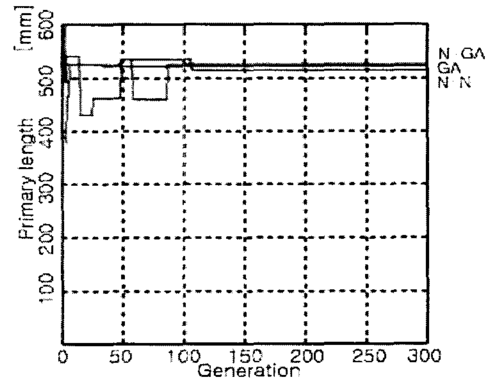
Fig. 4 Object function (thrust)



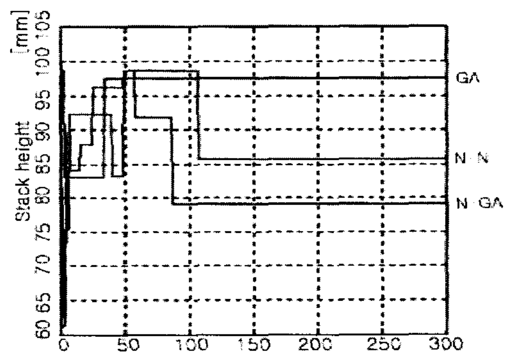
a) Slot width



b) Teeth width



c) Primary length



d) Stack height

Fig. 5 Optimized design variables - object function F_x

Fig. 6 shows the simulation results of the optimization when the object function is the weight of the LIM primary component W_g. In this simulation the thrust is given as a maximum value, which is obtained from the first optimization result. The weight of the LIM decreases less than in the first optimization: 71% for the GA, 70% for the N-GA and 72% for the N-N. From the second step of optimization, the thrust and weight converge at almost the same value. Fig. 7 indicates the optimized design variables when the object function is the weight W_g with a constant thrust of 18.7[N]. Table 3 indicates the optimized design parameters obtained from two steps of optimization.

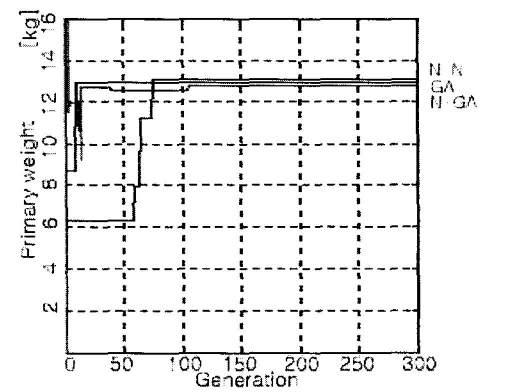
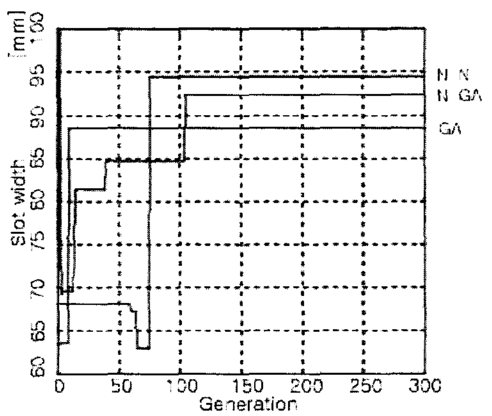
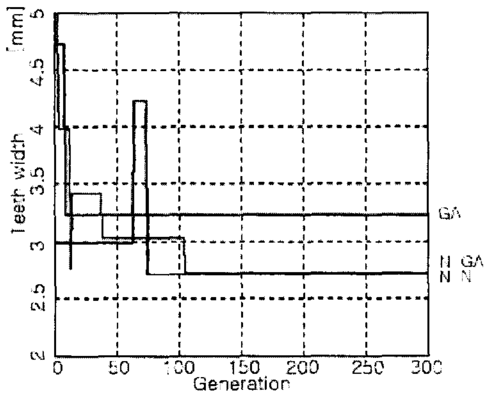


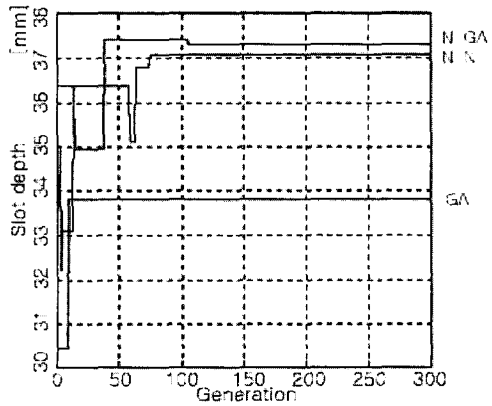
Fig. 6 Object function (Primary weight)



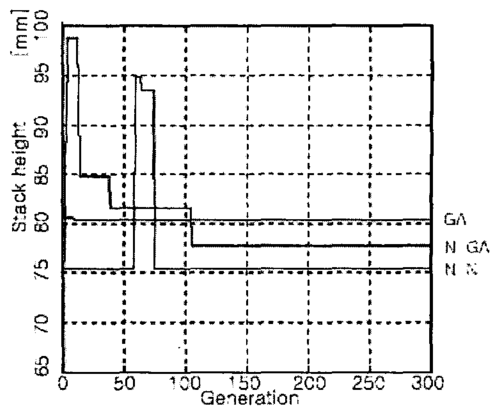
a) Slot width



b) Teeth width



c) Slot depth



d) Stack height

Fig. 7 Optimized design variables–object function W_g

Table 3 Design Parameters Following Optimization

Design Parameters	Object Functions					
	F_x			W_g		
	GA	N-GA	N-N	GA	N-GA	N-N
V_1	220	220	220	220	220	220
f_1	60	60	60	60	60	60
I_1	11.464	12.699	12.01	16.3	12.917	12.54
J_1	7.298	8.08	7.64	10.4	8.22	7.99
L_1	522	525	514	522	517	525
p	4	4	4	4	4	4
N_S	3	3	3	3	3	3
τ	108.6	109.4	107.1	108.7	107.7	109.4
ds	37.34	37.26	36.87	33.8	37.317	37
W_S	8.8	9.02	9.1	8.8	9.24	9.45
t_S	12.07	12.1	11.9	12	11.96	12.2
Z_t	3.27	3.12	2.8	3.23	2.73	2.71
B_{tm}	0.3528	0.4253	0.4487	0.463	0.4975	0.4998
r_1	2.923	2.778	2.83	2.449	2.735	2.814
x_1	5.166	4.807	4.978	3.616	4.712	4.853
σ_1	$1.0\text{x}10^7$	$1.0\text{x}10^7$	$1.0\text{x}10^7$	$1.0\text{x}10^7$	$1.0\text{x}10^7$	$1.0\text{x}10^7$
σ_2	$2.7\text{x}10^6$	$2.7\text{x}10^6$	$2.7\text{x}10^6$	$2.7\text{x}10^6$	$2.7\text{x}10^6$	$2.7\text{x}10^6$
h	97.46	79.04	85.8	80.317	77.8	75.5
g	20	20	20	20	20	20
d_1	6	6	6	6	6	6
d_2	300	300	300	300	300	300
Fx	18.7	18.5	18	18.7	18.7	18.7
Wg	18.8	14.4	14.5	12.9	12.7	13
Fx/Wg	0.99	1.28	1.24	1.45	1.47	1.44

5. Conclusion

This paper presents the optimum design of the LIM used for transferring molten metal in the steel making plant. Three optimization methods have been used: GA, N-GA and N-N. From the initial design, two optimization steps have been applied. The first step is the optimum design when the thrust is object function oriented. The second step is the optimum design when the weight of the LIM is object function oriented, with maximum thrust obtained from the first optimization. Right from the initial step the thrusts of the optimized design rise more than in the original: 156% for the N-N, 163% for the GA and 161% for the N-GA.

From the second step of optimization, the weight of the LIM decreases less than in the first optimization: 71% for the GA, 70% for the N-GA and 72% for the N-N. The thrust and weight converge at almost identical values. The final design has been obtained from the N-GA of the two step optimization method, which produces the higher thrust and carries less weight than in the original: 162% for F_x and 70% for W_g.

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