2003 International Symposium on Advanced Intelligent Systems
September 25-28, 2003, Jeju, Korea

Reliability Optimization Problems using Adaptive Hybrid Genetic Algorithms

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Abstract - This paper proposes an adaptive hybrid genetic algorithm (aHGA) for effectively solving the complex reliability optimization problems. The proposed aHGA uses a local search technique and an adaptive scheme for respectively constructing hybrid algorithm and adaptive ability. For more various comparisons with the proposed adaptive algorithm, other aHGAs with conventional adaptive schemes are considered. These aHGAs are tested and analyzed using two complex reliability optimization problems. Numerical result shows that the proposed aHGA outperforms the other competing aHGAs.

1. INTRODUCTION

The redundancy allocation problem consisting of n stages maybe is the most common type in reliability optimization problem. In this redundancy allocation problem, there are a specified number of subsystems and, for each subsystem, there are multiple component choices assuming unlimited supply of each, and used in parallel. For those systems designed with known cost, reliability, and weight, the system design and component selection become a combinatorial optimization problem which can be formulated as a nonlinear integer programming (nIP) problem. Even though a lot of conventional heuristic algorithms have been performed to solve the problem, most of these methods have not to been proved as an effective solution.

Recently GAs have been proved to be a more effective approach for the reliability optimization problems. However, conventional GA approaches have some weaknesses in its application. That is, pure GA-based approaches may converge to a local optimal solution prematurely before locating the global optimal solution because of their fundamental requirement. These approaches have also a weakness in taking too much time to adjust fine-tuning structure of the GA parameters (*i.e.*, crossover rate, mutation rate, and others). Therefore, these two kinds of "blindness" may prevent them from being really of practical interest to many complex optimization problems such as reliability optimization problems mentioned above. To improve these weaknesses of GA-based approach, various hybrid methodologies using conventional heuristics and adaptive schemes have been developed (Gen and Cheng, 2000; Li and Jiang, 2000; Yun, Gen, and Seo, 2003). By applying the conventional heuristics and the adaptive schemes to GA, recently hybridized GAs are more effective and more robustness than pure GA-based approach or other conventional heuristics.

Based on these contributions to GA, this paper proposes a new hybrid GA (aHGA) with a local search technique and an adaptive scheme. For various comparisons with the proposed aHGA, the other aHGAs with conventional heuristic adaptive schemes are also suggested, and these aHGAs are tested and analyzed in numerical examples using reliability optimization problems with nIP types.

2. RELIABILITY OPTIMIZATION PROBLEMS

Reliability optimization problems are usually decomposed into functional entities composed of units, subsystems, or components. We can thus formulate these problems into a general mathematical form of non-linear separable integer programming problem as follows:

$$\max \quad f(x) = \prod_{j=1}^{n} R_j(x_j)$$

$$\text{s.t.} \quad \sum_{j=1}^{n} g_{ij}(x_j) \le b_i, \qquad i = 1,2,\ldots,m$$

$$x_j^L \le x_j \le x_j^U \quad : \text{integer}, \qquad j = 1,2,\ldots,n$$

where $R_j(x_j)$ is the j-th non-linear objective function represented a system reliability, $g_{ij}(x_j)$ is the j-th nonlinear function on the i-th constraint represented a system resource restraint, *bi* is the i-th right-hand side constant or available resource, x_j^L and x_j^U are the lower and upper bounds for the integer decisions variable x_j, respectively. The objective is to determine the number of redundant components at each subsystem with the known component reliability.

3. ADAPTIVE HYBRID CONCEPT AND LOGICS

In this section, we suggest basic concepts and searching procedures for constructing aHGAs. First, we apply GA procedure. Secondly, the local search technique for finding a better solution within GA loop is proposed. In last step, the concept and logics of adaptive schemes are proposed to regulate the rates of crossover and mutation operations in GA.

A. Genetic Algorithm

We use a real-number representation instead of a bit-string one, and the detailed heuristic procedure for applying it is as follows:

Step 1: Initial population
 Population obtained by random number generation.
Step 2: Genetic operators
 Evaluation: fitness values of all individuals
 Selection: elitist strategy in enlarged sampling space
 Crossover: uniform arithmetic crossover operator
 Mutation: uniform mutation operator
Step 3: Stop condition
 If a pre-defined maximum generation number is reached during genetic search process, then stop; otherwise, go to Step 2.

B. Local Search Technique

The suggested local search technique is incorporated into the GA loop. With this hybrid approach, the local search technique is applied to each newly generated offspring to move it to a local optimum before injecting it into the new population of GA. For the suggested hybrid methods, we employ the iterative hill climbing technique suggested by Michalewicz (1994).

C. Various Adaptive Scheme

In this section, we suggest two adaptive schemes with conventional heuristics and propose one adaptive scheme with a fuzzy logic controller (FLC). These three adaptive schemes adaptively regulate the rates of crossover and mutation operators.

The first adaptive scheme inserts the heuristic scheme used in the study of Mak, Wong, and Wang (2000) into GA procedure. They employed the fitness values of parent and offspring at each generation in order to construct adaptive crossover and mutation operators. For the second adaptive schemes, we combine GA procedure with the adaptive scheme drawn from the study of Srinivas and Patnaik (1994). This adaptive scheme considers both the exploitation and exploration properties in the convergence process of GAs. The balance between these two properties of the GA is adaptively regulated by the rates of crossover and mutation operations at each generation. The proposed adaptive scheme combines the FLC used in a basic concept of Song *et al.* (1997). The heuristic updating strategy for the rates is to consider the change of the average fitness of each GA population in two continuous generations. For example, in maximization problem, we can set the change of the average fitness at generation t, $\Delta f_{avg}(t)$ as follows:

$$\Delta f_{avg}(t) = (\overline{f_{par\_size}}(t) - \overline{f_{off\_size}}(t))$$
$$= \left(\frac{\sum_{k=1}^{par\_size} f_k(t)}{par\_size} - \frac{\sum_{k=par\_size+1}^{par\_size+off\_size} f_k(t)}{off\_size}\right)$$

where *par_size* and *off_size* are the parent and offspring sizes satisfying the constraints, $\overline{f_{par\_size}}(t)$ and $\overline{f_{off\_size}}(t)$ are the average fitness values of parents and offspring at generation t.

The $\Delta f_{avg}(t-1)$ and $\Delta f_{avg}(t)$ are used to regulate crossover rate (p_C) and mutation rate (p_M) as follows:

Procedure: regulation of p_C and p_M using average fitness

begin
  if $\varepsilon \le \Delta f_{avg}(t-1) \le \gamma$ and $\varepsilon \le \Delta f_{avg}(t) \le \gamma$ then
    increase p_C and p_M for next generation ;
  if $-\gamma \le \Delta f_{avg}(t-1) \le -\varepsilon$ and $-\gamma \le \Delta f_{avg}(t) \le -\varepsilon$ then
    decrease p_C and p_M for next generation ;
  if $-\varepsilon < \Delta f_{avg}(t-1) < \varepsilon$ and $-\varepsilon < \Delta f_{avg}(t) < \varepsilon$ then
    rapidly increase p_C and p_M for next generation ;
  end
end

where ε is a given real number in the proximity of zero, γ and $-\gamma$ are respectively a given maximum and minimum values of a fuzzy membership function.

4. ADAPTIVE HYBRID GENETIC ALGORITMS WITH VARIOUS ADAPTIVE SCHEMES

In this section, the detailed implementation procedures of adaptive hybrid genetic algorithms with various adaptive schemes are proposed.

A. Adaptive Hybrid Genetic Algorithms

The first aHGA (aHGA1) combines the GA procedure with the heuristic scheme (heuristic 1) used in the study of Mak, Wong, and Wang (2000). Its combined heuristic procedure is as follows:

Steps 1 and 2: Apply the same steps with Section 3-A.
Step 3: Apply the iterative hill climbing technique
Step 4: Apply the heuristic 1 for adaptively regulating GA parameters.
Step 5: Stop condition
  If a pre-defined maximum generation number is reached during genetic search process, then stop; otherwise, go to Step 2.

For the second and last aHGAs (aHGA2 and flc-HGA), we consider i) the procedure of the heuristic scheme (heuristic 2) drawn from the study of Srinivas and Patnaik (1994), and ii) the FLC scheme from Song *et al.* (1997), respectively. These two procedures are respectively used for Step 4 of the procedure defined in this Section.

5. NUMERICAL EXAMPLES

In this Section, two complex reliability optimization problems with the redundancy allocation types of components are suggested. For GA implementation under a same condition, we set the GA parameters (maximum generation number: 5,000, population size: 20, crossover rate: 0.5, mutation rate: 0.1, creeping value for the iterative hill climbing technique: 0.6). Altogether 20 iterations with different initial random seeds for GA population are executed.

The presented examples are an optimal redundancy allocation problem (T-1) taken from Rabi, Murty, and Reddy (1997) and more complicated problem (T-2) from Prasad and Kuo (2000). The optimal solutions of the T-1 and T-2 were known as 0.94561 and 0.99660, respectively. These two examples are implemented in Visual Basic language under IBM-PC Pentium 4 computer with 2.4 Ghz CPU speed and 248 MB RAM. The computational results using these two problems are appeared in Table 1.

Table 1. Computational results for T-1 and T-2

		GA	aHGA1	aHGA2	flc-HGA
T-1	Best	0.94520	0.94561	0.94561	0.94561
	Avg.	0.94355	0.94544	0.94537	0.94561
	CPU	1.28	2.81	3.79	2.53
	NGS	17	2	4	0
T-2	Best	0.99450	0.99510	0.99450	0.99660
	Avg.	0.94873	0.99343	2.08435	0.99660
	CPU	1.265	1.262	0.997	2.153
	NGS	20	20	20	0

* GA: canonical genetic algorithm

In Table 1, "Best," "Avg.," "CPU," and "NGS" respectively mean the best fitness value, average fitness value, average CPU time (unit: Sec.), and number of getting stuck as a local optimum, after 20 iterations were executed in each algorithms.

For the result of the T-1, all the algorithms with adaptive schemes (aHGA1, aHGA2, and flc-HGA) show better performance than the GA in terms of the Best, Avg., and NGS. Especially, in the detailed comparison among the adaptive algorithms, the proposed flc-HGA outperforms the other adaptive algorithms significantly. Also in the comparison of the CPU times, the flc-HGA is superiors to the aHGA1 and aHGA2, though it is slightly slower than GA.

In the result of the T-2, the flc-HGA locates the optimal value alone in all trials. However, aHGA1 and aHGA2 do not locate the optimal value in all trials, though these two algorithms have additional adaptive schemes rather than the GA, which means that the adaptive schemes of the aHGA1 and aHG2 are less effective than that of the flc-HGA.

For the comparison of adaptive schemes used in the aHGA1, aHGA2 and flc-HGA, Figure 1 shows the various behaviors of average fitness of all the adaptive algorithms until the generation number of each algorithm is reached to 500.

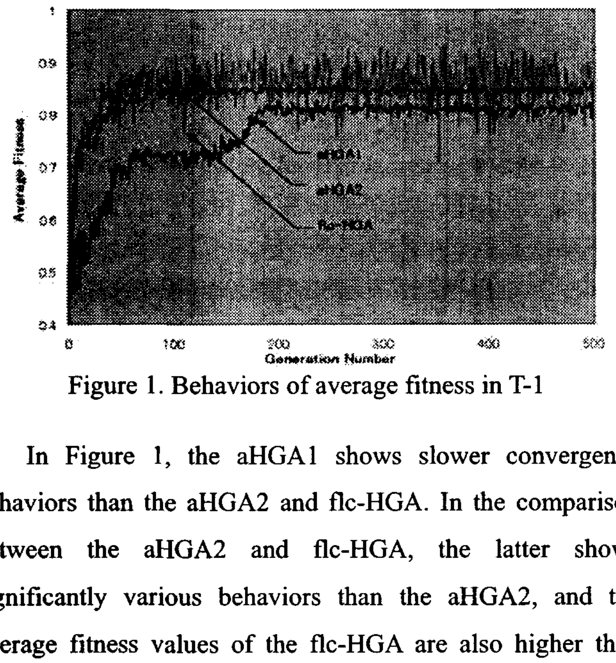

Figure 1. Behaviors of average fitness in T-1

In Figure 1, the aHGA1 shows slower convergence behaviors than the aHGA2 and flc-HGA. In the comparison between the aHGA2 and flc-HGA, the latter shows significantly various behaviors than the aHGA2, and the average fitness values of the flc-HGA are also higher than those of the aHGA2.

Based on the results of Table 1 and Figure 1, it can be proved that the adaptive scheme using the FLC is more a reasonable choice than the other competing heuristics, when we want to improve the GA performance for complex reliability optimization problems.

6. CONCLUSION

In this paper, we have suggested several adaptive hybrid genetic algorithms (aHGAs) for effectively solving complex reliability optimization problems. For the aHGAs, a local search technique and several adaptive schemes have been used. The aHGAs have been tested and analyzed using two complex optimization problems.

Finally, it has been proved that using the FLC for adaptive ability of GA is more efficient than using the other competing algorithms.

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