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Improved genetic algorithm for fuel loading optimization of the DNRR with HEU fuel

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Abstract: This paper investigates the performance of genetic algorithm (GA) with improved selection techniques, i.e. Tournament and Roulette Wheel, applied to in-core fuel management of the Dalat nuclear research reactor (DNRR). Numerical calculations have been performed based on the DNRR core with 100 HEU fuel bundles. The optimal fitness function was chosen to maximize the k_{eff} and minimize the power peaking factor. The statistical analysis using Mann-Whitney test shows that the performance of GA with Tournament selection is advantageous over the Roulette Wheel selection in the ICFM problem of the DNRR. The optimal core configurations obtained with the improved GA methods have the k_{eff} values greater by about 500 pcm, and the PPF lower by about 4.0% compared to the reference core.

Keywords: *Genetic algorithm, Tournament, Roulette Wheel, fuel reloading optimization, DNRR.*

I.INTRODUCTION

In-core fuel management (ICFM) is to determine optimal fuel loading patterns of fresh and spent fuel bundles in the core to maximize fuel utilization while satisfying operational and safety constraints. This is a multi-objective problem with two main objectives typically considered: (1) maximization of fuel cycle length and (2) minimization of power peaking factor. Ordinarily, a fitness function is used to combine these objectives in the optimization process. Various meta-heuristic approaches have been contributed to solve the ICFM problem, such as Simulated Annealing [1], Genetic Algorithm [2-3], Particle Swarm Optimization [4], Differential Evolution [5], and so on. Genetic Algorithm (GA), initially developed by Holland, is among the meta-heuristic search algorithms based on Darwin's principle of the natural selection and evolution of the population [6]. The GA searching process was implemented in three steps: selection of parents (selection), reproduction on the selected parents (crossover), and generation of some random changes to maintain the diversity of the following population (mutation). GA ordinarily was designed to simulate natural adaptive behavior to solve the traveling salesman problem [6], a combinatorial optimization problem. Taking into account the advantage of GA in a combinatorial optimization problem, the GA applications to design the safe and efficient fuel loading pattern (LP) have been studied [2,3,7]. Selection technique is a critical step in GA, allowing the search process to escape from a local optimum. Several selection approaches are available for

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selecting the parents, such as: Roulette Wheel, Tournament, Rank-based, Elitism selection techniques [8]. Many studies have been conducted to address this issue, and it is found that no single selection approach was superior to the others in general [9-11]. Thus, the choice of the selection method primarily depends on a specific problem. Among several selection strategies developed for GA, Tournament and Roulette Wheel selections are the most common strategies with the proven efficiency in multi-objective optimization problems [12]. Therefore, this paper investigates the performance of Tournament and Roulette Wheel selection techniques deployed in the GA for the ICFM problem. Numerical calculations have been conducted based on the DNRR core with 100 HEU fuel bundles.

II.PROBLEM AND METHODOLOGY

A. LP optimization problem

The DNRR research reactor is a 500 kW pool-type research reactor using the Russian VVR-M2 fuel type. The reactor core consists of 121 hexagonal cells for loading fuel bundles (FBs), control rods, irradiation channels, and beryllium blocks. A neutron trap is located at the core center, a water cylinder with a diameter of 6.5 cm and a height of 60 cm surrounded by six beryllium blocks. The DNRR is controlled by seven control rods: two safety rods (SR), four shim rods (ShR), and one automatic regulating rod (AR). A more detailed description of the DNRR core and the VVR-M2 fuel can be found in Ref. [13]. The LP optimization problem of the DNRR was performed to the core loaded with VVR-M2 highly enriched uranium (HEU) fuel bundle.

Figure 1 shows the reference core configuration with 100 HEU fuel bundles. The core consists of 100 HEU FBs, including 11 fresh FBs and 89 spent FBs with burnup levels from 7.5% to 12.4% (percent loss of ^{235}U). In the reference core, the fresh HEU FBs are loaded at peripheral positions. Since the DNRR core with HEU fuels is available with previous calculation data and verification, it is used as a reference core to evaluate the performance of the newly developed optimization algorithms. Neutronics calculations were performed based on a 3D model of the DNRR core using CITATION and WIMSD codes [14,15].

Fitness function is used to combine two objectives: Maximization of cycle length and

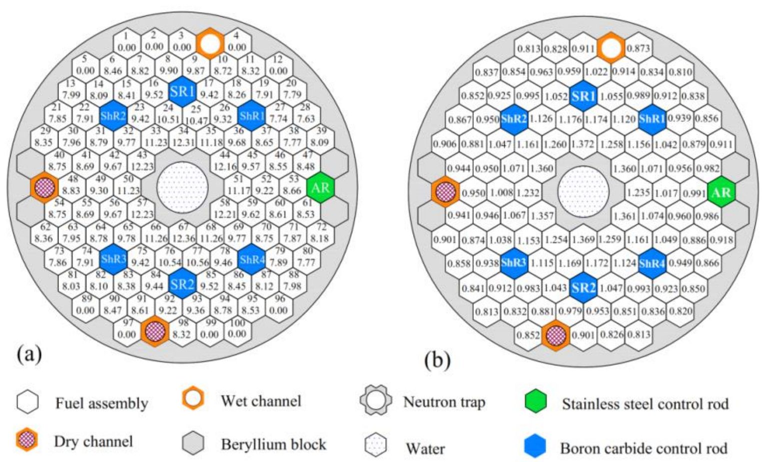

Fig. 1. (a) The reference core configuration of the DNRR, each hexagonal block shows the identification number of the FB (upper) and the burnup level in percent loss of ^{235}U (lower), and (b) the radial power distribution of the reference core [5]

flattening of power distribution to avoid a high power peaking factor (*PPF*). In the present work, *fitness* function was constructed as follows:

$$Fitness = \alpha \times (k_{eff} - 1) + \beta \times (2 - PPF) \quad (1)$$

Where, α = 1000 and β = 100 are the weighting factors for k_{eff} and *PPF*, respectively. These values of factors are selected based on a preliminary investigation of the behavior of the search process [5].

B. Genetic operators

For the ICFM problem of the DNRR, a parameter vector (or a solution) representing a fuel LP has *D (D=100)* integer variables with the value in the range from 1 to *D*. To initiate the search process, an initial *NP*-size population is randomly generated. A population at generation *G* consists of *NP* parameter vectors $X_{i,g}$:

$$X_{i,G} = [x_{j,i,G}] \quad (2)$$

Where, $i = 1, 2, \ldots, NP$; $j = 1, 2, .., 100$.

1. Selection operator

The selection operator is responsible for selecting the solutions to build up a parent population and generate next generations. The selection carries solutions with better fitness to the next generation. Among several selection strategies, Tournament and Roulette Wheel selections are commonly used with the proven efficiency in many optimization multi-objective problems. However, the selection strategies based on stochastic mechanisms do not guarantee that the good solutions would be kept from one generation to the next. This could lead to a slow convergence speed of the search process and a lower possibility to reach optimal solutions. It is recognized that an elitism strategy can significantly improve the GA's performance in many optimization problems and prevent the loss of good solutions during the search process [16]. In this work, the elitism strategy has been deployed simultaneously with the selection mechanisms to solve the problem of fuel LP optimization.

2. Elitism strategy

Potential individuals of the population at generation *G* would be passed to be the members of the parent population without any modification to generate a new generation. The elitism strategy is performed by creating an elitist archive that contains the best non-dominated solutions found during the search process. A solution $X_{1,G}$ is said to dominate another solution $X_{2,G}$ if it satisfies the following conditions: $k_{eff1} > k_{eff2}$ and $PPF_1 < PPF_2$. In that case, $X_{2,G}$ is called the dominated solution. Any solution $X_{1,G}$ which is not dominated by others in the generation *G*, is referred to as a non-dominated solution (known as Pareto-optimal solution).

At the beginning, non-dominated solutions are stored in the archive until the archive is full. If a new solution dominates any member in the archive, that member will be replaced by the new solution. Suppose a solution neither dominates nor is dominated by any archive member, but its fitness is better than some members in the archive, it will replace the member with the lowest fitness in the archive. The archive size N_a should represent a small portion of the population to maintain diversity and avoid premature convergence. All the elitist archive members are transferred to the parent population, and other members (NP-N_a) in the parent population are selected from the current generation based on the tournament or roulette wheel selection.

3. Tournament selection

A group of N_{tour} candidates is randomly chosen from the current generation for running a tournament. The tournament size, N_{tour}, is a selection parameter with the integer value of 2, 3 or 4. These candidates are then ranked according to their fitness values, and the best fitness candidate was selected for reproduction. The whole process is repeated for (NP-N_a) times and for the entire population.

4. Roulette wheel selection

Roulette wheel selection, known as fitness proportionate selection, associates to the probability of an individual to be selected as a parent individual to generate the next generation. This could be achieved by dividing the fitness of a candidate by the total fitness of all candidates, thereby normalizing them to 1. Then a random selection is made similarly to how the roulette wheel is rotated. The probability of an individual to be selected is given by the expression:

$$p_i = \frac{Fitness_i}{\sum_{j=1}^{NP} Fitness_j} \qquad (3)$$

Where, the summation of probabilities of elements p_i is equal unity:

A roulette wheel is performed by setting the range of an individual i in the roulette wheel as ($pros_{i-1}$,$pros_i$]. Where, $pros_{i-1}$ and $pros_i$ are the sums of the probabilities of elements as follows:

$$pros_{i-1} = \sum_{j=1}^{i-1} p_j,$$

$$pros_i = \sum_{j=1}^{i} p_j$$

A single random number in the range $(0,1)$ is generated (a spin) and checked if the number is within the range:

$$pros_{i-1} < rand() \le pros_i \qquad (4)$$

Then, the solution i with $fitness_i$ is selected as the individual in the parent population. This process was repeated for (NP-N_a) times and for the entire population to select (NP-N_a) individuals of the parent population. After the selection phase, the parent population consists of N_a individuals selected from the elitist strategy, and (NP-N_a) individuals selected by the tournament or roulette wheel technique.

5. Crossover operator

The crossover randomly picks two individuals from the parent population to produce two offspring. One-point crossover and two-point crossover techniques are used to mix parts of two-parent vectors to create two offspring vectors. One-point crossover is implemented as follows: A random number l was Generated in [1, D-1] to select a variable position of the parent vectors. Then, two new vectors are created by swapping all variables between positions $(l+1)$ and D of two-parent vectors orderly with a crossover probability c_p. Two-point crossover operator is similar to one-point, but two variable positions are selected instead of one. Then, the alternating segments are swapped along the parent vectors to get the new vectors. By this process, some variables of the new vectors may have the same values after the recombination. If this case occurs, a modification of the crossover operator is needed by adding random numbers on range (0,1) to the same values and re-ranking to form a standard offspring vector. After the crossover phase, NP offspring vectors are generated.

6. Scramble mutation

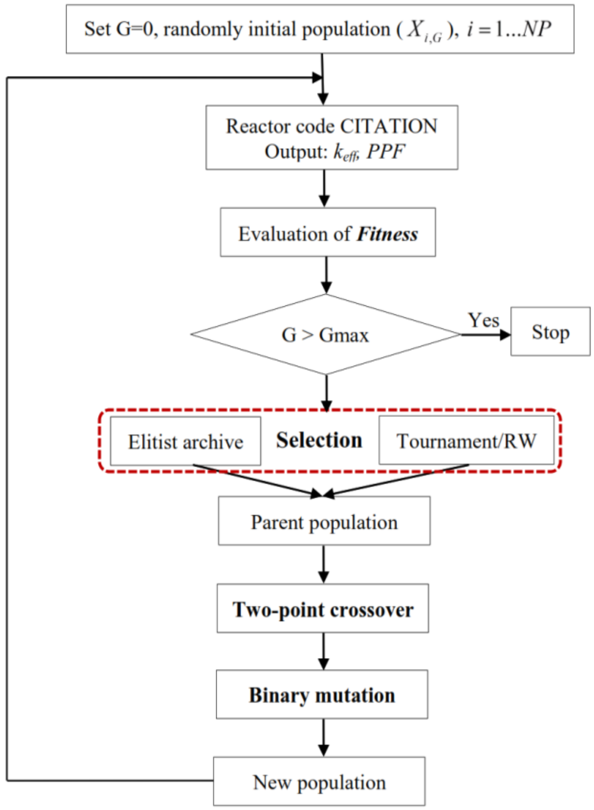

Fig. 2. Flowchart of the GAs for fuel loading optimization of the DNRR

The mutation operator makes random changes in the solutions to maintain the diversity of the population and prevent a premature convergence to a local optimal solution. In this study, the scramble mutation is conducted by randomizing a non-continuous set of locations in the offspring vector then shuffling the values of the selected locations to generate a new vector for the next generation. First, a vector is randomly selected with a mutation probability m_p. Then, the positions of the selected variables of the vector are exchanged. Finally, the new generation is created at the end of the mutation phase.

The GA method applied to the ICFM problem of the DNRR is described in Figure 2. The GA variant using the tournament selection is referred to as GA1 and the other using roulette wheel selection is referred to as GA2. Numerical calculations were performed for the core with 100 HEU fuel bundles to evaluate the performance of the two GA methods in comparison with each other.

III. RESULTS AND DISCUSSION

A. Selection of crossover

The efficiency of the GAs mainly depends on the setting parameters, including population size *NP*, number of generations, elitist archive size, selection type, crossover type, mutation rate. Thus, surveys were conducted to determine these parameters. The population size of 30 was chosen consistently with the previous studies [2,5]. The maximum number of generations was chosen as 500 as the stop criteria for the search process.

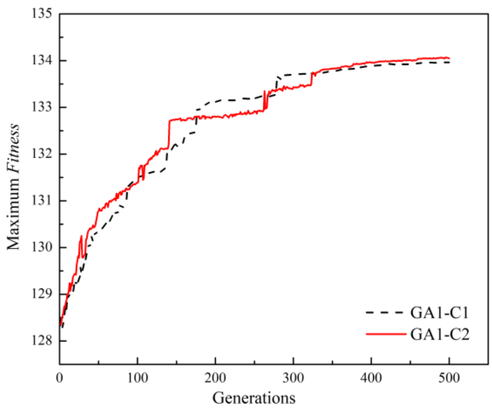

Fig. 3. Evolution of maximum *Fitness* of the GA1 variants with two crossover strategies: one-point crossover GA1-C1 and two-point crossover GA1-C2 (average of 5 runs)

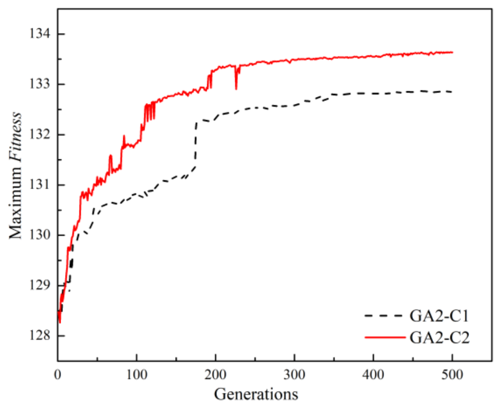

Fig. 4. Evolution of maximum *Fitness* of the GA variants with two crossover strategies: one-point crossover GA2-C1 and two-point crossover GA2-C2 (average of 5 runs)

The surveys on the GA variants were conducted independently, considering the crossover types and mutation rate. Figures 3 and 4 show the evolution of the maximum fitness over generations of the GA1 and GA2 with the one-point crossover (C1) and two-point crossover (C2). The fitness values were taken as the average of five independent runs. The crossover probability c_p = 0.5 was kept consistently in this examination. The maximum fitness obtained from GA1-C2 and GA2-C2 are better than those obtained with GA1-C1 and GA2-C1, respectively. This indicates that the two-point crossover is more effective than the one-point crossover in improving the performance of the GA method. Therefore, the two-point crossover was chosen for the GA search schemes of the DNRR for further investigation.

B. Determination of control parameters

The mutation probability m_p in the GA was defined in the range of (0, 1) to maintain the diversity and avoid premature convergence. The mutation probability should not be higher than the crossover probability like the natural evolution process. Therefore, the m_p values were examined in the range from 0.1 to 0.5. The convergence capacity to good solutions with m_p = 0.1, 0.2, 0.4, and 0.5 was nearly equal in the GA1 (Figure 5), while the GA2 with m_p = 0.1 **was** more advantageous than others (Figure 6). Therefore, m_p = 0.1 was selected for both the GA1 and GA2 methods for further investigation.

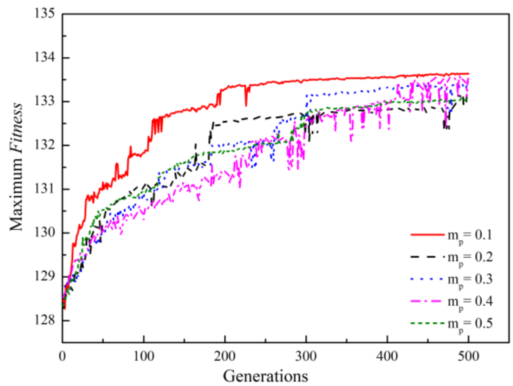

Fig. 5. Evolution of maximum *Fitness* of the GA1 examined with the mutation factor in the range from 0.1 to 0.5 (average of 5 runs).

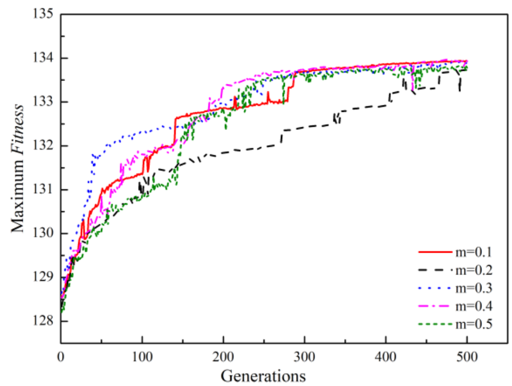

Fig. 6. Evolution of maximum *Fitness* of the GA2 examined with the mutation factor in the range from 0.1 to 0.5 (average of 5 runs).

Figures 7 and 8 display the evolution of the maximum fitness with the elitist archive sizes of 5%, 15% and 25% of the population size (*NP*). It is found that the search processes with the archive size of N_a = 7, corresponding to 25% of *NP*, produced the best performance, as shown in Figures 7 and 8. Thus, the final GA parameters were chosen with the two-point crossover, the crossover probability of 0.5, the mutation probability of 0.1, and the elitism strategy with an archive size of 25% of the population size as summarized in Table I.

C. Comparison between two GAs

Numerical calculations for optimizing the LP of the DNRR with 100 HEU FBs were using the GA1 and GA2 methods. Each method was implemented in 30 independent runs with *NP* = 30 and 500 generations, equivalent to 450,000 evaluations. Figure 9 shows the evolution of the maximum fitness functions over generations taken as the average of 30 independent runs of each method. The result indicates the trend and convergent probability

Table I. The control parameters from surveys

Parameter	**GA1**	**GA2**
Selection	Tournament	Roulette wheel
Crossover	Two-point, c_p = 0.5	Two point, c_p = 0.5
Mutation	Scramble, m_p = 0.1	Scramble, m_p = 0.1
Elitism strategy	Elitist archive, size = 7	Elitist archive, size = 7

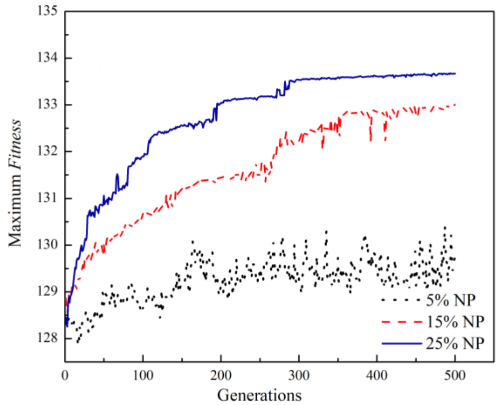

Fig. 7. Evolution of the maximum fitness the GA1 with the elitist archive sizes of 5%,15% and 25% of population size (average of 5 runs)

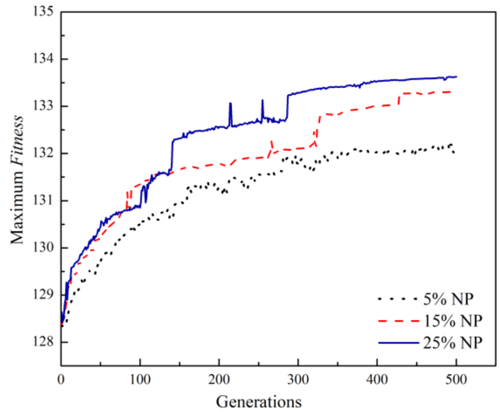

Fig. 8. Evolution of the maximum fitness the GA2 with the elitist archive sizes of 5%,15% and 25% of population size (average of 5 runs)

of the solutions found by the GA1 are better than the GA2.

Table II presents the optimal parameters of the best solutions obtained from the GA1 and GA2 methods in 30 independent runs. The selected LPs have greater k_{eff} values than the reference one by about 500 pcm, while the *PPFs* are smaller by a factor of 4.0% compared to the reference LP (k_{eff} =1,06040, *PPF* =1.374). The gain in k_{eff} value would extend the reactor operation time to about 1700 hrs. with full power. In addition, the *PPF* reduction of 4.0% contributes to the increase of safety margin and the efficiency of fuel utilization.

In a mathematical approach to get the performance comparison between the GAs

Table II. The best LPs obtained from the GA1 and GA2 methods in 30 independent runs.

Best LP	***Fitness***	k_{eff}	***PPF***
GA1	134.1625	1.06620	1.321
GA2	133.9888	1.06612	1.321

Table III. Descriptive statistics of the sample GA1 and sample GA2.

Sample	**Mean**	**Median**	**Maximum**	**Minimum**	**IQR***	**Std. Dev.**
GA1	133.3685	133.9208	134.1625	131.3966	1.850925	0.974278
GA2	133.0515	133.5987	133.9888	130.7851	1.910375	1.050826

IQR* is interquartile range of the sample, which measures how spread out the data points in a sample are from the mean of the sample.

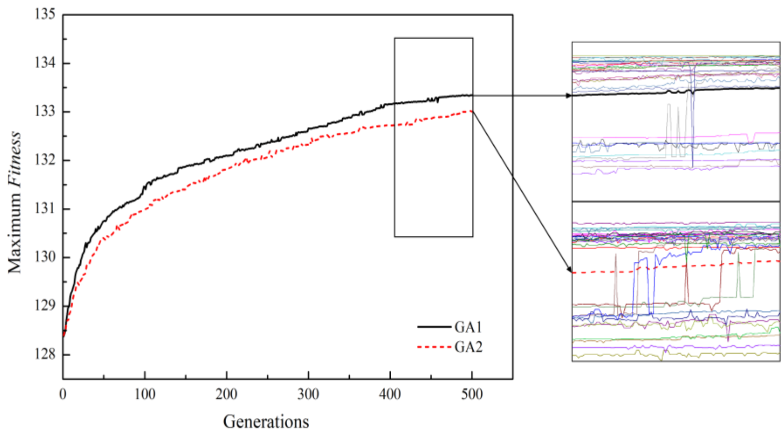

Fig. 9. Evolution of the maximum fitness functions with the number of generations (average of 30 runs)

Table IV. Comparison of the GA1 and GA2 variants using the Shapiro-Wilk normality test, Levene's test, and Mann-Whitney U Test

P-value		
Shapiro-Will test	**Levene's test**	**Mann-Whitney U test**
0.000	0.896	0.003

variants in this optimization problem, the maximum fitness of solutions would be the sample data to test. The data were selected into two independent samples consisting of 30 best solutions of 30 independent runs for the GA1 and GA2. Table III reports the descriptive statistics of the samples, including mean, median, maximum, minimum, IQR, and standard deviation values. It is reckoned that GA1 dominates GA2 on all statistical values. For further comparison, the statistical analysis was implemented to evaluate statistically significant difference between the two samples in *R* 3.0.2 software (R Development Core Team, 2011). Table IV summarizes the p-values obtained from these tests. Shapiro-Wilk normality test with a null hypothesis of normal distribution was chosen to check normality for parametric tests in *R* with the level of marginal significance at 5% (p-value = 0.05). P-value is less than 0.05, which indicates that the null hypothesis would be rejected and the samples are abnormally distributed. Levene's test with a null hypothesis is that two samples of each group have equal variances selected to test the homogeneity of variances. Levene's test showed that the GA variances were equal with p-value = 0.133.

Based on Shapiro-Wilk normality test and Levene test, it is found that the two sample sets are abnormal distributions with equal variances and the same shape. Mann-Whitney U test was then used to test the null hypothesis is that the medians of the samples are equal with the level of marginal significance at 5%. In fact, the p-value of 0.003 is less than 0.05. This means that the null hypothesis would be rejected, and there exists a significant difference between the GA1 and GA2 samples. This indicates that the probability that the GA1 sample with the larger median is the better group than the GA2 one. This means that the GA1 using **t**ournament selection implements better than the GA2 using **r**oulette **w**heel selection in the LP optimization problem of the DNRR.

IV. CONCLUSIONS

A comparative study on the performance of improved GAs with two selection techniques, i.e., Tournament and Roulette Wheel selections, applied to fuel loading optimization of the DNRR research reactor has been conducted. Based on a survey of several parameters, final GA methods were implemented to include the elitist strategy, Tournament and Roulette Wheel selections, two-point crossover, and swap mutation. Statistical analysis using the Mann Whitney u test shows that the Tournament selection is advantageous over the Roulette Wheel selection in the ICFM problem of the DNRR. Compared to the reference core, the optimal core configurations obtained with the improved GA methods have the k_{eff} values greater by about 500 pcm, and the *PPF* lower by about 4.0%.

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