DEVELOPMENT OF A SYSTEM FOR BWR FUEL ASSEMBLIES AXIAL OPTIMIZATION USING GENETIC ALGORITHMS

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ABSTRACT

This paper presents the methodology and the results of an ongoing research project related to the development of a system for the fuel assembly (FA) axial design optimization. The system named AXIAL is based in the Genetic Algorithms (GA) Optimization Method[1], and uses the 3D steady state physics reactor simulator code Core-Master-PRESTO[2] (CM-PRESTO) to evaluate the objective function. The feasibility of this methodology is investigated for a typical Boiling Water Reactor (BWR) fuel assembly. The axial location of different fuel compositions is found in order to minimize the FA mean enrichment needed to obtain the cycle length, under the safety constraints. Thermal limits are evaluated at the end of cycle using the Haling calculation; the hot excess reactivity and the shutdown margin at the beginning of cycle are also evaluated. A little improvement was obtained with the system in the FA average enrichment related to the reference case that has been studied. The main accomplishment of this work is related to the flexibility and completeness of the objective function; additional constraints can be easily introduced in order to obtain an improved solution.

1. INTRODUCTION

The FA axial design optimization problem has received a considerable attention in the literature because of its importance to the nuclear industry in terms of economics and safety. It requires a search of the axial distribution of different fuels, containing different enrichment and burnable poisons, that optimizes the performance of the reactor. Finding the best design is a large combinatorial problem. Performance is evaluated, using a reactor physics core simulator, through a number of different measurements, some of which are subjected to constraints. In order to find the optimal fuel axial design, an optimization code is linked to the core simulator. Several optimization methods have been used. Previous works related with this problem[3,4] have used the Method of Approximation Programming in which the non-linear functions are locally linearized and the resulting linear problem is solved by standard algorithm. Other previous work[5] based on the flexible polyhedron search method, has the advantage that does not need any derivative information to solve the constrained minimization problem of a non-linear function, nevertheless the solution method showed to be quite unstable. Genetic algorithms have proved to be an efficient method to optimize functions without direct derivative information[6], they have been used for fuel management related problems, specially for the reload pattern design optimization[7].

In the present work, GA are used to determine the optimal axial location of different fuel compositions in a FA. The optimization task consists to minimize the FA mean enrichment needed to obtain the cycle length, proposed for the reactor operation, under safety constraints. Several constraints can be considered. For a typical BWR it is important to look at the power parameters as the Maximum Linear Heat Generation Rate (MLHGR), the Fraction of the Limiting Average Planar Heat Generation Rate (XMPGR), the Power Peaking Factor (PPF), the Minimal Critical Power Ratio (MCPR) and the Maximum Relative Nodal Power (MRNP), measured during the full power cycle operation. The Hot Excess reactivity (HEX) and the Shutdown Margin (SDM) during the cycle can be also other constraints to be measured.

2. SYSTEM DESCRIPTION

2.1 Genetic Algorithms

The Genetic Algorithm is a mathematical algorithm highly parallel that transforms a set (*population*) of individual mathematical objects (chains of chromosomes), each of them associated to an aptitude, into a new population (next *generation*) using genetic operations. These operations are modeled based in the Darwin theory of reproduction and surviving of the most capable as result of the execution of a series of genetic operations (sexual recombination). The GA technique requires five basic components:

- A representation of possible problem solutions.
- A form of creation of the first population (normally a random process).
- An evaluation function that plays the role of environment, classifying the solutions in terms of their aptitude.
- Genetic Operators that modifies the composition of the descendants that will be created for the next generations.
- Values for the different parameters used by the GA (size of the population, crossover probability, mutation probability, maximum number of generations, etc.).

2.2 System Characteristics

The system optimization procedure is summarized in Figure 1. Each individual of the population is a FA design and is represented by a genotype: an array of twenty-five entire numbers, which are related to a fuel composition number in the 3D core simulator. One bottom and two top positions (of a total of 25 positions) correspond to fixed natural fuel cells. The system generates randomly a first population of FA designs. Each FA design is evaluated in a loading pattern using the reactor physics simulator code. The cycle energy (cycle burn-up) and the power parameters MLHGR, XMPGR, PPF, MCPR and MRNP are evaluated at the end of cycle using the Haling principle, in order to avoid the control rod pattern programming and to reduce simulator calculation time. The hot excess reactivity and the shutdown margin are only evaluated at the beginning of cycle to save time, but the system is prepared to evaluate these parameters during the cycle. The simulator evaluates each of them and a qualification is assigned in terms of the objective function. They are ordered according to the higher qualifications (aptitudes); afterwards, genetic operators are used to generate a new population of FA designs; they are the selection, the crossover and the mutation. Each new individual is evaluated and qualified. The individuals with higher qualifications are selected for the next generation and the process is repeated until the number of maximum generations is reached.

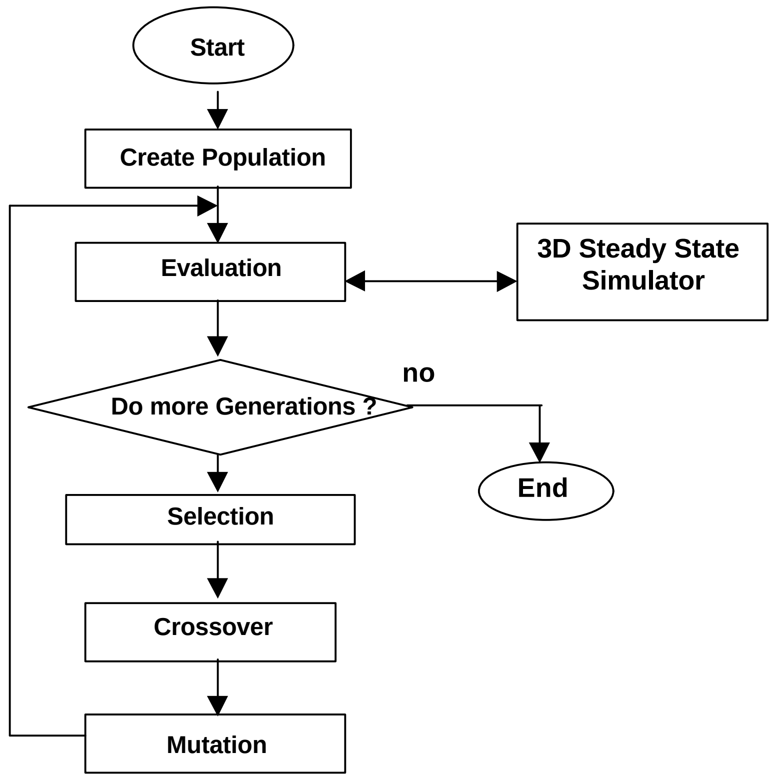

Figure 1. System Description

2.3 Genetic Operators

The selection genetic operator selects couples of individuals that will be crossed. Several types of selection operators can be used; proportional selection using the roulette method has been implemented in AXIAL system.

The crossover genetic operator modifies the composition of the new couple (of descendants), combining parts of the parents' couple, in order to maintain a good diversity and to explore the search space. In the AXIAL system a crossover reproduction using only one crossover point has been implemented. The crossover point is randomly selected excluding two bottom and three top assembly positions in order to have a real crossover.

The mutation genetic operator changes randomly one gene in the chromosome. It allows the introduction of new genetic material in the population to maintain diversity and explore the search space. Other operation is the genetic inversion and it has been implemented in AXIAL system.

2.4 Objective Function

The goal of the optimization task is to minimize the FA mean enrichment needed to obtain the cycle length, proposed for the reactor operation, under the safety constraints. Assembly designs with good qualities correspond to individuals with a high fitness, a crucial issue in the selection process. It is important to have an appropriate mathematical representation of the quality, according to the various optimization criteria and their associated constraints given by the designer. Genetic algorithms have the capability to learn even from bad solutions: unaccepted assembly designs in terms of violated constraints should be assigned with poor quality values. This is done by means of penalty terms.

The optimization goals and constraints are gathered in an objective function that has to be maximized. At the first stage of the work, only power peaking factor was considered as constraint. The solution obtained had to be evaluated in parallel to verify if the typical constraints for a BWR calculation were satisfied. It was observed that the objective function was not able to find a good solution. Taking into account that MLHGR, XMPGR, MCPR and MRNP can be obtained from the same core simulation, without adding too much time in the optimization procedure, they were introduced in the objective function to obtain a better solution. It is clear that a BWR evaluation is very poor without a hot excess reactivity calculation and/or without a shut down margin calculation. Finally these constraints were also included in the objective function.

The objective function to be solved can be written in the following way:

$$\max f(\mathbf{e}) = 10000 - \left|\Delta\, Energy(\mathbf{e})\right| \times w1 + \Delta\, Enrichment(\mathbf{e}) \times w2 + \Delta\, MLHGR_k(\mathbf{e}) \times w3 + \Delta\, XMPGR_k(\mathbf{e}) \times w4 + \Delta\, MRNP_k(\mathbf{e}) \times w5 + \Delta\, PPF(\mathbf{e}) \times w6 + HEX(\mathbf{e}) \times w7 + \Delta\, SDM(\mathbf{e}) \times w8 + \Delta\, MCPR_k(\mathbf{e}) \times w9$$

subject to the additional constraint at EOC in accord with the Haling principle:

$$\lambda(\mathbf{e}) = \lambda_{trg}$$

Where:

$\Delta Energy(\mathbf{e}) = Energy(\mathbf{e}) - Energytrg$

$\Delta\, Enrichment(\mathbf{e}) = Enrich_{max} - Enrich(\mathbf{e})$

$\Delta\, MLHGR(\mathbf{e}) = MLHGR_{max} - MLHGR_k(\mathbf{e})$, $k = 1, \ldots, K$

$\Delta\, XMPGR(\mathbf{e}) = XMPGR_{max} - XMPGR_k(\mathbf{e})$, $k = 1, \ldots, K$

$\Delta\, MRNP(\mathbf{e}) = MRNP_{max} - MRNP_k(\mathbf{e})$, $k = 1, \ldots, K$

$\Delta\, PPF(\mathbf{e}) = PPF_{max} - PPF(\mathbf{e})$

$\Delta\, MCPR(\mathbf{e}) = MCPR_k(\mathbf{e}) - MCPR_{min}$, $k = 1, \ldots, K$

And the following constraints at BOC:

$HEX_{min} \leq HEX(\mathbf{e}) \leq HEX_{max}$

$\Delta\, SDM(\mathbf{e}) = SDM(\mathbf{e}) - SDM_{min}$

Energy(**e**), w1	Calculated cycle energy (cycle burn-up) and its weighting factor
Energytrg	Energy target value
$Enrich_{max}$	Maximum possible enrichment value
Enrich(**e**), w2	FA mean enrichment obtained by the system and its weighting factor
MLHGR, w3	Maximum Linear Heat Generation Rate and its weighting factor
XMPGR, w4	Fraction of the Limiting Average Planar Heat Generation Rate (APLHGR) and its weighting factor
MRNP, w5	Maximum Relative Nodal Power and its weighting factor
PPF, w6	Power Peaking Factor (radial) and its weighting factor
MCPR, w9	Minimal Critical Power Ratio and its weighting factor
HEX, w7	Hot Excess reactivity at BOC and its weighting factor
SDM, w8	Shutdown Margin at BOC and its weighting factor
λ, λ_{trg}	Calculated eigenvalue and target eigenvalue
e	Vector of enrichments (e_1 , e_2 , ... , e_K, ... , e_{25})
e_{min} , e_{max}	Enrichment limits in each node
K	Axial nodes in the 3D simulator calculations (25)

The energy weighting factor (w1) has a positive value in order to penalize those designs that move away from the energy target. The enrichment weighting factor (w2) is also positive, to give a high qualification to those designs with lower enrichment. The weighting factors w3 to w9 are set to zero when their associated variable limit is satisfied, and they have a positive value when their associated variable limit is not satisfied. This action penalize only when de limit is violated.

3. RESULTS

Results for cycle 5 of Laguna Verde Nuclear Power Plant (LVNPP) are presented in this paper. This cycle has a reload of 112 fresh fuel assemblies of one type. The actual axial design of the fresh FA of this cycle has seven axial regions, three of them of natural uranium, at the edges of the assembly. The other 4 axial regions are distributed between the twenty-two inner nodes with typical BWR enrichments in U-235 (from 3.80% to 3.95%). In the optimization system AXIAL, the three natural uranium regions were kept unchanged and the other twenty-two axial enriched nodes were relocated by the system using the fuel types of the actual assembly.

Several values for the different parameters used by the GA, as size of the population, crossover probability, mutation probability and maximum number of generations, were tested and different results were obtained. The convergence of the results depends on these parameters. It is better to have a slow convergence in order to explore well the search space. The results presented here have the following values: size of the population equal 25, crossover probability equal 50, mutation probability equal 80, maximum number of generations equal 110. A total of 2251 evaluations were done with a total execution time of 10256.08 seconds in a 600 Mhz Digital Alpha Station.

Figure 2 shows the average energy cycle and the assembly enrichment as a function of the generation number. Figures 3 ,4, 5 and 6 show the PPF, MCPR, MLHGR, and SDM respectively as a function of the generation number. The assembly enrichment is also plotted in all these graphics. Finally the qualification obtained with the objective function in each generation is presented in Figure 7. These figures show how the system can obtain a converged solution for the different variables in a short number of generations.

Table 1 shows the results for the actual design (reference case), as well as the results obtained with the AXIAL system for the design with higher qualification. A minor improvement was obtained in the assembly average enrichment related to the reference case, which was a fuel vendor's optimum design.

Table 1. Comparison between reference case and AXIAL results

	Reference Case	AXIAL Case
Enrichment	3.50	3.486
Burn-up Cycle	9280.8	9280.9
PPF	1.5316	1.5290
MCPR	1.579	1.583
MLHGR (W/cm)	363.3	365.3
XMPGR	0.7934	0.7975
MRNP	1.8156	1.823
HEX %δk (BOC)	1.56	1.52
SDM (BOC)	2.44	1.69

4. CONCLUSIONS

The system has shown the capability to search an optimum for the BWR fuel assembly axial design using genetic algorithms, at least as good as that obtained for the actual assembly. The system has the flexibility to change the objective function and to incorporate one or several additional constraints with only a minor effort.

Future work is in progress to add other genetic algorithm operators, and to perform hot excess reactivity and shut down margin calculations at different burn-up steps during the cycle.

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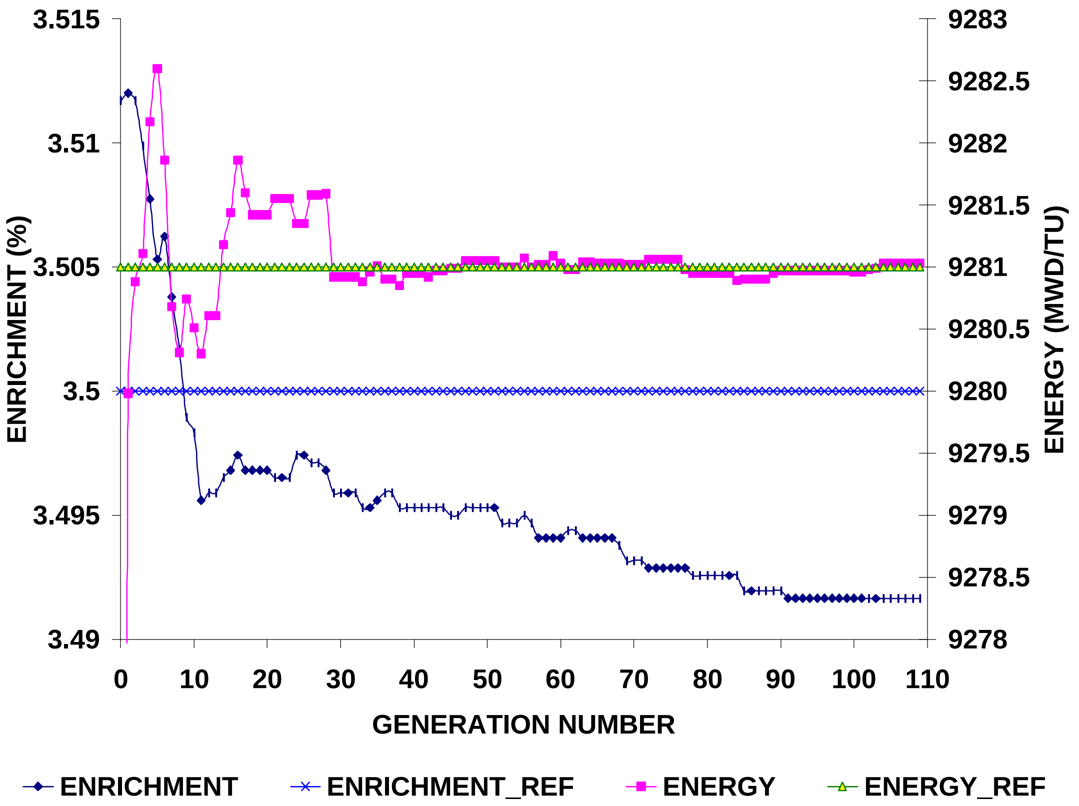

Figure 2. Energy Cycle & Assembly Enrichment vs Generation Number

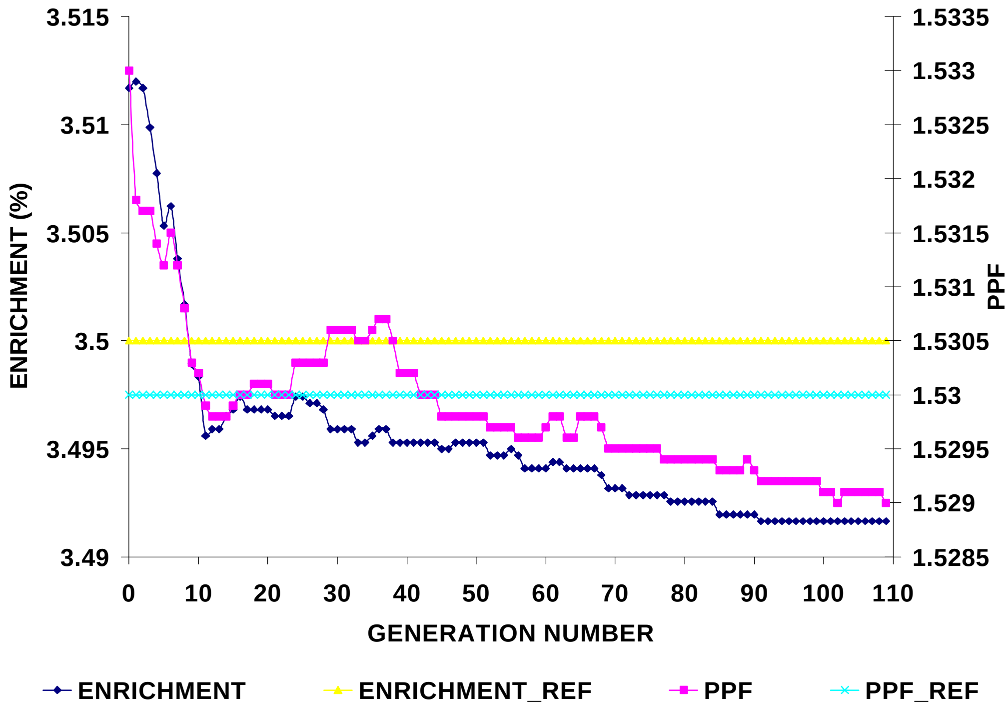

Figure 3. PPF vs Generation Number

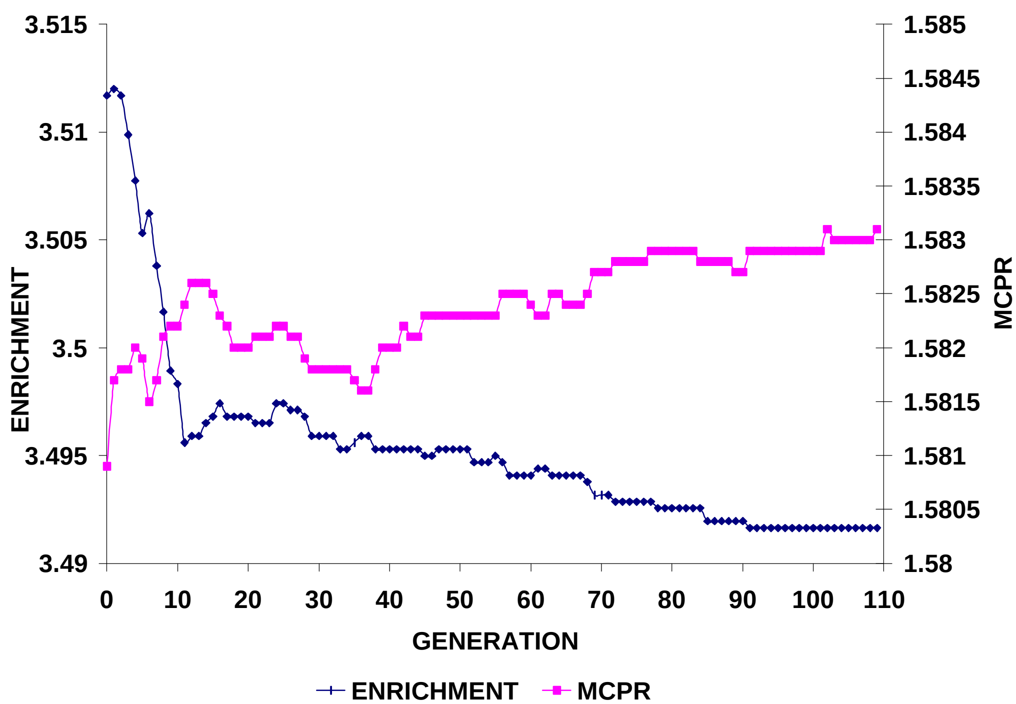

Figure 4 MCPR vs Generation Number

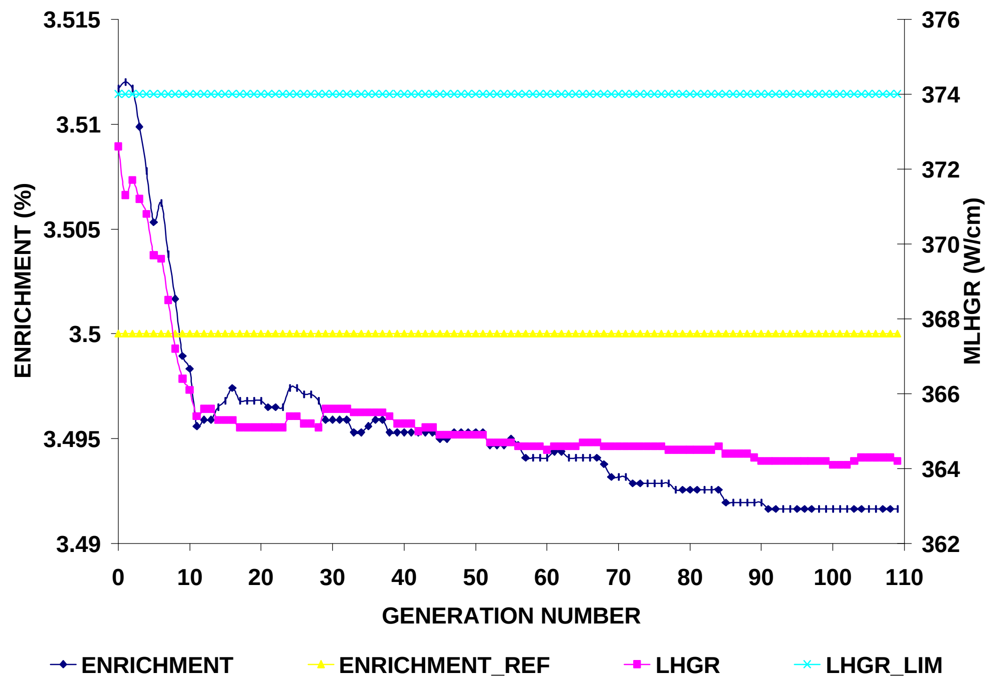

Figure 5 MLHGR vs Generation Number

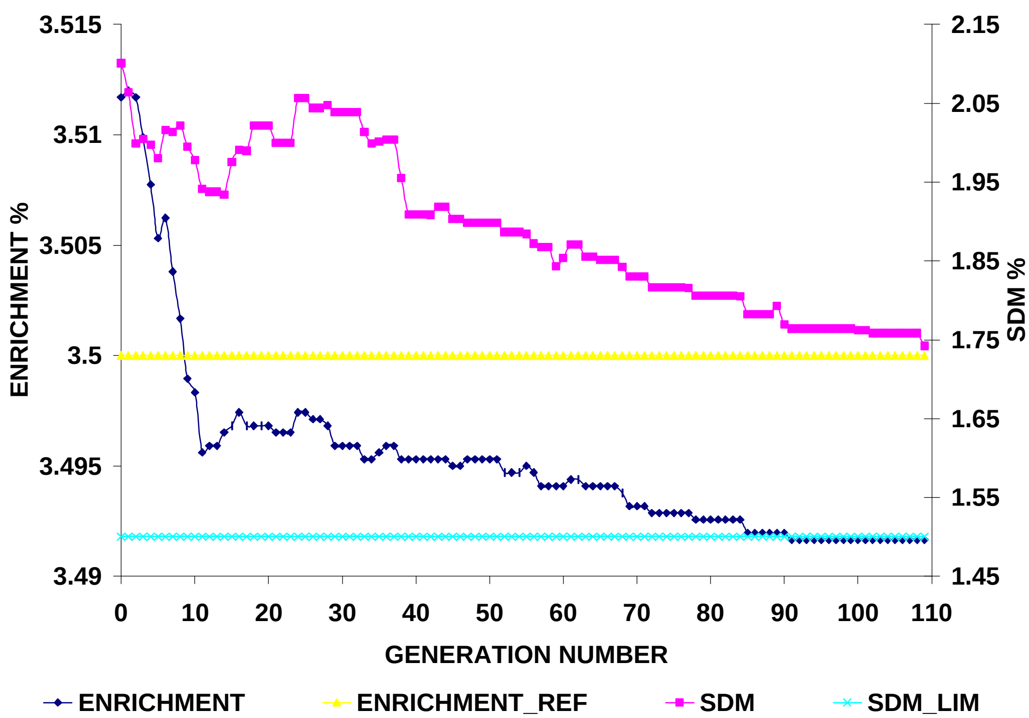

Figure 6 SDM vs Generation Number

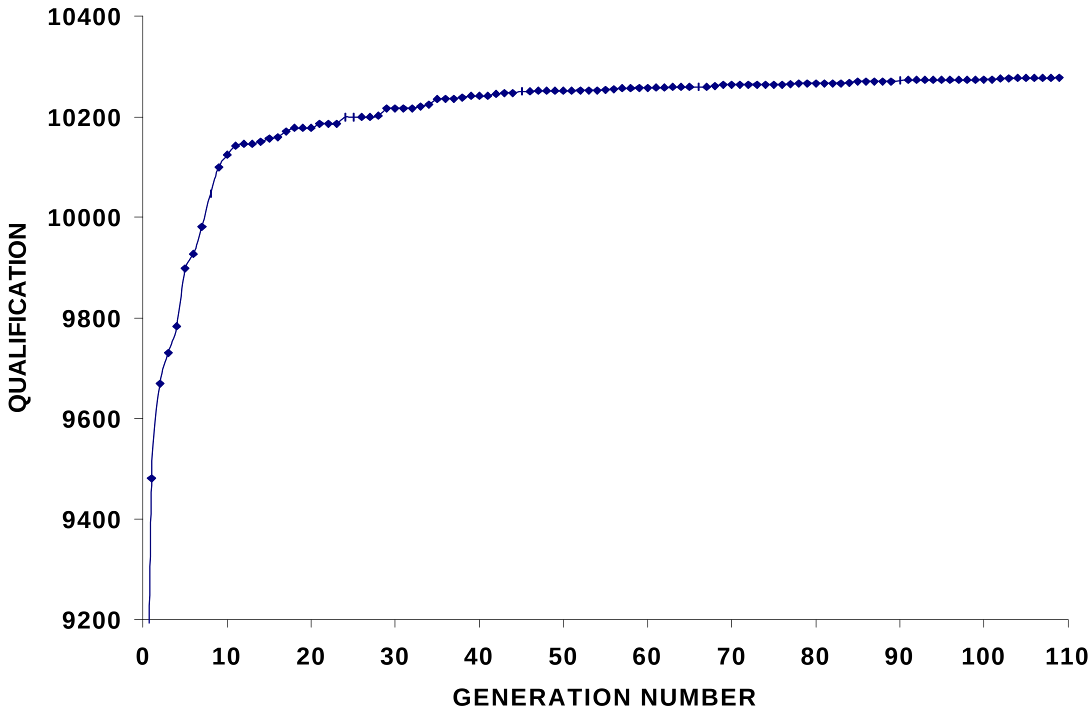

Figure 7. Qualification vs Generation Number