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PERFORMANCE EVALUATION OF GENETIC ALGORITHMS ON LOADING PATTERN OPTIMIZATION OF PWRs

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ABSTRACT

Genetic Algorithm (GA) based systems are used for search and optimization problems. There are several applications of GAs in literature successfully applied for loading pattern optimization problems. In this study, we have selected loading pattern optimization problem of Pressurised Water Reactor (PWR). The main objective of this work is to evaluate the performance of Genetic Algorithm operators such as regional crossover, crossover and mutation, and selection and construction of initial population and its size for PWR loading pattern optimization problems. The performance of GA with antithetic variates is compared to traditional GA. Antithetic variates are used to generate the initial population and its use with GA operators are also discussed. Finally, the results of multi-cycle optimization problems are discussed for objective function taking into account cycle burn-up and discharge burn-up.

1 INTRODUCTION

The main goal of in-core-fuel management activities is to meet design objectives. Safety is major concern during the operation of a nuclear power plant, and requires the knowledge of power distribution and depletion characteristics of the fuel assemblies from the beginning-of-cycle (BOC) through the end-of-cycle (EOC).

Other unknowns, such as amount and enrichment of the fresh fuel assemblies, fraction of the depleted assemblies to be removed, burnable poison (BP) requirements and core loading pattern (LP) map, must be determined. Such calculations are required to optimize core-loading pattern under some constraints to satisfy safety requirements and utility's demand. In the last 3 decades, considerable work has been completed employing several optimization techniques in determining the core-loading pattern that minimizes the fuel cost. With the emergence of artificial intelligence tools and further advances in computer performance and architecture, adaptive optimization techniques were developed. However, these adaptive methods such as simulated annealing and genetic algorithms need to evaluate large numbers of trial loading patterns. One of the drawbacks of these techniques is the computational cost that mainly depends on the technique used to obtain core power distribution and the total number of trial loading pattern evaluation.

Genetic algorithm, first introduced by Holland [1] in 1970's is one of the stochastic optimization techniques that have become popular in the last decades. By using genetic algorithm, Parks developed in-core fuel management strategy that can be used to optimize more than one parameter [2]. A loading pattern with minimum feed enrichment, maximum burn-up and power peaking factor under given constraint was sought. DeChaine and Feltus [3], [4] used expert knowledge concept to create an initial population of fairly good solutions for GA optimization system. Using expert knowledge for creation of initial population, they found the best population more rapidly. More recently, genetic algorithms were used to solve PWR's and BWR's fuel management optimization problems.

In this study, we shall be concerned with optimization for in-core fuel management of PWR's via genetic algorithm, and we present performance analyses of genetic algorithm. We present the use of GA with different objective functions. And, we discuss the effects of objective functions on the optimization of PWR's loading pattern. We also address the question of population sizing and diversity problem in genetic algorithms. The use of basic genetic algorithm operators and antithetic variates to obtain new set of solutions and their contributions to the performance of the algorithm are discussed.

The outline of this manuscript is as follows. In section 2, we introduce genetic algorithm and its basic operators used in the modelling of optimization problem and introduce the utilisation of non-binary genetic algorithm for the PWR optimization problem. In section 3, we examine the performance of genetic algorithms on the optimization of loading pattern problem of Almaraz PWR's first cycle. Section 4 is devoted for the empirical results obtained and used for the performance analyses of genetic algorithms. Last sections summarise the results and describe avenues for future work.

2 GENETIC ALGORITHMS

Genetic algorithms belong the class of stochastic methods inspired by evolution and use both the Monte Carlo and the gradient-descent method [5]. In GA, basic genetic operators are applied to set of selected solutions. The selection process depends on the fitness values of the solutions and low fitness solutions are eliminated according to the rule introduced in the selection operator.

One of the basic GA operators is called crossover operator. Crossover operator creates new set of solutions by swapping the part of the selected solutions using crossover operator. Another one is called the mutation operator and used to generate new solutions called mutant by perturbing part of the solution depending on an algorithm used in mutation. Using genetic operators the next set of solutions are expected to have better average fitness values when compared with the previous set of solutions.

The main difference of the GA compared to other optimization techniques is the use of set of initial solutions with specified population size rather than using one solution. And evolution process goes from one set of solutions to another set of solutions by refining them. Thus, it guaranties to find better solutions than the previous generations as a result of the fitness evaluation based selection rules used in selection process. Moreover, GA does not require derivative information and is insensitive to the problem and works well with discrete functions. This property of GA is especially becomes important in the Loading Pattern optimization problems.

But, the GA results indicate that it is not always possible to guarantee to get the complete solutions of the optimization problem. Despite this fact, GA can be utilized by taking advantage of some heuristic rule or by introducing heuristics in the stage of selection. Moreover, The GA is also a robust algorithm.

2.1 Non-binary Genetic Algorithm for Loading Pattern Optimization

In this study, we use non-binary GA for initial loading pattern optimization of the Almaraz PWR nuclear power plant. The initial loading pattern of Almaraz reactor is composed of seven assembly types. The number of assemblies and types used in the first cycle were as follows:

- Type 1 is 2.1 % enriched (53),
- Type 2 is 3.1 % enriched (36),
- Type 3 is 2.6 % enriched with 12 BP rod (4),
- Type 4 is 2.6 % enriched with 16 BP rod (40),
- Type 5 is 2.6 % enriched with 20 BP rod (8),
- Type 6 is 3.1 % enriched with 12 BP (8),
- Type 7 is 3.1 % enriched with 16 BP (8). And, the total number of assemblies was 157.

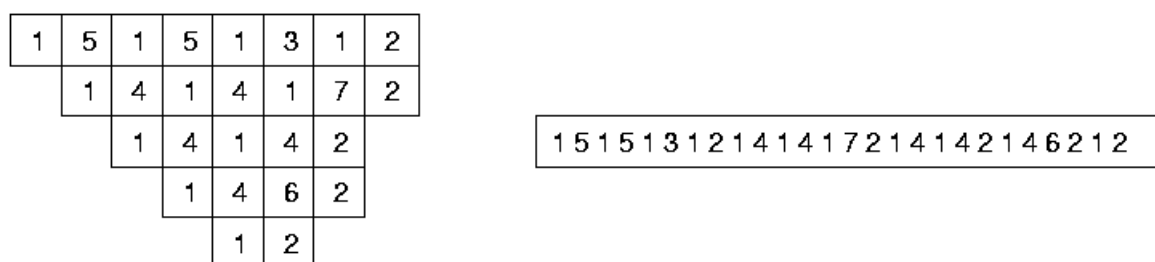


Figure 1: 2-D and 1-D LP representation of ALMARAZ reactor used in GA.

In GA, each individual is represented by a chromosome which is a 1/8 symmetric core loading pattern, and a gene denotes the type of assembly in the 1/8 symmetric core loading pattern and its fitness is the value of objective function.

In this study, one and two-dimensional arrays are used to represent the LP of Almaraz reactor as shown in Fig.1. During the evolution of loading pattern, fitness calculation is performed with 2-Dimensional Burnup Dependent Diffusion Code developed at HUNEM, which is based on the computer code RPM developed by Sauer and Driscoll [6]. The code was utilized to calculate the power peaking factors at BOC and EOC, boron concentration at BOC and cycle length. The simulation takes less than 0.1 sec. The validation of the code was performed using the measured data of the Almaraz nuclear power plant [7]. The main components and flow scheme of the genetic algorithm are given in Fig. 2 .

1. Generate a set of LP for the initial generation
2. Satisfy the total number of assemblies of each type using ranking
3. Evaluate the fitness of each individual in current generation
4. Select the individuals according to fitness values
5. Apply genetic operators to each selected individual
 - 5.a With probability P_C Crossover
 - 5.a.1 one point
 - 5.a.2 two point
 - 5.a.3 regional
 - 5.a.3.1 regional with self avoiding random walk (RWSAV)
 - 5.a.3.2 regional with non self avoiding random walk(RWNSAV)
 - 5.b With Probability P_M Mutation
6. Satisfy the total number of assembly of each type using ranking
7. Check for same LP
8. Evaluate the fitness values of new individuals
9. Select the set of individuals according to their fitness values for new generation
- 10 End of search, else go to step 4.

Figure 2: Flow Scheme of GA

One of the contributions of this study is using antithetic variates in the generation of initial population, crossover and mutation operators. The sequence of antithetically correlated random variables, ζ and $1-\zeta$, are used to generate initial loading patterns. In crossover, two-selected individual, one having the best fitness among the others and the other one chosen randomly are used to generate four new individuals instead of two, using the sequence of antithetically correlated random variables. In one-point crossover randomly selected parts of the 1-D chromosomes are combined to generate new patterns. In two-point crossover, randomly selected regions of the 1-D chromosomes are combined to generate new patterns. In regional crossover, 2-D chromosomes are used. Randomly selected regions of the 2-D chromosomes are combined to generate new patterns. In the case of regional crossover RWSAV, the regions are selected by using self-avoiding random walk and the number of steps used in RWSAV is selected randomly. The regional crossover with non-self avoiding random walk RWNSAV is similar to self avoiding one but visiting of the same location more than once is allowed. After all these crossover operations, ranking is used to satisfy the number of the assemblies of each type.

The mutation operator makes random changes in the type of the assembly located at random point chosen from 1-D chromosome. Mutation operator is also used with antithetic variates and after mutation two new patterns are generated instead of one. After mutation, the ranking is also applied. During the evolution of individuals, the number of new patterns generated in each step is fixed to the population size used in GA run.

In loading pattern optimization problems, the previous works indicate that there exists very diverse set of objective functions used in optimization problems. Mainly, they include two factors. One of them is the minimization of power peaking factors and the other one is the maximization of cycle length. In our study, we use six objective functions.

These objective functions are defined as follows:

$$F_1 = B_C - \frac{1}{2} [\text{Sgn}(ppf - ppf_{set}) + 1] (ppf - ppf_{set}) \quad (1)$$

$$F_{11} = B_D - \frac{1}{2} [\text{Sgn}(ppf - ppf_{set}) + 1] (ppf - ppf_{set}) \quad (2)$$

$$F_2 = B_C - \frac{1}{2} [\text{Sgn}(ppf - ppf_{set}) + 1] (ppf - ppf_{set}) - \frac{1}{2} [\text{Sgn}(bor - bor_{set}) + 1] (bor - bor_{set}) \quad (3)$$

$$F_{22} = B_D - \frac{1}{2} [\text{Sgn}(ppf - ppf_{set}) + 1] (ppf - ppf_{set}) - \frac{1}{2} [\text{Sgn}(bor - bor_{set}) + 1] (bor - bor_{set}) \quad (4)$$

$$F_3 = (B_C - B_{Cset})w_1 + (ppf_{set} - ppf)w_2 + (bor_{set} - bor)w_3 \quad (5)$$

$$F_{33} = (B_D - B_{Dset})w_1 + (ppf_{set} - ppf)w_2 + (bor_{set} - bor)w_3 \quad (6)$$

Where;

B_C is cycle burnup (MW/D/kgHM),

B_D is discharge burnup of assembly type 1,

ppf is the maximum power peaking factor during the cycle,

bor is the boron concentration at the beginning of cycle at hot zero power with Xe equilibrium (ppm),

B_{Cset} is cycle burnup penalty factor,

ppf_{set} is the power peaking penalty factor,

bor_{set} is the boron concentration penalty factor,

w_1 is cycle burnup weighting factor,

w_2 is the power peaking weighting factor,

w_3 is the boron concentration weighting factor,

w_1 , w_2 and w_3 are used to fix the boundaries of the search space of the problem.

3 GA RESULTS FOR LP OPTIMIZATION OF ALMARAZ REACTOR

The results of GA with the objective functions given in Section 2.1., are presented in Table I. The results are obtained using 300 generation with population size 8. The table shows that, the objective function used in the fitness evaluation effects the search space, at the same time, there exist strong dependence on the form of the objective function used in GA.

Table 1. GA results with different objective functions

Objective Function	Function Parameters		ppf _{BOC}	Ppf _{EOC}	B _C	B _D	Boron
F1	ppf _{set} =1.40	-----	1.391	1.373	17.790	20.441	1134.01
F11			1.387	1.379	17.811	22.721	1116.89
F2		Bor _{set} =950	1.197	1.379	16.479	18.826	937.10
F22			1.380	1.371	16.136	20.708	947.43
F1	ppf _{set} =1.30	-----	1.263	1.300	17.105	18.289	1068.44
F11			1.287	1.275	16.648	20.819	1033.29
F2		Bor _{set} =950	1.192	1.296	16.080	17.435	939.99
F22			1.294	1.263	15.835	19.249	941.77
F1	ppf _{set} =1.22	-----	1.206	1.220	16.674	18.393	1054.03
F11			1.218	1.219	16.117	18.446	1070.27
F2		Bor _{set} =950	1.238	1.240	15.688	18.117	944.31
F22			1.256	1.252	15.650	18.434	939.89
F3	w ₁ =10 w ₂ =270 w ₃ =2		1.247	1.271	15.766	17.707	932.22
F33	w ₁ =10 w ₂ =270 w ₃ =2		1.174	1.204	15.675	18.181	930.54
ALMARAZ original loading pattern			1.215	1.191	15.162	17.453	937.01

In the case of using F1 as an objective function, the results become sensitive to the power peaking factors (ppf). EOC ppf values determine the cycle length. To maximize the cycle length, leakage reactivities need to be minimized. The decrease of ppf constraint is results in an increase in EOC leakage reactivity.

Using F2 as an objective function determines the boron concentration and power peaking factors. Boron concentration constraint forces to minimize the ppf values at the BOC to increase the leakage reactivity to minimize boron concentration.

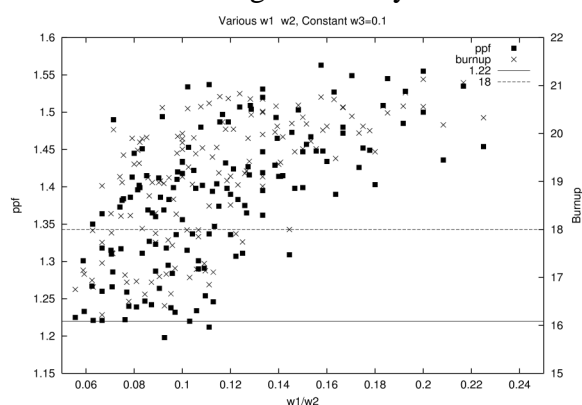


Figure 3: Work-space search

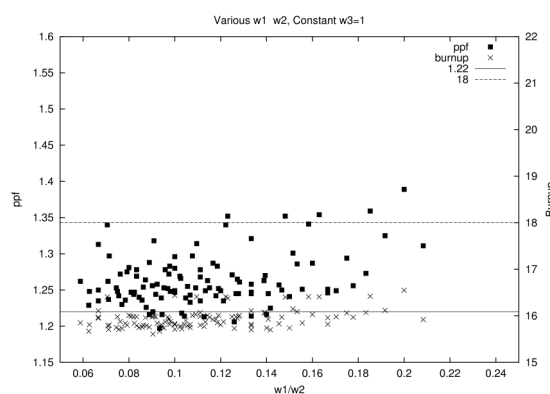


Figure 4: Work-space search

Fig.3 and 4 show the sensitivity analyses of weight factors used in objective function F3. In this case, the search space is increased and the results depend on the penalty factors and weights. The weights used in F3 determine the optimum loading pattern and the solution depends on weights used in F3. As can be seen from Fig.3 for w1 to w2 ratio is about 0.1 and w3 is equal to 0.1, cycle burnup values reaches above 18 MWday/kg and the boron concentration is about 1100 ppm. When we increase the penalty factor (w3), the cycle burnup decreases and the boron concentration is less than 950 ppm. The increase of the w3 used in fitness evaluations mainly effects the loading pattern to maximize the BOC leakage reactivity to reduce boron concentration. As a result of that the EOC leakage reactivity increases and the cycle burnup decreases.

Using the objective functions F11, F22 and F33, discharge burnup of assembly type 1 is increased, while the cycle burnup values remain in the range of cycle burnup obtained by using objective functions F1, F2 and F3.

4 MODELLING OF GA PERFORMANCE

To perform performance analyses, we simplify the results by developing an empirical model of the observed performance curves similar to the method given in the thesis of Kubalı [5], in which GA implemented for the TSP (Travelling Salesman Problem). Since, the GAs are stochastic algorithms, the observations fluctuate around the mean and we can approximate $f(pat_t)$ as;

$$f(pat_t) = f(\infty) + (f(0) - f(\infty)) * \exp(-\alpha\sqrt{pat_t})$$

where f_∞ is the best fitness values available in the library, $f(pat_t)$ and $f(0)$ are the expected values of the fitness functions as a function of fitness evaluations and population size for a given GA run. The best fitness values of the initial generation depend on population size.

Further, $f(pat_t)$ denotes the expected best fitness value in the t^{th} generation of a given GA run with pat_t fitness evaluation. Since, the completion time mainly correlated with the total number of fitness evaluation, pat_t , the total number of fitness evaluations performed until the t^{th} generation, is used in the empirical model.

The governing equation for the rate of convergence is given by

$$\frac{d}{dpat_t} \log[f(pat_t) - f(\infty)] = \frac{\alpha}{2\sqrt{pat_t}} \quad (8)$$

To perform performance analyses, we used Eq.7, and α value is determined using linear regression method. Optimum population sizing problem and the contribution of using antithetic variates in the generation of the initial population and in evolution process is analysed using the alpha values obtained from the performance data of GA run.

4.1 Effects of Initial Population and Size on the Performance of GA

Initial population size and the random numbers used to generate the initial population strongly effects the convergence rate and $f(0)$. $f(0)$ is the supremum of the fitness values over all individuals of initial population. Fig 5 shows the performance of the GA for initial population sizes 4, 8, 16, 32 and 64 as a function of generation number. The diversity of initial population increases when we use antithetic variates. And, the resulting alpha values with and without using antithetic variates are summarised in Fig. 6.

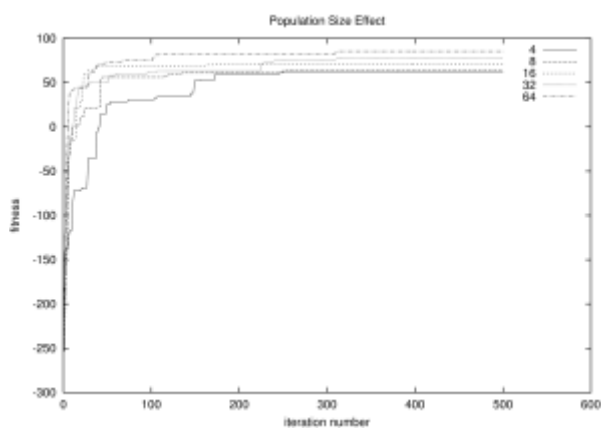


Figure 5: Fitness as a function of iteration #

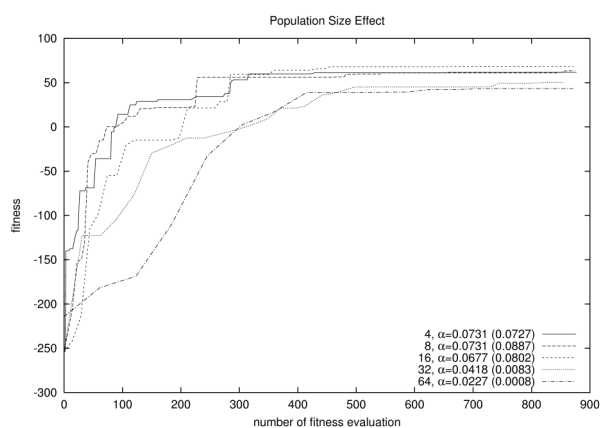


Figure 6: Fitness as a function of evaluation

As shown in Fig.5, increasing of population size enables faster convergence as a function of iteration number. However, total fitness evaluation and amount of computation per generation also increases with population size. Therefore, as summarised in Fig. 6, the α values of population size 4 and 8 are greater than the alpha values of population size 16, 32 and 64. The previous results of GA for TSP [5] indicate that the optimum size that maximizes the convergence rate and minimizes the expected run time is between 7 and 8 with square logarithmic convergence. Using the probabilistic models of GA, Goldberg showed that the convergence is logarithmic and the optimum population size is about 3. The results of LP optimization problem using GA support the results of Kubali [6], Goldberg [8] and they are in agreement.

4.2 Effects of Crossover Operators and Antithetic variates on the Performance of GA

For fixed population size, Fig.7 and Fig.8 show the performance of GA using one-point, two-point, and regional with RWSAV and RWNSAV. The use of antithetic variates in crossover and mutation operators increases the search space and the convergence rates. The results show that, the use of antithetic variate increase the convergence rates compared to standard GA runs. Two-point and regional crossover operators give better results compared to one point crossover operator.

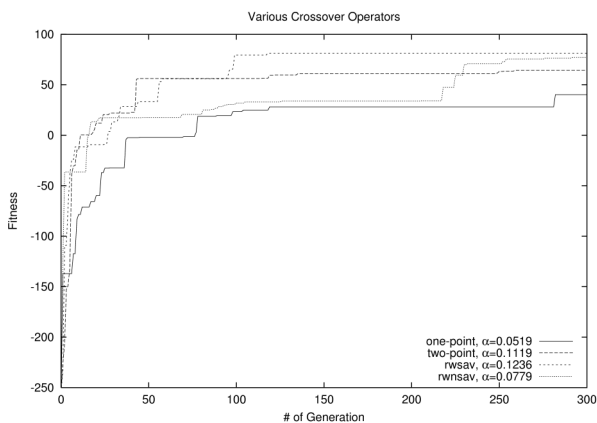


Figure 7: Fitness as a function of generation #

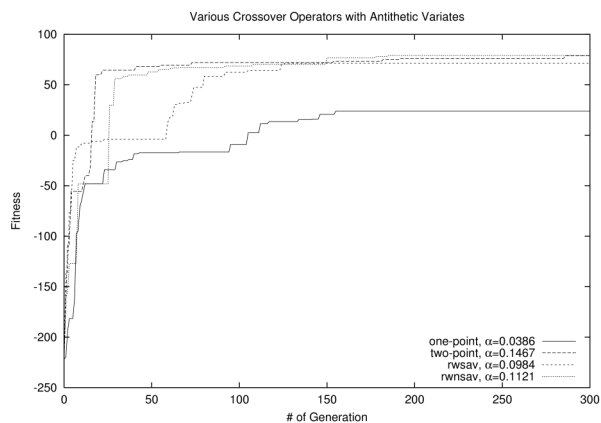


Figure 8: Fitness as a function of generation #

5 CONCLUSION

The GAs are quite successful for LP optimization problems, since the objective is to search for results better than the acceptable ones. Moreover, as pointed out in the study of Kubali, it is also possible to find the best solution by using number of independent runs.

In this study, we showed that the objective function used in fitness evaluation effects the search space. Using discharge burnup as one of the parameter in fitness evaluations gives better results compared to using cycle burnup. As shown in Table I, the increase of ppf constraint increases the effects of using discharge or cycle burnup on LP optimization problem. Another important factor is related to boron constraint. The reduced boron concentrations favour high leakage core and reduce BOC ppf values.

We also showed that, one could use GA with population size of order 8 and perform successive cycles to obtain target solution compared to runtime of GA with larger population size. Of course our analyses based on serial computing, and in the case of parallel computing, population size is correlated to the number of available nodes used in parallel algorithm, and it can be as large as possible depending on the available node number.

We also demonstrate that the rate of convergence is increased using antithetic variates on the generation of initial population, and during GA operations. The search-space and diversity of the population are also increased using antithetic variates. Moreover, it should be pointed out that the computational costs of GA algorithm with the diffusion code used in fitness evaluations are small enough to make detailed search within one hour. It takes one minute to make 600 evaluations in PC with 900 MHz AMD processor. Our results indicate that using 20-node parallel computer cluster in GA reduces the total computation cost of GA run with 30000 evaluation into order of a few minutes.

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