Niching Genetic Algorithm with Restricted Competition Selection for Multimodal Function Optimization

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Abstract - **Niching method enables the genetic algorithm to be applied to the problems that require the location of multiple solutions in the search space. In this paper, a new niching method using restricted competition selection (RCS) is proposed to identify and search multiple niches (peaks) efficiently in a multimodal domain. To verify its validity, the proposed method is applied to some traditional mathematical problems and an induction motor design.**

Index terms — **Genetic algorithms, niching methods, induction motors**

I. INTRODUCTION

There is often a need to identify several good solutions for the problem such as shape or structural optimization of electromagnetic device [1]. For example, in case of efficiency maximization of induction motor design, several quite different designs may be actually almost equal in terms of efficiency. But some of these designs may be better than other designs in terms of easy manufacture, easy maintenance, reliability, and other factors. Usually, finding a satisfactory way to combine all these factors into a single objective is difficult, so an effective multi-objective optimization algorithm is required.

But there are a few problems to perform multiobjective optimal design for the induction motor. First, because of the different sensitivity of the multiple objectives in the different sub-domains of the feasible domain the solution might not represent the designers preference, in particular when utility functions are used. Second, all of the geometrical constraints and manufacturing considerations such as stator coil winding cannot be taken into account. Finally, the analysis such as transient temperature rise calculation of stator winding cannot be performed in the course of optimization process because it takes too much time.

We, therefore, use only the most important criteria in constructing the objective function and apply niching methods [1,2] that identify multiple optimal profile by locating local optima as well as global. And the possible solution alternatives among multiple optima can then be 'post-processed' using other criteria. That is to say, the designer uses other criteria and his experiences to select the best design among generated solutions.

Two general niching methods, crowding and fitness sharing [2], form the basis for current multimodal optimization. But these methods are unsatisfactory in view of the number and quality of the obtained optima. In this paper, therefore, a new niching genetic algorithm using restricted competition selection (RCS) is presented. To verify its validity, it is applied to some traditional mathematical multimodal problems and an induction motor design.

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II. NICHING GENETIC ALGORITHM

Genetic algorithms (GAs) are stochastic optimization methods based on the mechanics of natural evolution and natural genetics. They have been successfully applied to find a global optimum. In the optimization of multimodal functions, a simple GA cannot maintain controlled competition among the competing schemata corresponding to different peaks and cause the population to converge to one alternative or other [2]. Moreover, in dealing with multimodal function with peaks of unequal value, a simple GA converges to the best peak; whereas, in addition to wanting to know the best solution, one may be interested in knowing the location of other optima. To overcome these limitations a natural remedy is tried.

In natural ecosystems, a niche can be viewed as an organism's task, which permits species to survive in their environment. Species are defined as a collection of similar organisms with similar features. The subdivision of environment on the basis of an organism's role reduces inter-species competition for environmental resources, and this reduction in competition help stable sub-population to form around different niches in the environment. By analogy, in multimodal GAs, a niche is commonly referred to as the location of each optimum in the search space, the fitness representing the resources of that niche. The organisms in a niche can be defined as similar individuals in terms of similarity metrics [1]. Two general niching techniques, crowding and fitness sharing, and a method proposed in this paper will be shown below.

A. Sharing

Sharing [3] derates each population element's fitness by an amount related to the number of similar individuals in the population. Specifically, an element's shared fitness, f', is equal to the prior fitness f divided by its niche count. An individual's niche count is the sum of sharing function (sh)

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values between itself and each individual in the population (including itself). The shared fitness of a population element i is given by the following equation:

$$f'(i) = \frac{f(i)}{\sum_{j=1}^{n} sh(d(i,j))} \quad (1)$$

The sharing function is a function of the distance $d(i,j)$ between two population elements; it turns a '1' if the elements are identical, a '0' if they cross some threshold of dissimilarity σ_{share}, and an intermediate value for intermediate levels of dissimilarity. If the distance between two population elements is greater than or equal to σ_{share}, they do not effect each other's shared fitness. A common sharing function is

$$sh(d) = \begin{cases} 1 - (\frac{d}{\sigma_{share}})^{\alpha}, \text{if } d < \sigma_{share}; \\ 0 \qquad , \text{otherwise} \end{cases} \quad (2)$$

where α is a constant that regulates the shape of the sharing function.

B. Deterministic Crowding

Mahfoud [2] improved standard crowding of De Jong [4], namely deterministic crowding (DC), by introducing competition between children and parents of identical niche. DC works as follows. First it groups all population elements into $n/2$ pairs. Then it crosses all pairs and mutates the offspring. Each offspring competes against one of the parents that produced it. For each pair of offspring, two sets of parent-child tournaments are possible. DC holds the set of tournaments that forces the most similar elements to compete. Similarity can be measured using either genotypic or phenotypic distances. But DC failed to maintain certain sought out optima when those could recombine to form more fit optima in the search process.

C. Restricted Competition Selection

Sharing and DC maintain many individuals in proportion to their fitness. But in the case of the problem such as shape or structural optimization of electromagnetic devices, one individual that the best fitness is needed per one niche because individuals in same niche have similar shape, structure and characteristics. So new niching method, restricted competition selection (RCS), is presented in this paper. The RCS restricts competitions among dissimilar individuals during selection to reach stable sub-population. From competitions among similar individuals that the distance between them in the search space is less than a dissimilarity threshold (niche radius), the loser' fitness is changed to zero and the winner's remains unchanged. Therefore the only best individual per one niche is maintained. And elite set is introduced to preserve the obtained local optima during the generation. The flow of this method is as follows:

Step 0 : *(Initializing)* Generate N individuals at random. Select M individuals in fitness order for Elite set. Setting the number of generation, g = 1.
Step 1 : Select 2 parents randomly no replacement Cross and mutate them. Repeat N/2 times to produce population.
Step 2 : Add Elite set to population to produce Competition set having N+M individuals.
Step 3 : *(Restricted Competition Selection)* FOR i = 1 to N+M-1, j = i+1 to N+M When d_{ij}(distance between x_i and x_j) < L(niche radius), compare fitness. The loser's fitness is set 0.
Step 4 : Select M individ. for new Elite set and N for new population in fitness order from Competition set.
Step 5 : If g < G_n then g= g+1 and go to step 1, else STOP.

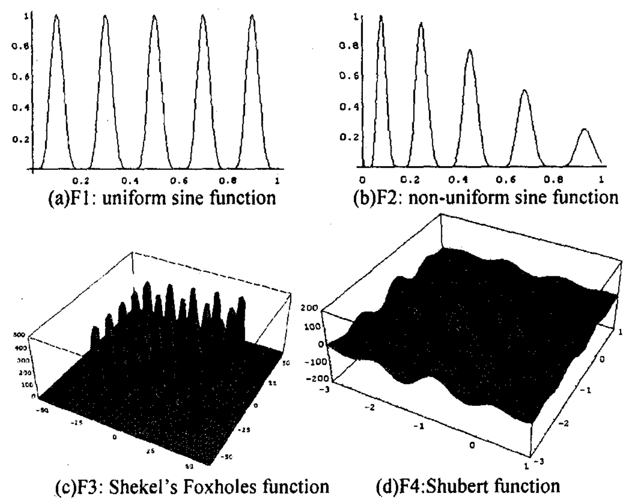
D. Numerical Examples

Four multimodal functions [2] are used to test niching methods, as shown in Fig. 1. The first function, F1, has equally spaced five peaks with same height. F2 function has unequally spaced five peaks with different height. F3 is a two-dimensional function with 25 peaks of different height. In F3, a(i)=16[(i mod 5) –2] and b(i)=16([i/5]-2). F4 is a two-dimensional function with 18 peaks of same height and with 760 sub-peaks. The functions are specified by the following equations:

$$F1(x) = \sin^6(5\pi x), \text{ where } 0 \le x \le 1 \quad (3)$$

$$F2(x) = e^{-2(\ln 2)(\frac{x-0.08}{0.854})^2} \sin^6(5\pi[x^{0.75} - 0.05]) \quad (4)$$

$$F3(x,y) = 500 - \frac{1}{0.002 + \sum_{i=0}^{24} \frac{1}{1 + i + (x - a(i))^6 + (y - b(i))^6}} \quad (5)$$



(a)F1: uniform sine function (b)F2: non-uniform sine function

(c)F3: Shekel's Foxholes function (d)F4:Shubert function

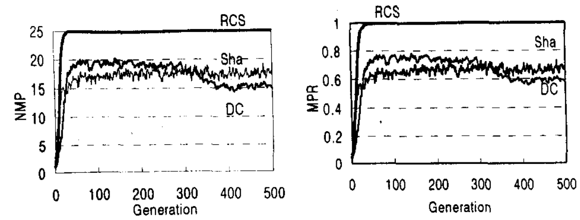
Fig. 1. Multimodal functions

$$F4(x,y)=\left\{\sum_{i=1}^{5} i\cos[(i+1)x+i]\right\}\cdot\left\{\sum_{i=1}^{5} i\cos[(i+1)y+i]\right\} \quad (6)$$
$$\text{, where } -10<x,y<10.$$

To compare niching algorithms, the maximum peak ratio (MPR) and the effective number of maintained peaks (NMP) [1] are selected as the performance criteria. A searched peak is considered to be detected if it is within niche radius of real peak location and its fitness value is at least 80% of the real peak value. We run each method 100 times on each test function and average the results. A population size is two times of the number of peaks. The probability of crossover and mutation are 0.8 and 0.2 respectively. The iteration of generation is 500. The number of bit per variable is 10. In RCS the number of Elite set is the number of peaks. But individuals of Elite set don't need function evaluations. Table I summarize all results and allows comparisons between three algorithms on various test functions. As shown in Table I, RCS works better than two general niching methods for identification of multiple peaks in terms of the number and quality of peaks obtained. Fig. 2 shows the variation of NMP and MPR according to increase of generation. It shows that RCS could be a robust and fast niching method

TABLE I
PERFORMANCE COMPARISON

	NMP	MPR	NMP	MPR
	F1		F2	
Sharing	1.30	0.2507	1.50	0.3677
DC	4.36	0.8683	3.59	0.8123
RCS	5.00	0.9896	5.00	0.9920
	F3		F4	
Sharing	12.56	0.4761	2.72	0.1401
DC	14.73	0.5697	6.09	0.3378
RCS	25.00	0.9974	16.89	0.9356



(a) Number of maintained peaks (b) Maximum peak ratio
Fig. 2. Convergence comparison for F3 function

III. Optimization of Induction Motor Design

Now, the proposed niching method is applied to the optimal design of induction motor for electric vehicle (EV) that is a real world problem. The first step of optimization is a design synthesis [5] of induction motor. The next step is to apply the niching method to find multiple solutions. The final step is that the designer selects the best for EV traction motor among alternative designs using evaluation criteria.

A. Synthesis

The synthesis [5] is a procedure for producing the motor on the basis of a set of design variables, other design data, and the motor specification. Synthesis includes the selection of independent design variables and feasible design flow. The selection of the independent variables is changed according to required motor specifications (or constraints). It is generally very difficult and demands a very deep knowledge of the physical relationships. We select the seven independent variables consisting of four flux densities for the stator and rotor punching, one current density for the rotor and two geometric variables. Two geometric variables are the depth of stator slot, the ratio of rotor teeth width to rotor slot bottom width. The continuous output power P_O and the ratio of breakdown torque to nominal torque k_{mt} are satisfied in a synthesis routine. Synthesis for induction motor design was represented in early paper [6].

B. Distance Criterion

All niching methods must differentiate similar individuals from dissimilar ones. The similarity metric can be based on either genotype or phenotype distance. Phenotypic distance is related to real parameters of the search space. The Euclidean distance that is a kind of phenotypic distance [2] is used in this paper.

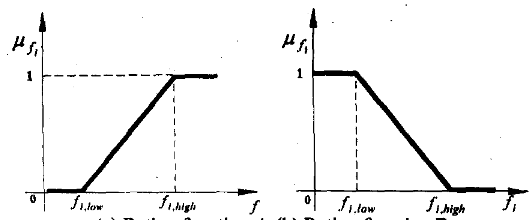
C. Objective Function

The electric vehicles have poor performance and high price relative to internal-combustion engine vehicles, a primary cause being short running distance per one-charge cycle of a battery. The battery is the limiting factor for a powerful electric road vehicle because of its high weight and low capacity [7]. Therefore the designer of traction motor should try to design high efficiency motor in order to improve running distance. From the above result, the efficiency of an induction motor is selected for the most important objective function of optimal design. And the weight of motor is selected as a constraint of optimization.

D. Evaluation Criteria

The designer should select the best for EV traction motor among alternative designs. Therefore, the evaluation criteria are needed to select the best design. The evaluation criteria for EV traction motor are as follows.

1. Efficiency at continuous rated output.
2. Efficiency at peak output.
3. Power factor at peak output.
4. Stator winding temperature rise at cont. rated output.



(a) Rating function A (b) Rating function B
Fig .3 Rating Functions on evaluation criteria

5. Stator winding temperature rise at duty cycle operation.
6. Material cost of active part.

The satisfactory degree of alternative design to evaluation criterion is represented using the linear rating functions. Two rating functions used in this paper are shown in Fig. 3. If the satisfactory degree increases with the increase of the evaluation criteria value (for example, the efficiency of the motor), the rating function A is selected. If the satisfactory degree decreases with the increase of the evaluation criteria value (for example, the weight of the motor), the rating function B is selected. Therefore a selection for best design depends on the determination of $f_{i,low}$ and $f_{i,high}$. For example, $f_{i,low}$ in rating function A and $f_{i,high}$ in rating function B can be assigned according to the specification of the motor, standard and the designer's experience. $f_{i,high}$ in rating function A and $f_{i,low}$ in rating function B is selected according to the highest value among evaluation criterion value of alternative designs.

E. Induction Motor Design

As an example design, a 3-phase squirrel-cage induction motor for 4 passenger EV is designed. The motor specifications and constraints are as follows:

i) Motor Specifications
P_O = 15[kW], peak output = 60[kW], base frequency =120 [Hz], V_1 = 170[V], phase number = 3, pole number = 4.

ii) Design constraints
Eff. @15kw > 93%, Eff. @60kw > 86 %, k_{mt} > 4.4,
Pf @60kw > 80%, Weight of active part < 36kg
Temperature rise < 125 [°C] (H class insulation)

Table II shows five different designs that result from selected through optimization using the proposed method. The best results on each evaluation criterion are shown in boldface. The range of efficiency of motor is 93.429 ~ 93.410 [%]. If the only efficiency at continuous output is used as evaluation criterion, the first design is selected. But, if evaluation criteria and rating functions presented in Table III are used, third design yields the best average rating function value. Therefore the third design result is selected as the best compromise solution.

TABLE II.
THE RESULTS OF OPTIMAL DESIGN

Evaluation Criteria	Candidates for best compromise solution				
	#1	#2	#3	#4	#5
1. Eff @15kw [%]	***93.429***	93.425	93.421	93.415	93.410
2. Eff @60kw [%]	87.02	87.37	87.64	87.20	***87.71***
3. Pf @60kw [%]	83.85	***84.25***	83.88	83.80	84.20
4. ΔT @15kw [°C]	64.9	65.3	***63.6***	66.2	65.7
5. ΔT @duty operating	107.0	105.1	***101.1***	107.9	103.6
6. Material cost [$]	77.07	77.97	***76.74***	78.84	77.57
Rating Func. Value (Avg.)	0.871	0.927	***0.976***	0.862	0.963

TABLE III
THE PARAMETERS OF RATING FUNCTIONS

Evaluation Criteria	f_{high}	f_{low}	Rating Function
1.Eff @15kw [%]	93.429	93.000	A
2.Eff @60kw [%]	87.71	86.00	A
3.Pf @60kw [%]	84.25	80.00	A
4. ΔT @15kw [°C]	125.0	63.6	B
5. ΔT @duty operating [°C]	125.0	101.1	B
6.Material Cost [$]	80.00	76.74	B

IV. CONCLUSION

In this paper, a new niching method using restricted competition selection (RCS) is proposed to identify and search multiple niches (peaks) efficiently in a multimodal domain. It is found that RCS performs better than two general methods for multiple optima identification in views of the number and quality of optima obtained by applying to several numerical functions. And the application of new niching GA to optimization of induction motor design for EV is presented. The proposed method can overcome some difficulties of multi-objective optimization. Moreover it could reflect the designer's experience, view and judgment effectively.

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