Application of Genetic Algorithm to Optimize Burnable Poison Placement in Pressurized Water Reactors

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ABSTRACT
An efficient and a practical genetic algorithm tool was developed and applied successfully to Burnable Poisons (BPs) placement optimization problem in the reference Three Mile Island-1 (TMI-1) core. Core BP optimization problem means developing a BP loading map for a given core loading configuration that minimizes the total Gadolinium (Gd) amount in the core without violating any design constraints. The number of UO_2/Gd_2O_3 pins and Gd_2O_3 concentrations for each fresh fuel location in the core are the decision variables and the total amount of the Gd in the core is in the objective function. The main objective is to develop the BP loading pattern to minimize the total Gd in the core together with the with residual binding at End-of-Cycle (EOC) and to keep the maximum peak pin power and Soluble Boron Concentration (SOB) at the Beginning of Cycle (BOC) both less than their limit values during core depletion. The innovation of this study was to search all of the feasible U/Gd fuel assembly designs with variable number of U/Gd pins and concentration of Gd_2O_3 in the overall decision space. The use of different fitness functions guides the solution towards desired (good solutions) region in the solution space, which accelerates the GA solution. The main objective of this study was to develop a practical and efficient GA tool and to apply this tool for designing BP patterns of a given core loading.

Categories and Subject Descriptors
J.2 [**Physical Sciences and Engineering**]: - *Engineering*

General Terms: Algorithms, Performance, Design

Keywords: Genetic Algorithm, Nuclear, Burnable Poison, Gadolinium, Optimization, Reactor, Decision Variables

1. INTRODUCTION
Deterministic and Stochastic Methods are widely used optimization techniques in nuclear fuel management. Li developed an automatic Pressurized Water Reactor (PWR) reload design expert system computer code [1]. This study presented two important deterministic techniques to develop an optimum PWR reload pattern. The first one is to develop a priority scheme, which represents the optimum placement of the fuel in the core for maximizing the cycle length or using minimum fresh fuel for a given cycle length. The second technique called Power Shape Driven Progressive Iteration (PSDPI) is to determine the burnable poison loading in the fresh fuel assemblies. This technique forces the Radial Power Distribution (RPD) to be as flat as possible by using the Haling Power Distribution (HPD) as a target power shape. Haibach performed a deterministic and stochastic fuel management study to optimize Integral Fuel Burnable Absorber (IFBA) designs for PWRs [2]. The deterministic results indicate it is not necessary to use large numbers of IFBA pins per assembly nor is it necessary to use exceedingly high boron enrichment in the IFBA pins. Their design reduced the maximum peak pin power by as much as 5 % over the vendor's IFBA configuration. The study developed optimal loading pattern by using different number of IFBA fuel assembly in the core. The author determined number of IFBA assemblies needed in the core by comparing power distributions with HPD.

Yilmaz S., et al. [3] developed a new deterministic technique called Modified Power Shaped Forced Diffusion (MPSFD), which uses RPD limit value instead of using HPD as a target to determine gadolinium loading for the fresh fuel assembly, which its radial power exceeds the limit.

DeChaine [4], Guler [5], and Hongchun [6] performed core optimization studies by using genetic algorithms (GAs). They all determined the optimum core configuration for a given cycle. Standard bit-based genetic operators were used to optimize the arrangement of assemblies, burnable absorber, and used assembly orientations. All of their developed systems had a modular structure with flexible GA operators, constraint conditions and objective function.

Kropaczek and Turinsky [7] combined the stochastic optimization technique of simulated annealing with a computationally efficient core physics model based on second-order accurate generalized perturbation theory. The model identifies the placements of feed fuel, exposed fuel with assembly orientations, and burnable poisons within core lattice that optimize fuel cycle performance or thermal margin.

Maldonado [8] presented the development of an optimization tool which has been coupled to the lattice-physics code CPM-2. The study also used Simulated Annealing (SA) algorithm to optimize the pin-by-pin placement and loading of nuclear fuel and burnable absorbers.

Keller [9] reintroduced genetic algorithm methodology into a modern version of the FORMOSA-P code [10], which was developed to determine the family of near-optimum loading patterns

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(LPs) for PWRs by utilizing SA optimization methodology developed by Patrick [11]. The reintroduction was motivated by the inconsistency of the existing SA algorithms in determining near-optimal feed fuel patterns.

The GA, which is a stochastic method, provides an opportunity to work conveniently with discrete functions and without any derivative information [12]. It is based on concepts from biological genetics, where improving the population of organisms is viewed as an optimization problem, with the best individual surviving and producing the most offspring. The GA incorporates an objective function to improve the population. The GA objective function can have one variable (single objective) or more than one variable (multi-objective) to guide the improvement process [13].

The solution to the simultaneous core loading and BP placement problem is highly coupled and requires complex optimization calculations. In practice, the fuel loading pattern design starts with used and fresh fuel in the inventory for which some heuristic rules are applied to place them in the core [14]. Then, the BPs are inserted into those fresh fuel locations in which the power limit constraint has been exceeded. The design of BP loading patterns depends on the vendor's U/Gd fuel assembly designs in the current approaches explained here. Vendor's reference fuel assembly designs were limited, and they did not cover all possible BP fuel assembly designs in the decision space defined later. The core designer had to develop loading pattern with these limited BP fuel assembly designs. Hence, the final design could not be the real good one. The innovation of this study was to search all of the possible U/Gd fuel assembly designs with variable number of U/Gd pins and concentration of Gd_2O_3 in the overall decision space. The main objective of this study was to develop a practical and efficient GA tool and to apply this tool for designing BP patterns of a given core loading.

2. PROBLEM DEFINITION

Core BP optimization problem means developing a BP loading map for a given core loading configuration that minimizes the total Gd amount in the core without violating any design constraints. A genetic algorithm (GA) has been developed to perform this optimization calculation. The number of UO_2/Gd_2O_3 pins and Gd_2O_3 concentrations for each fresh fuel location in the core are the decision variables and the total amount of the Gd in the core is in the objective function. The main objective is to develop the BP loading pattern, which keeps maximum peak pin power and SOB BOC concentration values less than the limit values, and minimizes the total Gd amount in the core. The Core BP optimization problem starts with the equilibrium core loading pattern remaining fixed. The BP optimization problem is directed toward optimizing BP pattern in the core during the calculations. The number of UO_2/Gd_2O_3 pins and Gd_2O_3 concentrations are two parameters that can be changed during evaluation to determine the best BP loading pattern. As the Gd is used in the fuel matrix mixed together with uranium, the different number of UO_2/Gd_2O_3 pins and concentration of Gd_2O_3 fuel represents different fuel type in the transport theory and reactor physics code structures such as CASMO-3 / SIMULATE-3 [15,16], and they have to be named with different segment names each representing fuel type characteristics such as uranium enrichment, number of UO_2/Gd_2O_3 pins and UO_2/Gd_2O_3 concentrations. Therefore, the Core BP optimization calculations require a comprehensive library, which includes the generation of all possible segment names and cross section data for different fuel types having different number of UO_2/Gd_2O_3 pins and Gd_2O_3 concentrations. This comprehensive library is generated once for all future SIMULATE-3 reactor physics calculations.

Figure 1 shows a sample core loading model with fresh fuel locations in dark color and used fuel locations in light color for the reference TMI-1 core. There are a total 10 fresh fuel locations given in the reference core loading. The initial core loading pattern has total 3 different fuel types, and each type is represented with different numbers presented in the table that are 0 for used fuel without any boron absorber, 1 for fresh fuel and 2 for used fuel with boron absorber. Number of U/Gd pins within a fuel assembly and their concentrations are also given in Figure 1.

	8	9	10	11	12	13	14	15
H	C-03 0 4.00 00 - 00	F 1 4.80 1	H-09 2 4.90 08 - 02 2.4P 180	H-13 2 4.75 08 - 02 2.7P 180	K-10 0 4.90 16^* - 03 180	F 1 4.70 2	M-11 0 4.30 08 – 04 90	N-12 2 4.90 08 - 02 2.3P 270
K		O-13 0 4.90 08 - 02 180	F 1 4.80 3	K-12 2 4.75 08 - 02 2.7P 270	F 1 4.55 4	L-13 2 4.90 08 - 02 3.5P 90	F 1 4.87 5	K-11 2 4.45 08 - 02 1.4P 90
L			L-09 0 4.90 16^* - 03 270	M-14 0 4.90 08 - 02 90	N-14 0 4.90 08 - 02 180	F 1 4.55 6	F 1 4.87 7	M-12 2 4.62 08 - 02 3.5P 90
M				F 1 4.55 8	M-13 0 4.75 16^* - 03 180	F 1 4.90 9	L-14 0 4.75 08 - 04 180	
N					O-12 0 4.85 08 – 04 180	F 1 4.90 10	K-14 0 4.75 08 - 04 180	
O						N-13 0 4.85 08 - 04 180		

Previous Location (F=Fresh)
Type (0:Used fuel, 1:Fresh fuel, 2:Used fuel with boron)
Fuel Enrichment (U-235 w/o)
No of U/Gd fuel pins (*: Mixed) – Gd_2O_3 concentration (w/o)
BP Loading (w/o) (P for Pulled) or fresh fuel number
Degree Rotation

Figure 1. Reference Initial Octant Core Loading for TMI-1 core

2.1 Design Constraints

Design constraints for Core BP placement optimization problem are summarized as follows;

1. Maximum peak pin power should be less than 1.55 until 450 EFPD (or 12.5 GWd/MTU cycle exposure), and then it should be less than 1.45 until end of cycle of 680 EFPD (or 20.68 GWd/MTU cycle exposure)

2. U-235 enrichment of the fuel assemblies in the reference core loading should be fixed during the calculations

3. Do not insert any BP into the used fuel

4. Use fresh fuel locations in 1/8 core symmetry for the reference core and keep their positions fixed in the core during calculations

5. Use maximum 20 U/Gd fuel pins and follow symmetric pattern within a fuel assembly

6. Use maximum 8 w/o Gd_2O_3 concentration for U/Gd fuel

7. Beginning of Cycle (BOC) Soluble Boron Concentration (SOB) should be less than 1700 ppm at equilibrium Xenon and Samarium

3. GENETIC ALGORITHM MODEL

GAs are search and optimization procedures based on natural genetics and natural selection [13]. GAs are robust search algorithms requiring minimal problem information. Basically, the GA employed in this study involves binary representation to define the genotype. However, integer representation is utilized to increase the efficiency of the calculation and reduce the problem size in one aspect of the problem. Decision variables are represented in binary strings to use GAs to determine good solutions, which satisfy all constraints. A black-box approach is used in GAs, which allows any reactor physics code to be used with GAs to evaluate the fitness of the individual. The fitness function is the objective function employed to determine the goodness of the selected solution.

3.1 Phenotype and Genotype Representation

Binary GA requires the representation of decision variables in binary strings [13]. There are total 8 different values for each of decision parameter creating the decision space. The decision space and decision variables of number of UO_2/Gd_2O_3 fuel pins and the Gd_2O_3 concentrations with their possible values are shown in Figure 2. Each decision variable is assigned to integer numbers based on its value. The next step converts the integer numbers into binary bits using 3 bit binary representation. The main objective of this conversion is to reduce the genotype length to greatly reduce the CPU time during the calculations. The 3 bit binary representation of a decision variable has a total 8 or (2^3) different gene value each referring to different solutions as shown in Figure 2. Any possible bias in the calculations is eliminated with this representation, because the number of decision variables covers all of the possible number of genes value. The range of the number of UO_2/Gd_2O_3 fuel pins is between 0 and 20. Classical binary representation would require at least 5 bit binary bits to include the maximum value of decision variable for this problem. The 5 bit representation has a total of 32 (2^5) different genes values or solutions increasing the genotype problem size by a factor of 40. Thus, the GA code would take much more CPU time to achieve good results due to problem size. The GA code runs were performed with the available reference designs. The UO_2/Gd_2O_3 fuel pin arrangement within a fuel assembly is another research topic and will be presented as a separate paper later.

The phenotype represents the original BP loading pattern as applied to the reactor physics code, and the genotype is the bit-string representation and formulation of the phenotype for the genetic algorithm operations. A gene is composed of bits, each of which may exhibit 0 or 1 called an allele. The conversion process of phenotype (BP loading pattern) to genotype (binary form of BP loading pattern) is called encoding, and the reverse process is named as decoding.

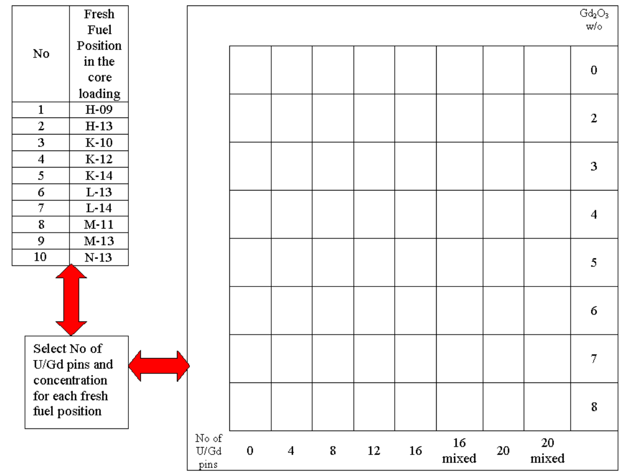

Figure 2 Decision space and its variables (16 and 20 mixed; mixed concentrations

Both a sample phenotype and corresponding genotype structure are shown in Figure 3 for a sample BP loading. This figure shows how the phenotype of integer numbers is encoded into a genotype structure for the sample BP loading. The total 10 fresh fuel positions in the reference core loading pattern require using a total of 20 decision variables. The genotype has 20 genes each represented by a 3 bit binary gene. The total of 60 bits representation is required to encode the decision variables representative of the number of UO_2/Gd_2O_3 fuel pins and their corresponding Gd_2O_3 concentrations. The GA code alters the population of BP patterns into new BP patterns by various selection methods. Each of the population BP patterns is then decoded into phenotypes and evaluated by a reactor physics code for evaluation of its fitness value. By choosing high fitness values for the next generation, the GA continues to improve the BP pattern design until the optimum is attained.

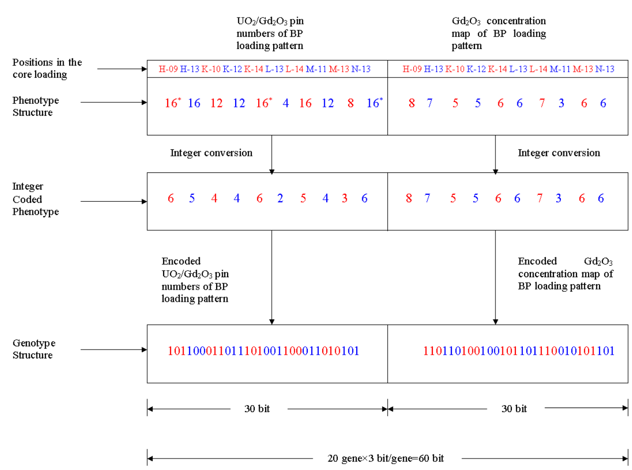

Figure 3. Sample phenotype and genotype structure

3.2 GA Operation

In this study, it was selected that 150 different genotypes each representing different BP loading pattern forms a GA population. The binary form of the genotype is decoded into a phenotype for evaluation by a reactor physics code. Figure 4 demonstrates the genetic algorithm flow diagram and its interaction with the reactor physics code. The genetic algorithm code starts with a randomly generated initial population. The evaluation of each population member requires an interface code shown in the dashed box to convert the decoded GA population member into the form of BP loading (U enrichment, No of BP rods, and Concentration), and to perform reactor physics calculations for determining core depletion parameters such as maximum peak pin power, maximum RPD power, BOC SOB concentration (ppm), and EOC SOB concentration (ppm). Finally, the core depletion parameters are used to evaluate the population members by calculating their fitness. Selection, cross-over and mutation operators are used to generate the next generation population members. The convergence criterion of the GA code was established by assigning a maximum generation number. The solutions were attained when the maximum generation number is reached. Data storage was performed during calculations and the good solutions are archived into a file for future evaluation and study. Table 1 summarizes the sample GA input data and operators type used for Core BP optimization problem.

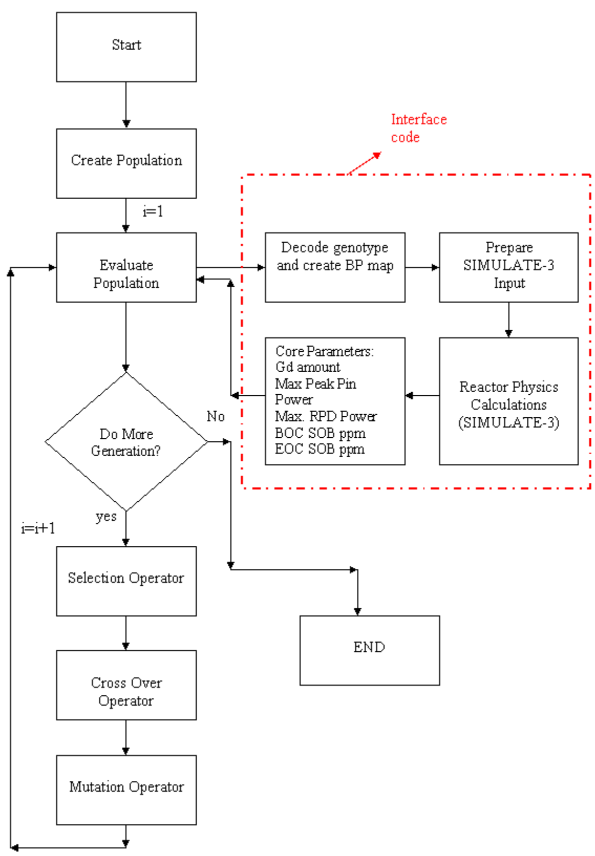

Figure 4. Genetic Algorithm flow diagram and interaction with the reactor physics code

Table 1. Genetic Algorithm Input Data and Operators Type

Parameter	Data
Population Size	150
Base Mutation Probability	1/Npop=1/150
Maximum Generation Number	100
Uniform Cross Over Probability	0.5
Selection Operator	Tournament selection with elitism technique
Uniform Cross Over Probability	0.5

4. OBJECTIVE FUNCTIONS AND CONSTRAINTS HANDLING

The main objective of the GA in this program is to minimize the Gd amount in the core while meeting all constraints. The total amount of Gd (SUM) in the core, which is a function of number of U/Gd pins and Gd_2O_3 concentration, is calculated by the following mathematical formula:

SUM= dimensionless fitness value in Region 2 representing total Gd amount in the octant core

Ni=No of U/Gd pin for ith fresh FA position in the core loading

Gdwi=Gd_2O_3 concentration for ith fresh FA in the core loading

The fitness definitions described below are used for a three regions solution space;

i=Region number

Region 1: Fitness=f1= -i×SUM (minimizing Gd amount)

Region 2: Fitness=f2= -i×w_2×maxpeakpinpower (minimizing maximum peak pin power)

Region 3: Fitness=f3= -10000 (Negative high penalty for violating BOC SOB constraint and cycle exposure constraint on where the maximum peak pin power occurs)

This definition guarantees that f1>f2>f3 in Figure 5.

w_2 is a coefficient that guarantees that Region 2 has always smaller fitness value than the Region 1)

The three regions solution space described above has a different objective function for each region to guide the solutions systematically into a good solutions space (Region 1 of Figure 5). None of the good solutions violate any of the constraints given in Section 2.1, and the fitness of a good solution is represented by its total Gd amount. Region 2 represents the population members having a maximum peak pin power greater than the limit value of 1.55, and the BOC SOB concentration is less than the constraint value of 1700 ppm. The fitness of an individual is calculated by using its maximum peak pin power value with the objective of minimizing maximum peak pin power value in the core depletion.

The GA developed in this program was designed to guide the GA solutions to move from the other two Regions into Region 1. Each solution produced during the GA analysis is placed into one of the three regions. If the solution violates all of the constraints, it is placed in Region 3 as shown in Figure 5. Solutions which violate the BOC SOB constraint of 1700 ppm, and cycle exposure constraint on where the maximum peak pin power occurs fall into Region 3. They are eliminated by using a high negative fitness penalty (-10000) during the calculations in order to permit solutions that violate only the maximum peak pin power constraint go into Region 2. The main purpose of this constraint handling technique is to remove individuals from the mating pool by reducing their probability of being selected for the next generation due to their low fitness value. Sufficient Gd must be in the core to prevent the violation of the BOC SOB constraint. This establishes a lower limit for the minimum Gd amount in the core. The core can exhibit a positive temperature coefficient if the BOC SOB is greater than the BOC SOB constraint for the TMI-1 core.

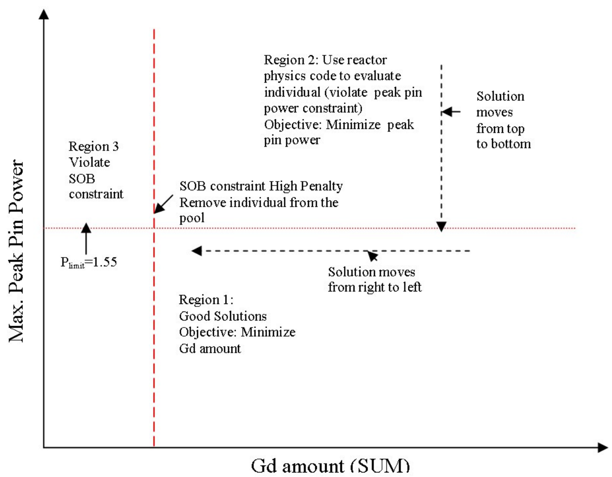

Figure 5. Solution Space demonstration and its objective functions

The fitness of the solutions in Region 2 ranges in maximum peak pin power values from above the maximum peak pin power limit of 1.55. Members of the solution in Region 2 are then further selected for the next generation using the fitness definition, which minimizes the maximum peak pin power and does not violate the other two constraints allowed in Region 3. The best solution improves in each generation and later reaches solutions having values at or below the maximum peak pin power limit. These solutions are moved from Region 2 to Region 1. Then, the objective function is changed to minimize the Gd amount in the core by keeping the individuals below all constraints. With this approach, the GA solutions are forced to move from top to bottom (Region 2 to Region 1) first by minimizing the maximum peak pin power in Region 2, and then from right to left in Region 1 as shown in Figure 5. The final result is to provide good solutions that minimize the total Gd amount in the core.

5. RESULTS

Figure 6 shows the solutions as a function of their maximum peak pin power and total Gd in the core. It can be observed that many solutions are found at and below the maximum peak pin power constraint. Of these solutions those that fall at the extreme left of Figure 6 have the minimum total Gd in the core. Figure 6 shows only those solutions in Regions 1 and 2, the optimum solution is the member which is at the extreme left in the figure and has a maximum peak pin power less than 1.55.

Figure 7 shows how the fitness of the solutions change during the evaluation process. All of the three fitness regions are shown in the Figure. Individuals violating constraints of the BOC SOB and cycle exposure where maximum peak pin power occurs are assigned a high negative penalty (-10000) to reduce the probability of being selected for the next generation and shown as Region 3 in the figure. The first solution in Region 1 appears after 3,750 evalutations (25 generation×150 evaluations/generation). The best fitness value versus generation number is shown in Figure 8, and GA run at the 25th generation enters the Region 1 from Region 2 as shown in the figure. Figure 9 shows all of the good solutions developed during evaluation, which do not violate any constraints.

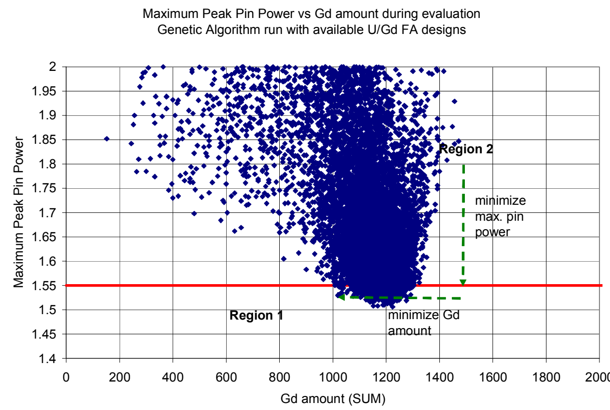

Figure 6. Max. Peak Pin power vs. Gd amount during evaluation

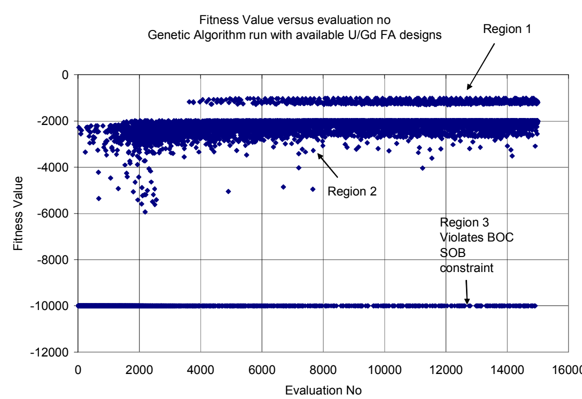

Figure 7. Fitness value change during evaluation

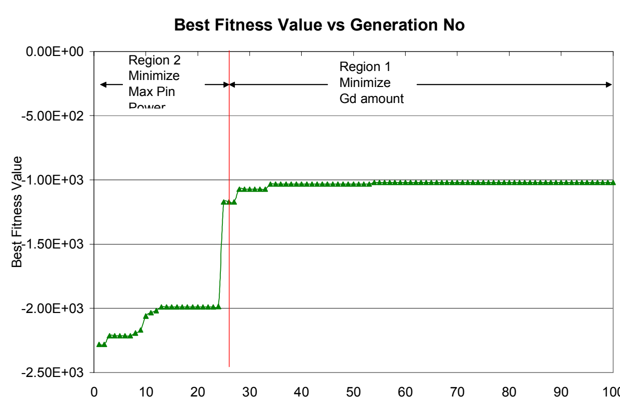

Figure 8. Best Fitness value vs. generation number

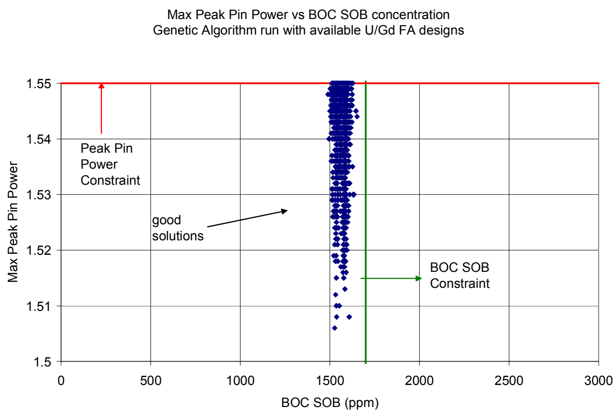

Figure 9. Good solutions not violating design constraints

Table 2 presents the best solution for the TMI-1 reference core loading, and it shows the number of U/Gd pins and Gd_2O_3 concentration needed to achieve the best BP design having the minimum total Gd that does not violate any constraint. These results were achieved using the reference fuel assembly design and U/Gd pin configurations in the calculations. Table 3 shows the maximum peak pin power, the maximum RPD power, the cycle exposure data where the maximum peak pin power occurs, the BOC and the EOC SOB values, the Gd amount (SUM), and the fitness values for the first ten good solutions developed during the evaluation. The best design has the maximum peak pin power value of 1.53, at 0 GWd/MTU cycle burnup, maximum RPD power value of 1.401, BOC SOB concentration value of 1632.8 ppm, and the EOC SOB value of 94.4 ppm having a total Gd amount (SUM) value of 1020. However, the design number 4 has EOC SOB 95.8 ppm which is larger than best design, but the total Gd amount is higher than the best design. This second solution may actually be better than the selected best solution (Design No 1) if a cost analysis shows that the increased lifetime in solution 4 provides greater cost savings than increasing the total Gd in the core. A cost analysis will have to be performed to make this decision.

Table 2. Best Solution and Core BP map for TMI-1 Cycle 16 with available U/Gd fuel assembly designs

Position in the core	No of U/Gd pins	Gd_2O_3 w/o
H-09	20*	7
H-13	20*	7
K-10	20	6
K-12	16	4
K-14	20	7
L-13	20	6
L-14	0	0
M-11	16	8
M-13	20	6
N-13	8	3

*Mixed concentrations (8 pins fixed at 8 w/o, and others with variable concentration)

Table 3. Good designs data from archived solutions

Design No	Max Peak Pin Power	Max RPD power	Cycle Exposure at maximum peak pin power (GWd/MTU)	BOC SOB (ppm)	EOC SOB (ppm)	Gd amount (SUM)	Fitness
1	1.53	1.401	0	1632.8	94.4	1020	-1020
2	1.547	1.391	10	1624.3	91.9	1024	-1024
3	1.535	1.399	10	1607.7	94.1	1032	-1032
4	1.543	1.371	0	1579.6	95.8	1036	-1036
5	1.546	1.396	10	1625.1	91.8	1036	-1036
6	1.545	1.419	0	1646.1	93.1	1040	-1040
7	1.535	1.376	1	1608.1	88.9	1052	-1052
8	1.539	1.392	0.8	1608.9	91.5	1056	-1056
9	1.544	1.432	0	1611.1	89.8	1068	-1068
10	1.547	1.386	0	1574.9	90.4	1072	-1072

Finally, Figure 10 shows the EOC SOB versus the total Gd amount (SUM) for all of good solutions. The best solution having 94.4 ppm increases the core lifetime over the 66.6 ppm solution by 13.1 EFPD. Also shown in Figure 10 is that the EOC SOB varies between 66.6 to 95.8 ppm when the Gd amount (SUM) changes from 1020 to 1300.

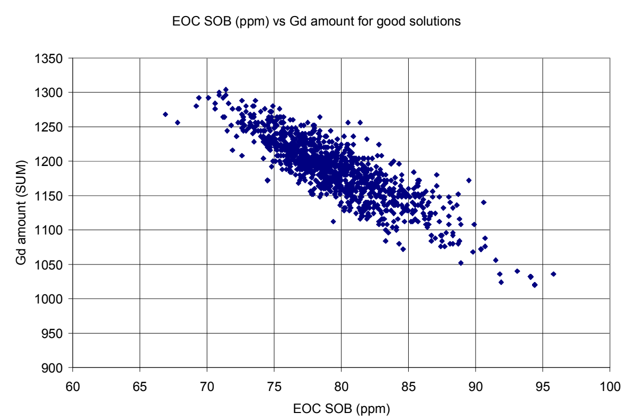

Figure 10. The total Gd amount vs. EOC SOB concentration for good designs

6. CONCLUSIONS

An efficient and practical genetic algorithm tool was developed and applied successfully to the BP placement optimization problem for a TMI-1 reference core loading. The use of different fitness functions guides the solution towards desired (good solutions) region in the solution space, which accelerates the GA solution.

The best design is between solution 1 and solution 4 given in Table 3, which has to be determined by a cost analysis. Solution 1 has the EOC SOB value of 94.4 ppm and a total Gd amount (SUM) value of 1020 whereas Solution 4 has 95.8 ppm EOC SOB concentration and the total Gd amount (SUM) of 1036. Solution 4 increases the core lifetime thus reducing fuel costs and Solution 1 decreases the total Gd amount in the core thus reducing the cost of the Gd. Both solutions are good but one is more cost effective. This can only be determined by a cost analysis. It is important to note that the difference of 29.2 ppm between the best and the worst solution in the good designs represent the potential of 13.1 Effective Full Power Days (EFPD) savings in reactor operation.

The innovation was to search all of the available and feasible vendor's U/Gd fuel assembly designs. Because, the U/Gd fuel pin positions are limited to those used by the vendor in the reference fuel assembly designs, the number of U/Gd fuel pins and Gd_2O_3 concentrations can only be varied for each U/Gd fuel pin configuration. This study established a GA that has been modified to cover any allowed U/Gd fuel pin configuration, number of U/Gd fuel pins and Gd_2O_3 concentration.

The complete optimization calculations should be performed in a two step process. The first step is to alter the genotype to include any allowed U/Gd fuel pin configuration. Then, the GA code was used to determine the optimum U/Gd fuel pin configurations for this PWR core so that the final GA code uses only the optimum U/Gd fuel pin configurations. During the second step, the core BP optimization calculations presented in this paper are repeated with the newly developed optimal U/Gd fuel pin configurations instead of using vendor's U/Gd fuel pin configurations. This advanced technique is to be subsequently published in an appropriate journal.

The hybrid use of GAs and Neural Networks (NNs) is being studied to improve and to speed up the optimization process. All GA solutions are forwarded to a reactor physics code for determining the fitness value of each solution regardless of how unacceptable that solution might be. The reactor physics code involves long running times for each computation (~ 10 sec for one SIMULATE evaluation due to 9 depletion steps used in the real core depletion calculations). The NNs could make it possible to determine the BOC SOB, EOC SOB, and the Radial Power Distribution (RPD) in the core with sufficient accuracy to identify GA solutions that are truly not valid without performing the reactor physics calculations reducing the computational time by an order of magnitude or more. The total CPU time is approximately 41.9 hours on IBM-600 Unix mainframe for a sample GA run. The NNs have potential to reduce the total CPU time by filtering out many invalid solutions that violate the constraints.

Genetic algorithms using parallel machine may present an effective way to further speed up the calculations. It is a promising and challenging future research area in the optimization calculations [17].

7. ACKNOWLEDGMENTS

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