CNPGS Unit-3 Core Reloading Pattern Generation using Multi-Objective Elitist Teaching–Learning–Based Optimization Technique

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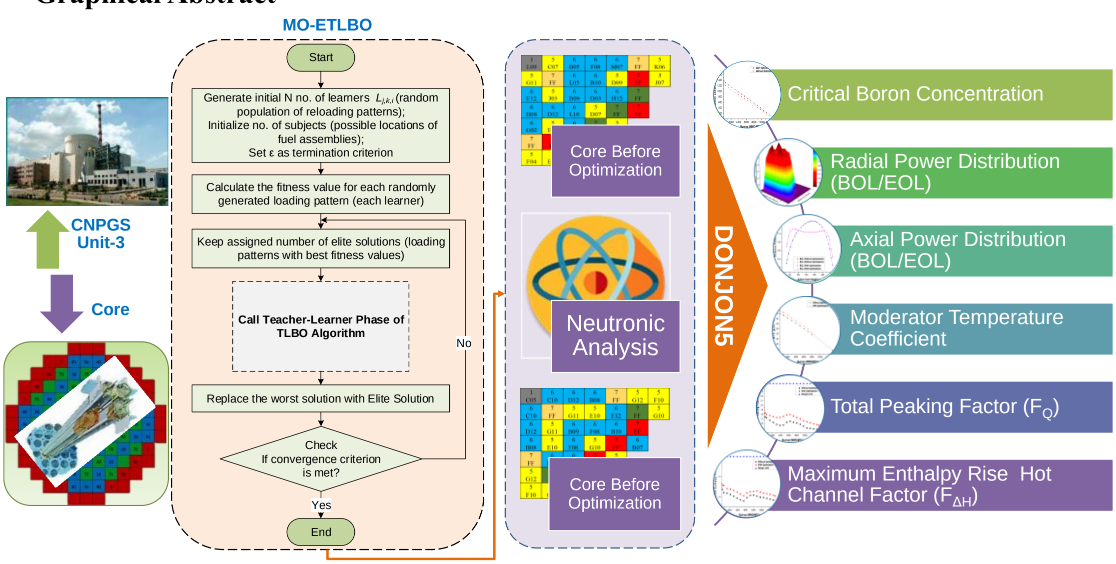
Abstract – *The core reloading pattern optimization in Pressurized Water Reactors (PWRs) is a crucial task aimed at enhancing reactor performance while ensuring safety and minimizing fuel consumption. In the present study, the application of Multi-Objective Elitist Teaching-Learning-Based Optimization (MO-ETLBO) technique is proposed to efficiently and effectively address the multi-objective loading pattern optimization problem for Chashma Nuclear Power Generating Station (CNPGS) unit-3. A multivariable objective function is designed to evaluate the quality of each loading pattern while maximizing critical boron concentration (CBC), minimizing power peaking factor (PPF) to optimally enhance the cycle length while ensuring adequate safety margins and design limits. It has been found that the equilibrium cycle can be further extended to 16.07 EFPDs while keeping the PPF and CBC within the design limits. To validate the effectiveness of TLBO, the optimized loading pattern of the equilibrium core is then evaluated using DONJON5 computer code for the analysis of neutronic parameters. The results determined that proposed algorithm is a promising approach for loading pattern optimization in CNPGS unit-3 offering potential improvements in reactor cycle length while ensuring safety, and overall performance.*

Graphical Abstract –



Keywords: CNPGS Unit-3, TLBO, 300MWe PWR, DONJON, Cycle Length Extension

I. Introduction

One of the most developed nuclear reactor types worldwide is the pressurized water reactor (PWR). They have been utilized to generate power in many countries in a range of types and sizes. PWRs are often utilized to produce power because they have a number of advantages **[1]**. These advantages include the ability to consistently and reliably produce vast amounts of power, their superior thermal efficiency when compared to fossil fuels, and their relatively low environmental impact. Due to its several layers of safety precautions, PWRs also have a solid safety track record. These precautions include redundant shutdown systems, emergency cooling systems, and multiple obstacles to prevent the discharge of radioactive elements **[2-4]**.

Finding the most efficient fuel-reloading pattern for PWR is of constant scientific interest since it will increase economy and guarantee safety. The optimal fuel-reloading pattern cannot be guaranteed by manual loading pattern searching, which consumes a lot of time. As a result, numerous optimization strategies have been investigated and implemented to improve the fuel-reloading pattern **[5-8]**. The main issue, besides optimization methods, is determining the essential parameters for a variety of fuel reloading patterns. It seems sense that the best fuel-reloading pattern would be found quickly if the core parameters could be accurately analyzed in a relatively short period of time. The machine-learning approach has been gaining popularity due to technique advancements and its noticeable benefit in quickly resolving non-linear issues. The rapid-evaluation model has been developed using an artificial neural network (ANN), and 90% of evaluation errors for power-peak factor were within 6%, with an evaluation time of 0.084 seconds **[9]**. By enhancing the ANN, Lysenko **[10]** was able to evaluate the k_{eff} with evaluation errors of 1.3% or less and a cost of roughly 100 ls for a single fuel-loading pattern. Jiang **[11]** used ANN to assess the reactor's CONSORT's k_{eff}. To increase prediction accuracy, Jang **[12]** changed the convolutional neural network (CNN) algorithm's internal structure. With this modification, the 98.3% evaluation errors for the power-peak factor and the 99.0% evaluation errors for the cycle length were both within 0.5%. Many deep-learning structures, such as VGGNet **[13]**, GooLeNet **[14]**, and ResNet **[15]**, have been constructed in CNN in recent years. The rapid evaluation model was developed following neural network training and sent to the GA module in DAKOTA **[16]** for fuel reloading pattern optimization. The above technique has been used to optimize the fuel-loading pattern for the Chinese CNP1000 PWR.

The tabu search **[17-18]**, modified genetic algorithms **[19-21]**, artificial bee colony algorithm **[22]**, fractional order particle swarm optimization **[23-25]**, simulated annealing **[26]**, ant colony optimization **[27]**, various architectures of artificial neural networks **[28-29]**, and many other artificial intelligence techniques have already been used to solve these problems. The size of the population, the number of generations, and other common control parameters are often required for all evolutionary and population-based optimization algorithms. Every optimization method has its own algorithm-specific parameters in addition to these common control parameters. For instance, the parameters of the GA include the selection operator, non-dominated sorting, and the probabilities of mutation, cross-over, and selection. Crossover probability, distribution index, and mutation probability have been used in Genetic Algorithm-II (NSGA-II). Harmony search algorithm (HS) requires the harmony memory consideration rate, the number of improvisations, and the pitch changing rate. Particle swarm optimization (PSO) requires learning rates for individual ability and society influence. The wrong choice of these method-specific parameters causes the algorithm to converge to local optimum instead of the global optimum, which increases computational time. The optimal loading pattern has been determined using a harmony search method that was influenced by the Catfish Effect. Two harmony memories (HM) of equal size has been employed in the algorithm to cover the entire range of variables. The new harmony was created from each history memory or from the entire set of potential solutions, according to specific probability rules **[30-31]**. For the pressurized water reactor (PWR) core's loading pattern optimization (LPO), a new adaptive genetic algorithm (AGA) has been presented in order to reduce the maximum radial power peaking factor (RPPF) at Xe's equilibrium while meeting cycle duration constraints **[32]**. For the purpose of flattening the power inside the reactor core of Bushehr nuclear power station (WWER-1000 type), the application and performance comparison of PSO and GA optimization methods for nuclear fuel loading pattern problem has been addressed **[33]**. The multi-swarm moth flame optimization approach with predator has been suggested as a new methodology **[34]**. The trees social relations (TSR) optimization technique has been presented to improve the multiplication factor, power flattening, and fitness of the final solution when optimizing the fuel assembly loading pattern of PWRs **[35]**. In order to determine the ideal PWR loading pattern based on BEAVRS, the Polar Bear Optimization Algorithm has been used **[36]**. To discover the best loading pattern with the highest k_{eff} and highest thermal fluxes while limiting the power peaking factor, a combination of the intelligent technique GA and the Monte Carlo (MC) algorithm SuperMC has been presented **[37]**. The teaching–learning–based optimization (TLBO) algorithm and the diffusion theory code PRIDE have been combined to create a software design package that optimizes the in-core fuel loading pattern of the Pakistan Research Reactor-1 (PARR-1) by maximizing the effective multiplication factor (k_{eff}) **[38]**.

Using the optimization approach MO-ETLBO suggested in the present study, it has been determined from the prior literature that the core of CNPGS unit-3 has never been optimized with the proposed algorithm. With the goal of maximizing the critical boron concentration (CBC), minimizing the power peaking factor (PPF), to enhance the cycle length while maintaining adequate safety margins and design limits, an MO-ETLBO technique is applied to the constrained non-linear optimization problem of the CNPGS unit-3 core reloading pattern. The obtained results are found to be in good agreement as compared to the existing reloading pattern before applying the optimization technique in terms of cycle length enhancement, and are further discussed in detail in the subsequent sections.

II. Materials and Methods

II.A. Description of CNPGS Unit-3 Core

For this analysis, a nuclear power plant with a reactor core made up of 121 Fuel Assemblies (FAs) and a 998.6MWth power rating is taken into consideration. Every assembly is made up of a 15×15 rod array with 204 fuel rods, 20 guide tubes, and one instrumentation thimble. In cold-pressed Zr-4 tubes, fuel rods with marginally enriched uranium dioxide pellets are stacked. The fresh core's fuel assemblies are initially loaded with three distinct enrichments, 2.4 w/o, 2.67 w/o, and 3.0 w/o, respectively. The outer most portions of the core include the fuel assemblies with the highest levels of enrichment **[39]**. The loading pattern of the CNPGS unit-3 quarter core is presented in Fig. 1 and the basic information on essential technical parameters is given in Table I.

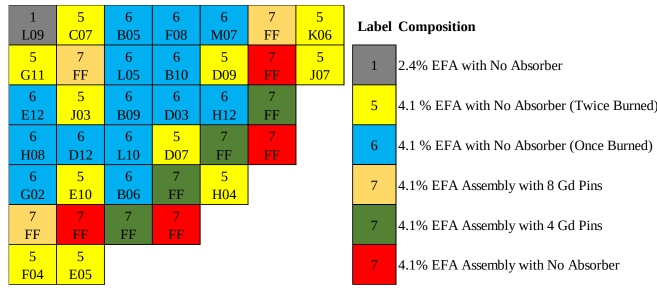


Fig. 1. Loading pattern of the quarter core with different enrichment fuel assemblies (EFA) ***[39]***.

Table I Basic information of core technical data ***[39]***.

Material	Density (g/cc)	Volume (cc)	Mass (Kg)
UO_2	10.181	3995384	40677
Zircaloy	6.55	1463969	9589
GH–4169A (Inconel)	8.24	57403	473
Steel	7.95	174941	1391
Water	0.998	8250500	8234

II.A. TLBO with Elitism

The TLBO algorithm just needs common controlling factors, such as the number of generations and population size, to function. It does not need any algorithm-specific parameters. TLBO is a population-based algorithm that was motivated by the classroom's teaching and learning process. In this approach, a class of students serves as the population, while the various subjects being taught serve as the design parameters of the issue to be optimized, and each student's performance serves as a measure of the system's fitness. The characteristics that the objective function depends on are represented by the design variables, and the optimal outcome is the best value of the objective function. The two phases of TLBO are referred to as the "Teacher's Phase" and the "Learner's Phase," respectively. In the teacher's phase, the teacher is seen as the class's most knowledgeable individual, reflecting the algorithm's best answer and imparting information to the students. There is no doubt that a class with a good teacher will produce better work. During the learner's phase, pupils interact with each other and learn from each other. Random interactions between students occur in the classroom through conversations, group projects, presentations, and formal or informal contact. A student can pick up fresh information from other students who have greater experience. This method of classroom learning is followed by the TLBO algorithm when it seeks the best answer **[40-41]**.

Rao and Savsani developed a concept of elitism in TLBO, which altered the fundamental TLBO by introducing the concept of elitism and employing the regulating parameter of elite size. In ETLBO, the elite solutions that were already preserved at the start of the iteration replace the worst solutions in each iteration. The final part of the learner's phase involves replacing the worst solutions with the best ones **[42]**.

II.B. CNPGS Unit-3 Core Reloading Pattern Generation using MO-ETLBO

The power peaking factor and the critical boron concentration are two parameters that are important to the multi-objective function in the current research work. These parameters are assessed by using the full core simulation code DONJON5, a modular deterministic computer code created by Canada's École Polytechnique de Montréal for use in 3-dimensional core calculations. A modular deterministic neutronics lattice code named DRAGON5, which can solve the Bateman equations for the neutron transport equation with depletion/burnup in both two and three dimensions, was utilized to generate group constants for assembly **[43–44]**. The complete flow of the MO-ETLBO algorithm with mathematical expressions used to modify other learners based on the best learner during the teacher phase and learner phase is shown in Fig. 2.

The MO-ETLBO algorithm's teaching factor is a key aspect in determining whether the algorithm converges slowly or quickly. Either 1 or 2 apply. However, other studies have indicated that choosing teaching factor 1 or 2 at random throughout each cycle will result in superior outcomes **[41]** to make sure the method converges successfully. In the present study, the adaptive teaching factor is used to ensure the faster convergence. The MO-ETLBO algorithm's convergence is measured using the following three termination criteria.

i) For the entire class, the relative error in the objective function value between two successive iterations is less than 0.1%.
ii) Every learner/student in the class has worked toward the same outcome, which means that each student's fitness value moved towards the same value.
iii) The algorithm will end after the maximum number of iterations if all of the aforementioned requirements are not satisfied. The algorithm has a maximum iteration limit of 500.

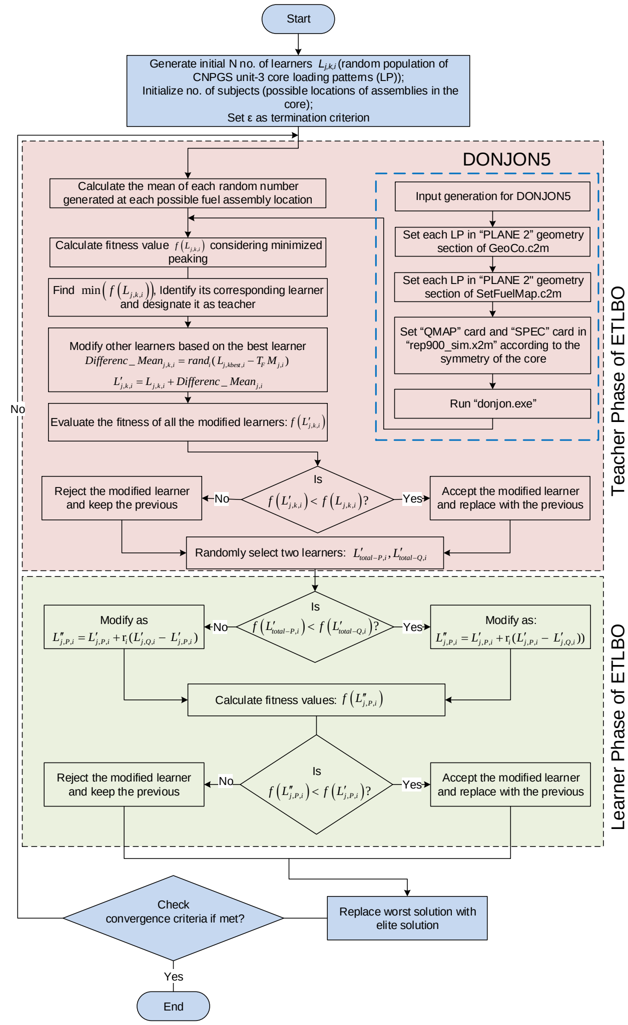


Fig. 2. Flow chart of MO-ETLBO algorithm coupled with DONJON5 for core reloading pattern optimization of CNPGS unit-3 extended cycle.

III. Results and Discussion

In this section, the multi-objective optimization problem is modeled by integrating normalized weighting factor in the objective function depending upon two parameters: the power peaking factor and the critical boron concentration. The multi-objective mathematical function for fitness evaluation is given by;

$$f(PPF, CBC) = \alpha\left(\frac{PPF}{maxPPF}\right) - (1-\alpha)(CBC/maxCBC) \quad (1)$$

where, PPF is core power peaking factor and maxPPF is the upper bound of PPF but not exceeding the design limit of 1.6, while CBC is the critical boron concentration measured in ppm and maxCBC is lower bound of CBCbut not exceeding the design limit of 1800ppm. The constant α is the normalized weighting factor for both the objective function terms. Its value can be taken between 0 and 1, however in current analysis the results for $\alpha = 0.6$ are presented, to obtain optimized values of PPF and CBC. Initial class of 100 students along with the adaptive selection of teaching factor was used for optimization procedure and elite size of 5 was considered. The number of iterations were set to 500. The algorithm converged in 177 iterations giving the optimal core with minimum PPF and maximum CBC with the enhancement of cycle length. Table II shows the comparisons of PPF and CBC of the extended core at zero burnup before and after applying the optimization algorithm. It can be observed that while keeping the PPF and CBC within the design limits for the optimized core, the equilibrium cycle can be further extended to 16.07 extended full power days (EFPDs).

Table II Comparisons of PPF and CBC before and after applying MO-ETLBO at zero burnup.

Parameters	Before applying MO-ETLBO algorithm	After applying MO-ETLBO algorithm	Difference
Power peaking factor (PPF)	1.4685	1.4649	-0.004
Critical boron concentration (CBC)	1580	1685	105
Extended cycle length (EFPDs)	468.69	484.76	16.07

The core loading pattern of equilibrium cycle is refueled with 40 fresh fuel assemblies of 4.1% enrichment in which 24 fuel assemblies contained different number of gadolinium pins (4 and 8 pins). The loading patterns of equilibrium cycle with gadolinium absorber before and after applying optimization algorithm are shown in Fig. 3(A) and Fig. 3(B) respectively. The critical boron concentration for the extended equilibrium cycle of CNPGS unit-3 is calculated. Fig. 4 depicts the behavior of the critical boron concentration in the reactor Hot Full Power (HFP) condition as a function of core average burnup for the extended cycle of CNPGS, unit-3 core designs before and after applying the MO-ETLBO algorithm. The core power maps in Fig. 5 and Fig. 6 show how the reactor's radial power distribution for equilibrium cycle behaves in relation to optimized core-average burnup for BOL and EOL respectively. These power maps display mesh plots of the typical power in each PWR core assembly at various stages of core life. The axial power distributions of equilibrium cycle of extended core at BOL and EOL with absorber are calculated. The results for cores with and without applying optimization algorithm are shown in Fig. 7(A) and Fig. 7(B) respectively. As a result, total power peaking initially declines in a manner similar to how $F_{\Delta H}$ declines at the start of the cycle.

Fig. 8 depicts the moderator temperature coefficient (MTC) for the extended equilibrium cycle core as it was determined under HFP conditions both before and after optimization. The figure makes it evident that the MTC for the extended equilibrium cycle core at HFP is negative throughout the whole cycle, both before and after optimization. The total peaking factor is a key variable in evaluations of reactor safety and fuel management. It has an impact on the thermal margins, fuel rod integrity, and certain aspects of reactor operation, such as core power distribution. When determining the overall peaking factor, both axial and radial power distribution are taken into account. The total peaking factor (F_Q) behavior for the core with and without optimization during the period of core life is shown in Fig. 9. The difference between the integral of the linear power along the fuel rod with the highest integrated power and the average integrated fuel rod power is known as the maximal enthalpy rise hot channel factor ($F_{\Delta H}$). The total maximum power produced in a fuel rod as a result is measured as $F_{\Delta H}$. The $F_{\Delta H}$ limit identifies the coolant flow channel with the largest enthalpy rise. The maximum enthalpy rise with the change in average core burnup without and with absorber, respectively, is shown in Fig. 10. For the figure, it can be seen that the extended cycle of CNPGS unit-3 core's $F_{\Delta H}$ value is within the design limit of 1.6 (Excluding uncertainties).

(A). Equilibrium cycle core before Optimization

1 L09	5 C07	6 B05	6 F08	6 M07	7 FF	5 K06
5 G11	7 FF	6 L05	6 B10	5 D09	7 FF	5 J07
6 E12	5 J03	6 B09	6 D03	6 H12	7 FF	
6 H08	6 D12	6 L10	5 D07	7 FF	7 FF	
6 G02	5 E10	6 B06	7 FF	5 H04		
7 FF	7 FF	7 FF	7 FF			
5 F04	5 E05					

Label	Composition
1	2.4% EFA with No Absorber
5	4.1 % EFA with No Absorber (Twice Burned)
6	4.1 % EFA with No Absorber (Once Burned)
7	4.1% EFA Assembly with 8 Gd Pins
7	4.1% EFA Assembly with 4 Gd Pins
7	4.1% EFA Assembly with No Absorber

(B). Equilibrium cycle core after Optimization

1 C05	6 C10	6 D12	6 B08	7 FF	5 G12	5 F10
6 C10	7 FF	5 G11	5 E10	6 E12	7 FF	5 G10
6 D12	5 G11	6 B09	6 F08	6 B10	7 FF	
6 B08	5 E10	6 F08	5 G10	7 FF	6 B07	
7 FF	6 E12	6 B10	7 FF	5 F10		
5 G12	7 FF	7 FF	6 B07			
5 F10	5 G10					

Label	Composition
1	2.4% EFA with No Absorber
5	4.1 % EFA with No Absorber (Twice Burned)
6	4.1 % EFA with No Absorber (Once Burned)
7	4.1% EFA Assembly with 8 Gd Pins
7	4.1% EFA Assembly with 4 Gd Pins
7	4.1% EFA Assembly with No Absorber

Fig. 3. Loading pattern of extended equilibrium cycle quarter core (A) before optimization, and (B) after optimization.

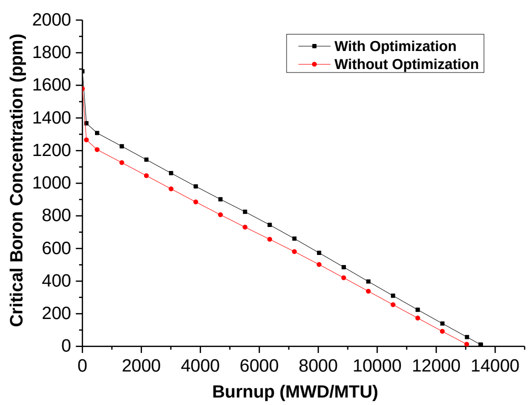


Fig. 4. Comparison of the letdown curve of equilibrium cycle core before and after applying MO-ETLBO.

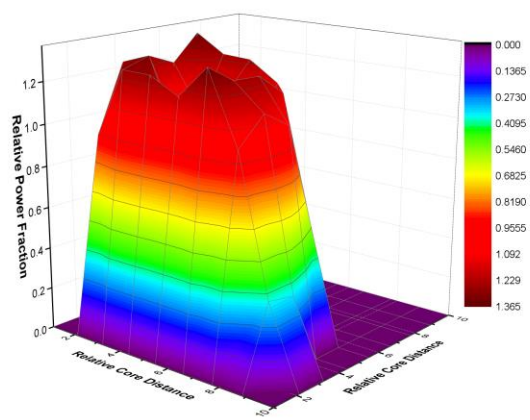


Fig. 5. Radial power distribution of equilibrium cycle of optimized core at BOL.

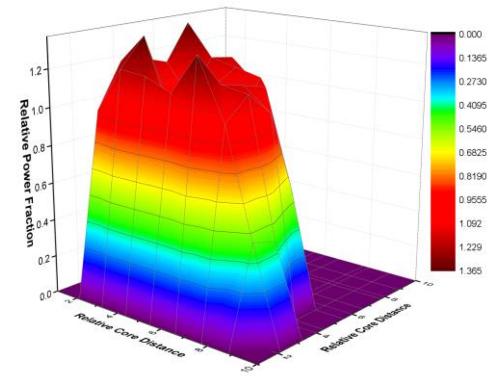


Fig. 6. Radial power distribution of equilibrium cycle of optimized core at EOL.

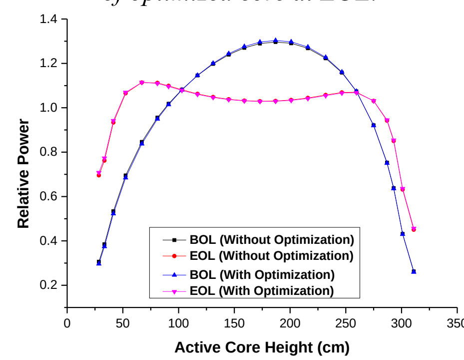


Fig. 7. Axial power distribution of equilibrium cycle core before and after applying MO-ETLBO.

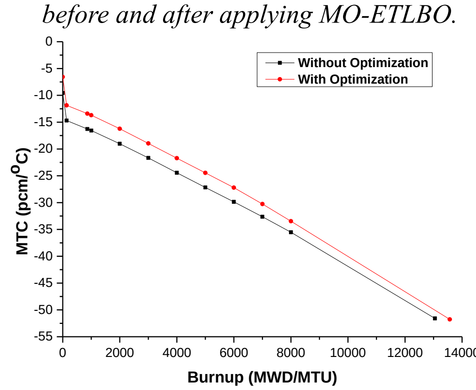


Fig. 8. MTC of equilibrium cycle core before and after applying MO-ETLBO.

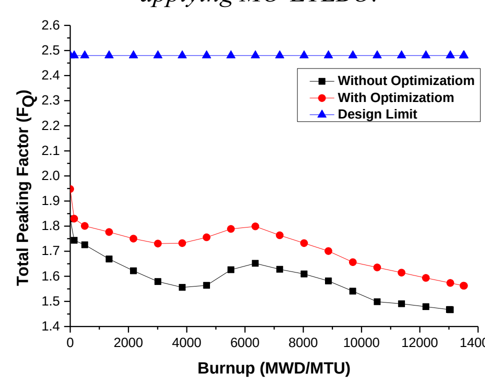


Fig. 9. Total peaking factor of equilibrium cycle core before and after applying MO-ETLBO.

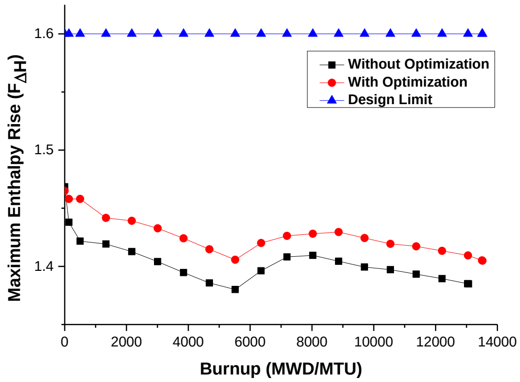


Fig. 10. Maximum enthalpy rise of equilibrium cycle core before and after applying MO-ETLBO.

IV. Conclusions

For the purpose of optimizing the fuel loading pattern for CNPGS unit-3 extended core, a multi-objective elitist teaching–learning–based optimization technique has been provided in this research study. For the purpose of evaluating multi-variable objective function depending upon the PPF and CBC, this method has been incorporated with the DONJON5 full core simulation computer code. An adaptive selection of teaching factor between 0 and 1 was made to get the fast convergence of the algorithm. The MO-ETLBO was applied to find the optimal core while minimizing the core PPF and maximizing the CBC. The results show that MO-ETLBO can perform better to search the optimized loading pattern. By using MO-ETLBO, the equilibrium cycle has been shown to be extendable to 16.07 EFPDs while keeping the PPF and CBC within the design limits. The extensive neutronic analysis was performed to observe the behavior of CBC, axial power distribution, MTC, total peaking factor and maximum enthalpy rise as a function of burnup for the extended equilibrium cycle core with and without optimization, and radial power distribution at BOL and EOL of optimized core. It was observed that the results are in good agreement. For future research, various multi-objective quantum-based meta-heuristic optimization techniques can be used to find the optimal loading pattern with faster convergence while keeping the neutronic parameters within the design limits. Furthermore, the artificial neural networks combined with hybrid optimization techniques can be applied to accurately find the optimal load pattern of PWR's.

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References

1. McMahon, M.V., et al., Reload light water reactor core designs for an ultralong operating cycle. Nuclear technology, 1999. 126(1): p. 32-47.
2. Stewart, R., C. Blakely, and H. Zhang, Investigation of a two-year cycle pressurized water reactor core design with increased enrichment and extended burnup limits. Nuclear Engineering and Design, 2021. 376: p. 111132.
3. Capps, N., et al., A critical review of high burnup fuel fragmentation, relocation, and dispersal under loss-of-coolant accident conditions. Journal of Nuclear Materials, 2021. 546: p. 152750.
4. Secker, J.R., et al., Optimum discharge burnup and cycle length for PWRs. Nuclear Technology, 2005. 151(2): p. 109-119.
5. Kim, T.K., Kim, C.H., 1997. Mixed integer programming for pressurized water reactor fuel-loading-pattern optimization. Nucl. Sci. Eng. 127 (3), 346–357.
6. Kropaczek, D.J., Turinsky, P.J., 1991. In-core nuclear fuel management optimization for pressurized water reactors utilizing simulated annealing. Nucl. Technol. 95 (1), 9–32.
7. Kennedy, J., Eberhart, R., Particle Swarm Optimization. IEEE International Conference on Neural Networks, Perth, Australia, 1995, 1942-1948.
8. Parks, G.T., 1996. Multiobjective pressurized water reactor reload core design by nondominated genetic algorithm search. Nucl. Sci. Eng. 124 (1), 178–187.
9. Kim, H.G., Chang, S.H., Lee, B.H., 1993. Pressurized water reactor core parameter prediction using an artificial neural network. Nucl. Sci. Eng. 113 (1), 70–76.
10. Lysenko, M.G., Wong, H.-I., Maldonado, G.I., 1999. Neural network and perturbation theory hybrid models for eigenvalue prediction. Nucl. Sci. Eng. 132 (1), 78–89.
11. Jiang, S., Pain, C., et al. Nuclear Reactor Reactivity Prediction Using Feed Forward Artificial Neural Networks. Advances in Neural Networks – ISNN 2008.
12. Jang, H., Shin, H., Lee, H., Refinement of Convolutional Neural Network for Neutronics Design Parameter Prediction of a Loading Pattern. Proceeding of the Reactor Physics Asia 2019 (RPHA19) Conference, Osaka, Japan, Dec. 2-3, 2019.
13. Simonyan, K., Zisserman, A., Very Deep Convolutional Networks for Large-Scale Image Recognition. The 3rd International Conference on Learning Representations. San Diego, CA, ICLR Committee, 2015.
14. Szegedy, C., Liu, W., Jia, Y., et al., Going deeper with convolutions. Proceedings of the IEEE conference on computer vision and pattern recognition. Boston, IEEE Computer Society, 2015, 1-9.
15. He, K., Zhang, X., Ren, S., et al., Deep Residual Learning for Image Recognition. Proceedings of the IEEE conference on computer vision and pattern recognition. Las Vegas, IEEE Computer Society, 2016, 770-778.
16. Brian, M., William, J., Bohnhoff, R., et al., Dakota, A Multilevel Parallel Object Oriented Framework for Design Optimization, Parameter Estimation, Uncertainty Quantification, and Sensitivity Analysis. SAND2021-5822, 2021. Google Inc., TensorFlow2.1.0, https://tensorflow.google.cn/versions/r2.1/api_docs?authuser=0.
17. Ahmad, S.I., Ahmad, N., 2006. Burn-up-dependent core neutronics analysis and calculation of actinides and fission

product inventories in discharged fuel of a material test research reactor. Ann. Nucl. Energy 48, 599–616.

18. Castillo, A. et al., 2007. Fuel loading and control rod patterns optimization in a BWR using tabu search. Ann. Nucl. Energy 34, 207–212.
19. Shaukat, N. et al., 2010. Optimization of core reload pattern for PARR-1 using evolutionary techniques. Nucl. Eng. Des. 240, 2831–2835.
20. Alim, F. et al., 2008. New genetic algorithms (GA) to optimize PWR reactors Part I: loading pattern and burnable poison placement optimization techniques for PWRs. Ann. Nucl. Energy 35, 93–112.
21. Wu, H.C., 2001. Pressurized water reactor reloading optimization using genetic algorithms. Ann. Nucl. Energy 28, 1329–1341.
22. De Oliveira, I.M.S., Schirru, R., 2011. Swarm intelligence of artificial bees applied to in-core fuel management optimization. Ann. Nucl. Energy 38 (2011), 1039– 1045.
23. Aneela Zameer, Muhammad Muneeb, Sikander M. Mirza, Muhammad Asif Zahoor Raja, Fractional-order particle swarm based multi-objective PWR core loading pattern optimization, Annals of Nuclear energy, Volume 135, 2020, 106982, ISSN 0306-4549, https://doi.org/10.1016/j.anucene.2019.106982.
24. Yadav, R.D.S., Gupta, H.P., 2011. Optimization studies of fuel loading pattern for a typical pressurized water reactor (PWR) using particle swarm method. Ann. Nucl. Energy 38, 2086–2095.
25. Ammar, A., Ahmad, S.I., 2018. Optimization of fuel loading pattern for a material test reactor using swarm intelligence. Prog. Nucl. Energy 103, 45–50.
26. Fadaei, A.H., Setayeshi, S., 2008. LONSA as a tool for loading pattern optimization for VVER-1000 using synergy of a neural network and simulated annealing. Ann. Nucl. Energy 35 (10), 1968–1973.
27. Lin, C., Lin, B.F., 2012. Automatic pressurized water reactor loading pattern design using ant colony algorithms. Ann. Nucl. Energy 43, 91–98.
28. Faria, E.F., Pereira, C., 2003. Nuclear fuel loading pattern optimization using a neural network. Ann. Nucl. Energy 30, 603–613.
29. Ortiz, J.J., Requena, R., 2004. Using a multi-state recurrent neural network to optimize loading patterns in BWRs. Ann. Nucl. Energy 31, 789–803.
30. Ammar, A., Ahmad, S.I., 2018. Optimization of fuel loading pattern for a material test reactor using swarm intelligence. Prog. Nucl. Energy 103, 45–50.
31. Zhang, L. et al., 2013. A Catfish Effect Inspired Harmony Search Algorithm for Optimization. Int. J. Non-linear Sci. Numer. Simul. 14 (6), 413–422.
32. Chol So, Il-Mun Ho, Jong-Suk Chae, Kwang-Hak Hong, PWR core loading pattern optimization with adaptive genetic algorithm, Annals of Nuclear Energy, Volume 159, 2021, 108331, ISSN 0306-4549, https://doi.org/10.1016/j.anucene.2021.108331.
33. F. Khoshahval, H. Minuchehr, A. Zolfaghari, Performance evaluation of PSO and GA in PWR core loading pattern optimization, Nuclear Engineering and Design, Volume 241, Issue 3, 2011, Pages 799-808, ISSN 0029-5493, https://doi.org/10.1016/j.nucengdes.2010.12.023.
34. Satomi Ishiguro, Tomohiro Endo & Akio Yamamoto (2020) Loading pattern optimization for a PWR using Multi-Swarm Moth Flame Optimization Method with Predator, Journal of Nuclear Science and Technology, 57:5, 523-536, https://doi.org/10.1080/00223131.2019.1700844.
35. Sajjad Shams, Hossein Azgomi, Ali Asghari, Fuel assemblies loading pattern optimization of pressurized water reactors using the trees social relations algorithm, Annals of Nuclear Energy, Volume 192, 2023, 109963, ISSN 0306-4549, https://doi.org/10.1016/j.anucene.2023.109963.
36. Amila Amatullah, Alexander Agung and Agus Arif, “Minimizing Power Peaking Factor of BEAVRS-based Reactor Using Polar Bear Optimization Algorithms”, 2021 IOP Conf. Ser.: Earth Environ. Sci. 927 012004, https://doi.org/10.1088/1755-1315/927/1/012004
37. Nadeem Shaukat, Ammar Ahmad, Bukhtiar Mohsin, Rustam Khan, Salah Ud-Din Khan, Shahab Ud-Din Khan, "Multiobjective Core Reloading Pattern Optimization of PARR-1 Using Modified Genetic Algorithm Coupled with Monte Carlo Methods", Science and Technology of Nuclear Installations, vol. 2021, Article ID 1802492, 13 pages, 2021. https://doi.org/10.1155/2021/1802492
38. Ahmad Ammar, Siraj-ul-Islam Ahmad, Teaching-learning based optimization algorithm for core reload pattern optimization of a research reactor, Annals of Nuclear Energy, Volume 133, 2019, Pages 169-177, ISSN 0306-4549, https://doi.org/10.1016/j.anucene.2019.05.025.
39. Ali, A., et al., Validation of DRAGON5 and DONJON5 computer codes with CNPGS Unit-3 cycle-1 design calculations. Progress in Nuclear Energy, 2023. 159: p. 104655.
40. Rao, R.V. et al., 2011. Teaching-learning-based optimization: A novel method for constrained mechanical design optimization problems. Comput. Aided Des. 43 (3), 303–315.
41. Rao, R.V., Patel, V., 2013. An improved teaching-learning-based optimization algorithm for solving unconstrained optimization problems. Sharif Univ. Technol., Sci. Iranica Trans. D: Comput. Sci. Eng. Electr. Eng. 20 (3), 710–720.
42. Rao, R.V., Savsani, V. J., 2012. An elitist teaching-learning-based optimization algorithm for solving complex constrained optimization problems. Int. J. Ind. Eng. Computations 3, 535–560.
43. Roy, R. and A. Hébert, The GAN generalized driver. Report IGE–158, Institut de génie nucléaire, Ecole Polytechnique de Montréal, Montréal, Québec, 2000.
44. Hébert, A., D. Sekki, and R. Chambon, A user guide for DONJON version4. École Polytechnique de Montréal Montréal QC, Canada, Tech. Rep. IGE-300, 2013.