Progress in Nuclear Energy 122 (2020) 103271

Contents lists available at ScienceDirect

Progress in Nuclear Energy

journal homepage: http://www.elsevier.com/locate/pnucene

Small modular reactor full scope core optimization using Cuckoo Optimization Algorithm

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ARTICLE INFO

Keywords:
Small modular reactor
Neutronic calculation
Thermal-hydraulic calculation
Cuckoo Optimization Algorithm

ABSTRACT

Small Modular Reactors (SMRs) with their excellent safety and economic features will be in high demand in the near future. Most SMR designs have longer burn-up cycle length with more fuel enrichment and smaller core size in comparison to the large conventional nuclear reactors. The small size of these reactors causes more neutron leakage (less core radius results in a higher area to volume ratio and more relative leakage). This feature of SMRs causes high values of maximum Power Peaking Factors (PPFs) through the core, so optimizing the safety parameters is of high necessity. Also, long burn-up cycle length needs a high initial excess reactivity, which results into use of some materials and methods to control this high excess reactivity. One of these methods is using a high number of Integral Fuel Burnable Absorber (IFBA) rods.In the present designs of IFBA rods, usually some amounts of fuel with lower enrichment are used at the top and bottom parts of the IFBA rods (known as cutback fuel) to flatten the axial PPFs. The small size of the SMRs (using a lower number of FAs) helps to have much less possible radial loading patterns (in comparison to the large reactors) and provides the possibility to optimize the axial variations in amounts of cutback fuel in IFBA rods simultaneously. Accordingly, the best axial and radial loading pattern according to the objective functions could be achieved. At the present work, the main goal is to optimize radial core loading pattern and axial variations of cutback fuel lengths at the IFBA rods of an SMR simultaneously using a multi-objective neutronic and thermal-hydraulic fitness function. The multi-objective fitness function includes burn-up cycle length, Minimum Departure from Nucleate Boiling (MDNBR), maximum and average radial and axial PPFs during the entire cycle lengths. The Cuckoo Optimization Algorithm (COA) as a new robust metaheuristic algorithm with high convergence speed and global optima achievement has been used. For the thermo-neutronic calculation, DRPACO package consists of the coupling system of DRAGON/PARCS/COBRA codes have been used. Finally, the results of SMR core axial and radial loading pattern optimization using COA presents a core configuration with improvement in the core safety and economic parameters in comparison to the reference SMR core.

1. Introduction

Optimization of nuclear reactor different parameters is necessary to achieve economically competitive and safe nuclear power plants. Small Modular Reactors (SMRs) with their excellent safety and economic aspects have received extensive positive attention recently. Low capital cost, high safety features, water desalination, heat and electricity cogeneration and the possibility to be built modular and being transported to the remote off-grid areas, are the incentives behind SMRs growing demand in near future (IAEA, 2018).

Researchers and nuclear engineers are trying to evaluate, improve and optimize various aspects of SMR designs; Peakman et al. (2019) have presented a core design of a Small Modular Pressurized Water Reactor for commercial marine propulsion. Akbari et al. (2019) have evaluated the neutronic parameters of SMART core. Li et al. (2019) have performed a safety analysis of a small modular reactor using fully ceramic microencapsulated fuel. Akbari-Jeyhouni et al., 2018a have assessed an integral small modular reactor during rod ejection accident by using DRAGON/PARCS codes also, Alam et al. (2019) have designed SMR core for civil marine propulsion using micro-heterogeneous duplex fuel. Uguru et al. (2020) and Akbari-Jeyhouni et al. (2018b) have investigated the use of Thorium fuel as an alternative fuel option for

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https://doi.org/10.1016/j.pnucene.2020.103271
Received 25 August 2019; Received in revised form 30 December 2019; Accepted 5 February 2020
Available online 13 February 2020

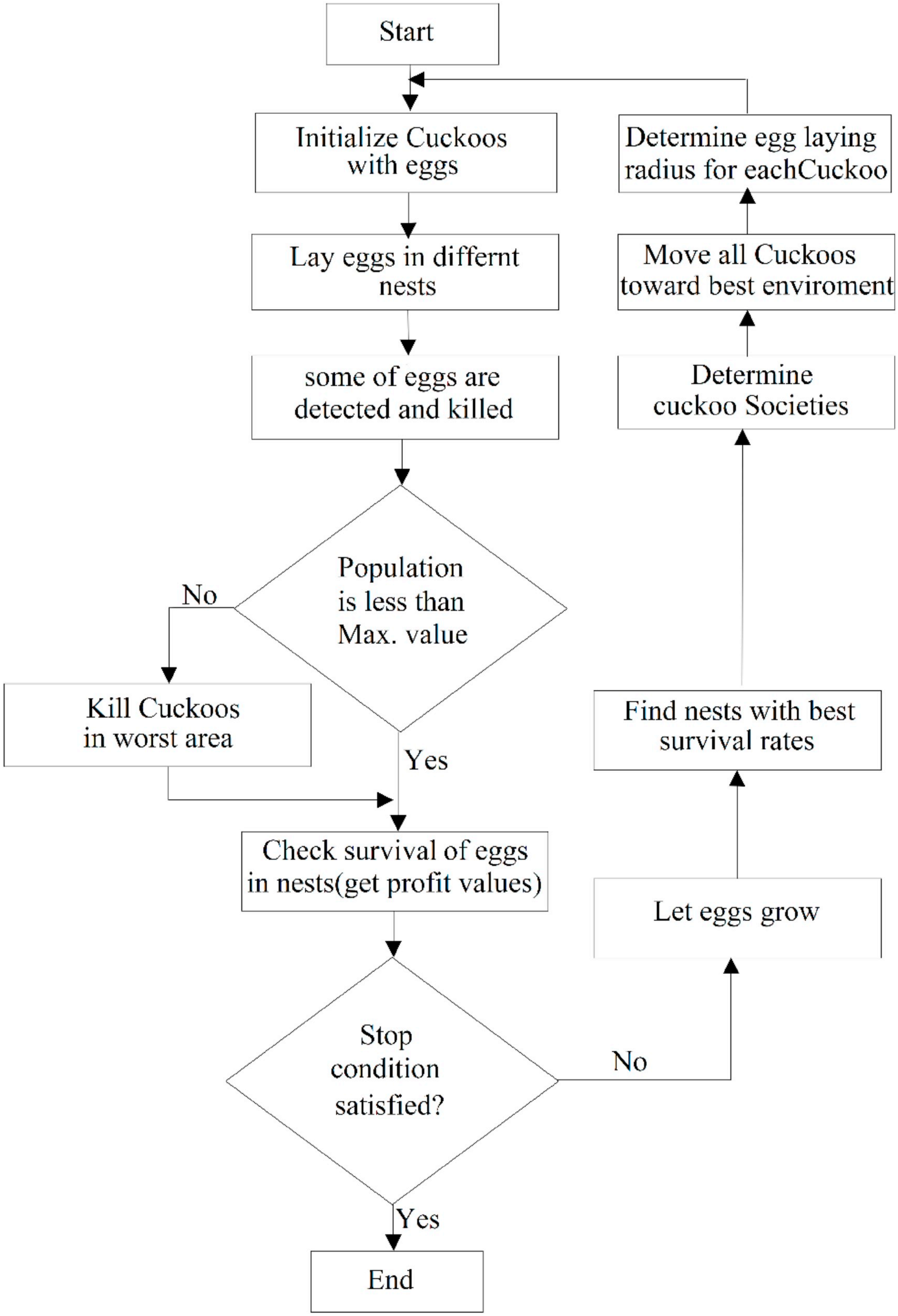

Fig. 1. COA Flowchart.

SMRs. In the present work, the core loading pattern of SMART reactor (as the first certified Integral SMR) has been optimized (IAEA, 2018).

The nuclear reactor cores can use numerous possible patterns for fuel Assemblies (FAs), burnable poisons and control rods that categorize this problem as a high complex NP-Hard combinatorial type problem. In the past decade, nuclear engineers have tried to solve and reduce the complexity of this problem using metaheuristic optimization algorithms. Akbari et al. (2018) have used the imperialist competitive algorithm for fuel loading pattern of a VVER-1000. Ahmad (2018) implemented the swarm intelligence algorithm for a material test reactor and also Hou et al. (2016) have presented 3D in-core fuel management optimization for breed-and-burn reactors using the simulated annealing algorithm. Mahmoudi and Aghaie (2019) have used Gravitational Search Algorithm. Meneses and Schirru (2015) have applied a cross-entropy method to the in-core fuel management of a PWR. Augusto et al. (2015) have used a combination of Particle Swarm Algorithm with Dynamic Topology for nuclear reactor reload optimization. Rahmani (2017) has implemented the Genetic algorithm in a transient cycle of a VVER-1000. Also, Nasr et al. (2019) have applied the Polar Bear Algorithm for the VVER-1000 core loading pattern optimization.

In the present work, the Cuckoo Optimization Algorithm (COA) as a robust metaheuristic algorithm with high convergence speed and global optima achievement have been used (Rajabioun, 2011). The COA has been widely used in different scientific areas recently. Kia and Hassanzadeh (2019) have used COA for finding a new hybrid routing protocol for low power Wireless Sensor Networks. Aranizadeh et al. (2019) present a novel optimal distributed generation planning in distribution network using COA. Sangaiah et al. (2019) utilized robust optimization and mixed-integer linear programming model for LNG supply chain planning problem. Hosseininejad and Dadkhah (2019) have presented mobile robot path planning in dynamic environment based on COA. Mohammadrezapour et al. (2019) have used COA optimal water allocation and crop planning under various weather conditions. Akbari and Rashidi (2016) have used COA for task allocation problem at compile time in heterogeneous systems, and Tavana et al. (2018) have used a discrete COA for consolidation in cloud computing; but in this study, the COA has been used for nuclear reactor core optimization.

Usually a wide range of core parameters are considered as reactor core optimization objectives such as: Power Peaking factors (PPFs), K_{eff}, burn-up cycle length, boron concentration, fuel centerline temperature, critical heat flux, coolant reactivity feedback, hot channel factor, economic of fuel cycle, the desirable flux in irradiation box for research reactors and etc. Some of the most recently used objectives are as follows. Mahmoudi and Aghaie (2019) have used burn-up cycle length, K_{eff} and PPF. Lin et al. (2017) have used particle swarm algorithm to search for a power ascension path of boiling water reactors. In the present study besides the neutronic parameter such as K_{eff}, PPFs and cycle burn-up length; thermal-hydraulic parameters including Minimum Departure from Nucleate Boiling (MDNBR), fuel rod centerline temperature and clad temperature have been considered simultaneously as the optimization objectives. For the thermo-neutronic calculations, a coupling system of DRAGON, PARCS, and COBRA codes (DRPACO package including deterministic codes for neuronic cell calculations, neutronic core calculations and thermal-hydraulic calculations) have been used (Marleau et al., 2016; Downar et al., 2006; Basile et al., 1999; Noori-Kalkhoran et al., 2014).

Most of the pressurized water SMR designs such as SMART (SMART Report, 2012; SMART SSAR, 2010), NuScale (NuScale FSAR, 2018) and MASLWR (Soldatov and Palmer, 2011) have used Integral Fuel Burnable Absorber (IFBA) rods with enrichment variations of U-235 in the axial direction. In the present work, calculations have been performed in such a way to reach the optimum state by changing the axial position of the fuel and burnable poison in IFBA rods (without any change in the amount of the fuel or the burnable absorber), simultaneously with radial pattern changing of the FAs through the core. These axial changes in the position of the fuel and burnable absorber in IFBAs, help to flatten the axial PPFs and improve the safety parameters of the core.

2. Cuckoo Optimization Algorithm

Ramin Rajabioun (2011) has developed COA according to the behavior of the cuckoo bird. Cuckoo is a member of brood parasite birds that lay their eggs on the other birds' nests and never build their own nests. This bird is the best known as the best brood parasite. They remove one of the host's eggs and replace it with their own egg very fast (less than 10 s). They carefully mimic the hosts' egg pattern and color,

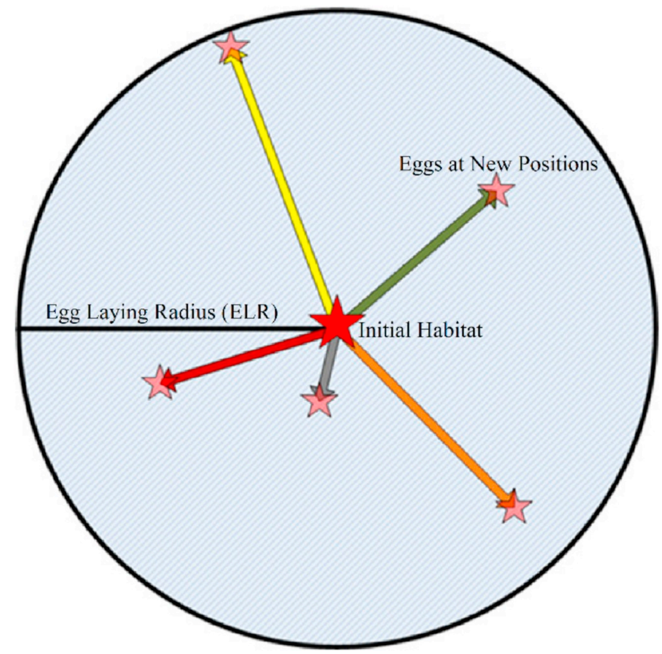

Fig. 2. Egg-laying Radius (ELR) of cuckoos.

that host parents couldn't be able to recognize cuckoo's egg. It has been proved that each group of cuckoos specialize on one particular bird species. As the time passes, some hosts may recognize the cuckoo's egg, but also cuckoos continuously improve their ability to mimic the host eggs.

2.1. Optimization algorithm according to the cuckoo lifestyle

The COA flowchart is shown in Fig. 1. In the beginning, cuckoos will have an initial population (similar to the other evolutionary methods). Each of these cuckoos lay some eggs in some hosts' nests. Only some of these eggs will survive and become a grown cuckoo. The summation of these grown cuckoos shows the nests suitability in each area. This suitability shows the profit of that area, and this position is the term that will be optimized.

The survived cuckoo eggs will grow up and create some group and societies. Each group has a habitat, and all groups choose the best habitat as their destination and are going to inhabit in somewhere adjacent to their destination. They have some deviation from their exact destination and each cuckoo according to the eggs that it has and also its distance to the destination, has an egg-laying radius. Then each cuckoo lays eggs in its egg-laying radius again. The procedure of immigration to the best habitat and laying eggs in the egg-laying radius of each cuckoo continues to the time that most of the population gathered around the same position with maximum suitability (profit value).

2.2. Producing initial habitat for cuckoos and egg-laying approach

Like any other optimization problem, the problem variable values should be formed as an array. In COA, "habitat" is the name of this array. In a problem with some variables (N_{var}), a habitat forms an $1 \times N_{var}$ array:

$$habitat = [x_1, x_2, \dots, x_{N_{var}}] \quad (1)$$

The suitability of each habitat is obtained by assessing the profit function (f_p) in that habitat:

$$suitability(or \ \ profit) = f_p(habitat) = f_p(x_1, x_2, \dots, x_{N_{var}}) \quad (2)$$

For objective function according to the problem, if decreases are

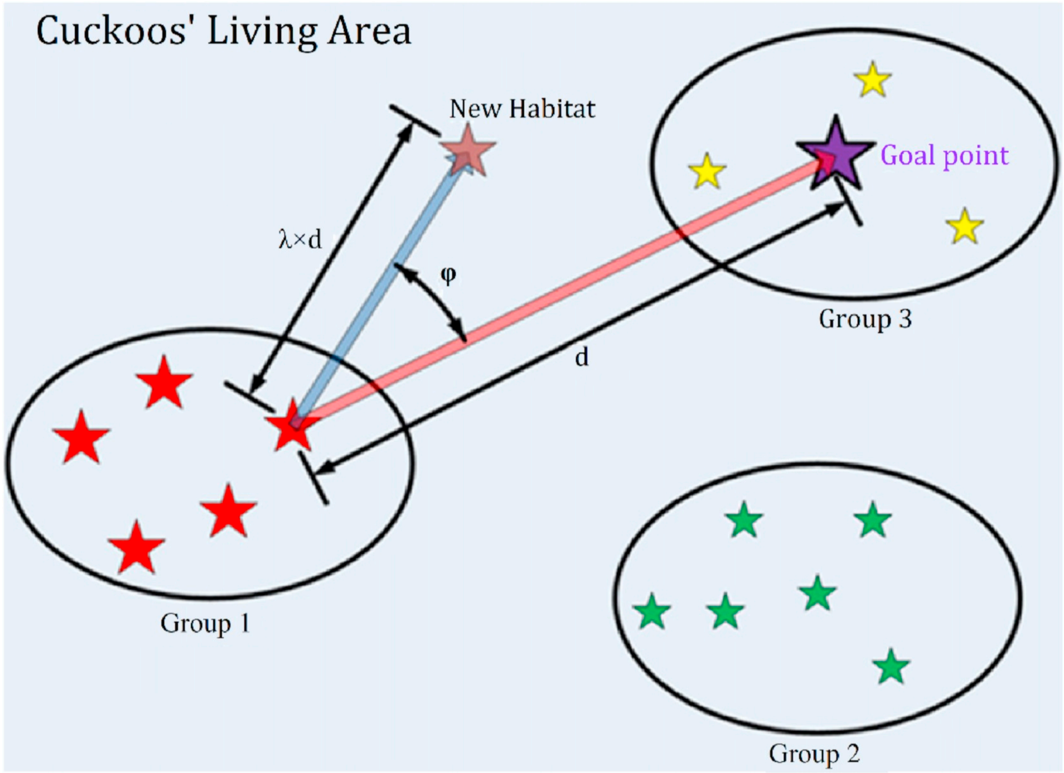

Fig. 3. Cuckoo immigration process.

desirable it called cost function and if increases are desirable it called fitness or profit function. The COA maximizes the profit function, for a minimization problem, where Eq. (3) can be easily used and maximized:

$$profit = -\cos t = -f_c(x_1, x_2, \dots, x_{N_{\mathrm{var}}}) \tag{3}$$

To initialize an optimization problem, habitat matrix with $N_{pop} \times N_{\mathrm{var}}$ size (N_{pop} = Cuckoo population) is allocated and a random number of eggs (according to the nature, each cuckoo put 5 to 20 eggs in other birds' nests) is dedicated to each habitat. Also, according to the nature of cuckoos, each cuckoo lays its eggs within a maximum range from its habitat that is called Egg-laying Radius (ELR):

$$ELR = \alpha \times \frac{\text{Number of current cuckoo's eggs}}{\text{Total number of eggs}} \times (\mathrm{var}_{hi} - \mathrm{var}_{low}) \tag{4}$$

where var_{hi} and var_{low} are the upper and lower limits of the variables and α is an integer number to control the ELR maximum value.

Fig. 2 shows the ELR concept for cuckoos. After egg-laying, p% of the eggs will be thrown out by the host of the nests (usually 10% of eggs with less profit values).

2.3. Immigration and elimination of cuckoos to the convergence point

After hatching out of survived eggs, the cuckoo chicks grow up and become a mature cuckoo and for sometimes will live in that habitat but, at the time of egg-laying, they will immigrate to the habitats with the best similarity to their eggs and more foods. After the formation of different groups of cuckoos, the area with the best profit value will be the goal point of other groups' immigration. As shown in Fig. 3, during

General algorithm →	Cuckoo optimization algorithm
Decision variable →	Cuckoo habitat
Solution →	Habitat
Old solution →	Old habitat
New solution →	New habitat
Best solution →	Habitat with best rate of life
Fitness function →	Distance between best habitat and recent habitat
Initial solution →	Random eggs for all cuckoos
Selection	---------
Process of generating new solution:	Emigration cuckoos toward best area

Fig. 4. Characteristics of COA.

Table 1
Main core parameters of SMART reactor.

Parameter	Value
Reactor thermal output (MWth)	330
Power plant output, gross (MWe)	100
Mode of operation	Load follow
Non-electric applications	Desalination, District heat
Lattice geometry	Square
Equivalent core diameter (m)	1.8316
Average fuel power density (kW/kgU)	23.079
Average core power density (MW/m3)	62.62
Average discharge burnup of fuel (MWd/kg)	36.1
Fuel cycle length (Months)	36
Primary coolant flow rate (kg/s)	2090
Reactor operating pressure (MPa)	15
Core coolant inlet temperature (°C)	295.7

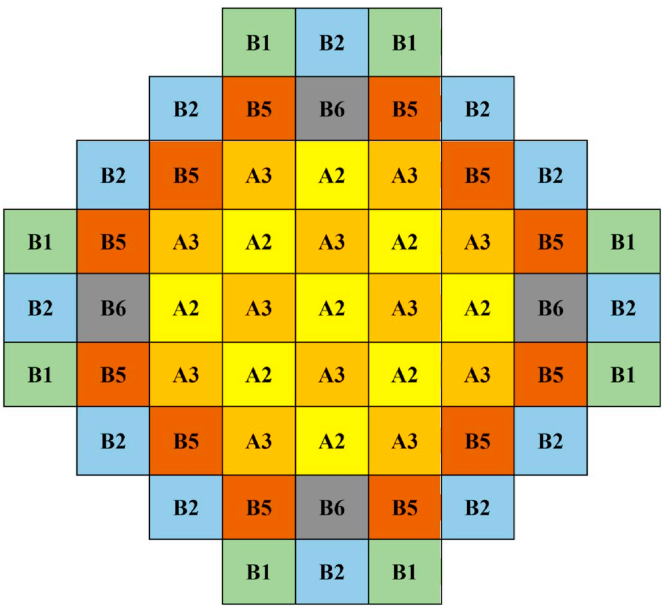

Fig. 5. Core configuration of SMART.

the migration toward the goal point, cuckoos don't fly all the path and have some deviations. They immigrate λ% of the goal point distance and have ϕ radians deviation. λ% is a random number between 0 and 1, also ϕ is a random angle from $-\pi/6$ to $\pi/6$. These two parameters help cuckoos to search much more areas in the environment.

After immigration, some eggs are dedicated to each cuckoo, and an egg-laying process in ELR starts again. The elimination process, due to the fact that in nature there is a population balance, will eliminate the cuckoos in habitat with lower profit (inspired by killing cuckoos by predators or lack of food in some habitats). N_{max} Controls the maximum population of live cuckoos, so the cuckoos in habitats with higher profit will survive.

After some iteration in the cuckoo lifecycle, the 95% convergence of all cuckoos to the identical habitat will end the COA. Finally, the general characteristics of the COA have been shown in Fig. 4.

3. Material and method

3.1. Selected SMR case description

System-integrated **M**odular **A**dvanced **R**eac**t**or, SMART, has been developed by Korea atomic energy research institute. This reactor received the design license in 2012 with 365 MW thermal and 107 MW electrical rated power meeting the demands of a community with a population of about 100,000. SMART as the first certified Integral SMR with enhanced safety and reliability features and capabilities such as electricity and heat co-generation, load follow mode of operation and water desalination, has been introduced as a pioneer SMR. Table 1 presents the general characteristics of SMART core design (IAEA, 2018; SMART Report, 2012; SMART SSAR, 2010).

Table 2
Description of the SMART FAs content.

Assembly type	No. of Assemblies	Normal fuel enrichment (w/o U-235)	No. of normal fuel rods per assembly	No. of Gd fuel rods per assembly	Gd content (w/o Gd_2O_3)
A2	9	2.82	256	8	8.0
A3	12		252	12	8.0
B1	8	4.88	260	4	8.0
B2	12		256	8	8.0
B5	12		244	20	8.0
B6	4		240	24	8.0

Table 3
Specifications of the SMART core components.

Parameter	Value
Active core height (cm)	200.0
Assembly pitch (cm)	21.504
Pin pitch (cm)	1.2598
UO_2 Fuel	
Pellet radius (cm)	0.4096
Material	UO_2
Stack height density (g/cm^3)	10.286
UO_2+Gd_2O_3 Fuel	
Pellet radius (cm)	0.4096
Material	UO_2+Gd_2O_3
Stack height density (g/cm^3)	10.017
Fuel clad	
Inner radius (cm)	0.41875
Outer radius (cm)	0.47500
Material	Zircaloy-2/4
Density (g/cm^3)	6.56
Guide and instrumentation tube	
Inner radius (cm)	0.56150
Outer radius (cm)	0.61200
Material	Zircaloy-2/4
Density (g/cm^3)	6.56
Control rod absorber	
Radius (cm)	0.43305
Material	Ag–In–Cd
Density (g/cm^3)	10.17
Control rod clad	
Inner radius (cm)	0.43690
Outer Radius (cm)	0.48385
Material	SS-304
Density (g/cm^3)	7.9

The SMART core consists of 57 FAs with 17 × 17 fuel rod configuration. As shown in Fig. 5, the SMART 2 batch core, contains central region FAs with 2.82% enrichment and outer region FAs with 4.88% enrichment. The number of each type of FA and FAs' identification (according to Fig. 5), Gd_2O_3 concentration in each IFBA rod, the number of IFBA rods in each FA and also the number of standard fuel pin per each FA have been presented in Table 2.

Table 3 presents the material and dimensional specifications of fuel rods, IFBA rods, guide and instrumentation tubes, and control rods. Different numbers of IFBA rods with various arrangements have been placed in each FA. The arrangements of the IFBA rods, instrumentation thimble, and guide tubes in each type of FA, is shown in Fig. 6. The arrangements of IFBA rods through each FA, help core designers to flatten the radial PPFs and burn the fuel burn more uniformly during the core cycle.

IFBA rods contain (UO_2+Gd_2O_3) with different enrichments of U-235

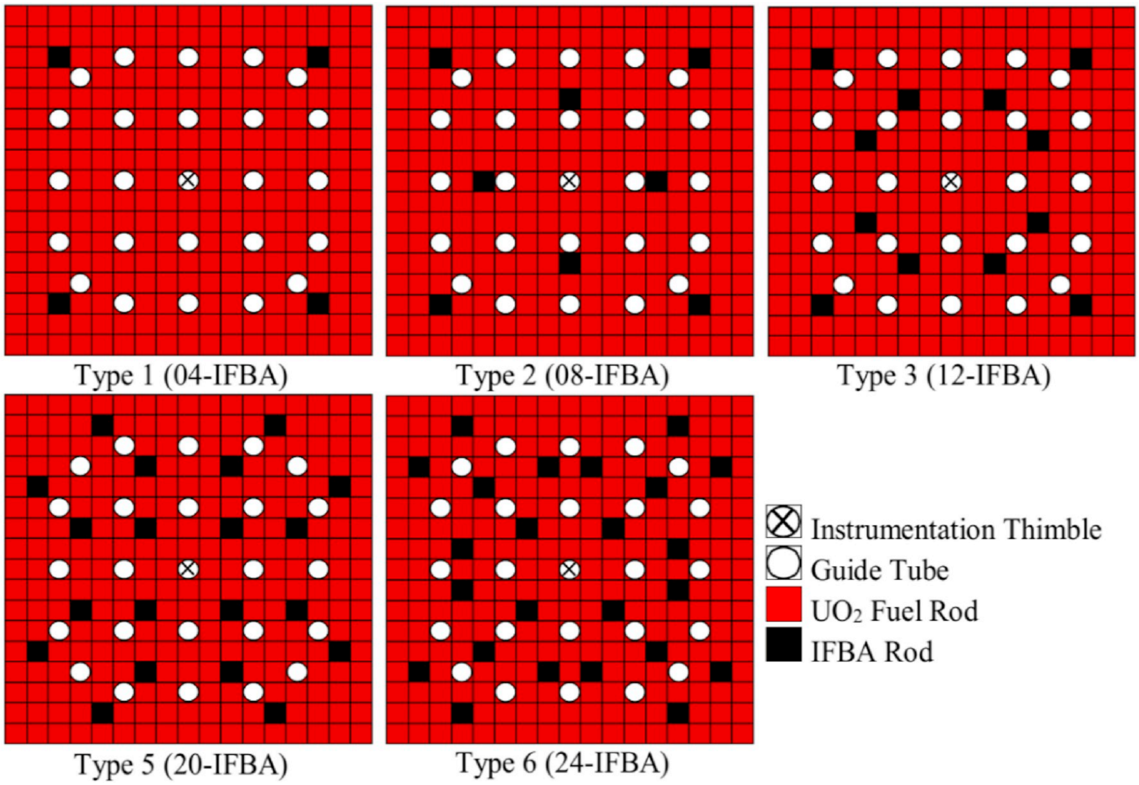

Fig. 6. Different arrangements of IFBA rods in SMART FAs.

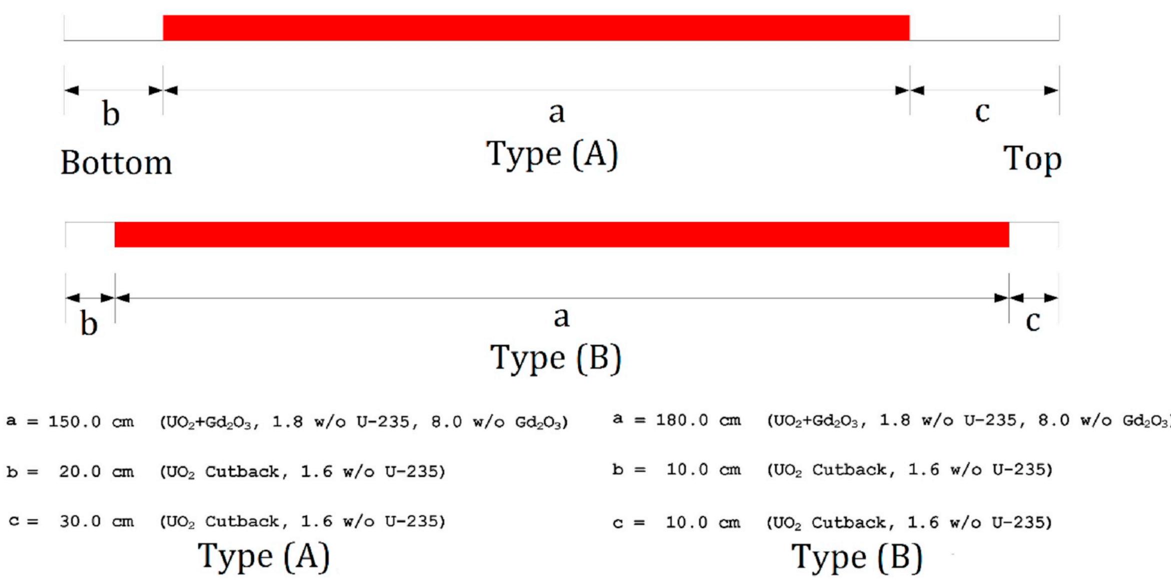

Fig. 7. Cutback fuel and UO_2+Gd_2O_3 in IFBA rods.

in comparison with standard fuel rods. In each IFBA rod of SMART core, fuel with 1.6% and 1.8% U-235 has been used where enrichment changes in the axial direction according to the type of IFBA rods. As shown in Fig. 7, cutback fuel with 1.6 w/o U-235 has been used at the bottom and top sections of each IFBA rod, while the mixture of fuel (1.8 w/o U-235) with Gd_2O_3 burnable absorber is located in the middle section of IFBA rod. In the SMART core, two types of IFBA rods with different length of cutback fuel and UO_2+Gd_2O_3 have been used to enable designers to flatten the axial PPFs (SMART Report, 2012; SMART SSAR, 2010).

3.2. Thermo-neutronic calculation procedure

In this study, thermo-neutronic calculations have been performed by DRPACO package developed by using a coupling system between DRAGON, PARCS, and COBRA-EN deterministic codes (Akbari-Jeyhouni et al., 2018a; Akbari-Jeyhouni et al., 2018b). The coupling algorithm flowchart, as shown in Fig. 8 includes:

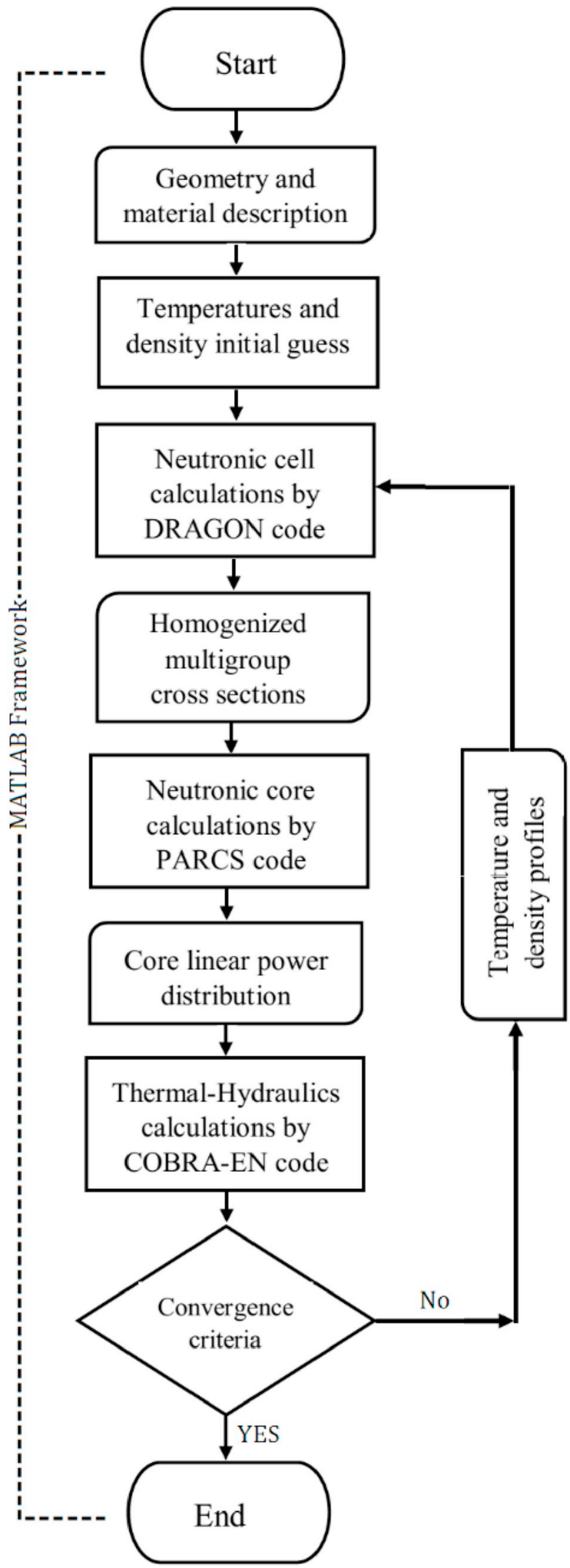

Fig. 8. Flow chart of the calculation procedure.

1. In the first step, all the geometry and material data required for DRAGON, PARCS, and COBRA-EN codes have been provided, and input decks for these codes are prepared.
2. In the second step, an initial guess for the fuel and clad temperature profiles and also coolant temperature and density profiles must be made. For example, the initial guess can be the inlet density and temperature of the coolant, values presented by expertise or any other reasonable values (the initial guess must not be too much out of range, because it is possible that the codes do not run correctly and send an error message).
3. The temperature and density profiles will be inserted into the DRAGON input deck for each determined mesh, and this cell calculation code will run. The SMART core has 57 fuel assemblies with 1/8th symmetry (Fig. 5), so there are 11 unique fuel assembly positions.
4. The homogenized multi-group macroscopic cross sections produced by cell calculations for all meshes and reflectors are read from the DRAGON code output and fed to the cross section block of the PARCS input deck by MATLAB software.
5. In this step, the PARCS executable code is called, and the core neutronic calculations are performed.
6. The radial and axial PPFs for each mesh are extracted from the PARCS code output, given a SMART core power of 330 MWth (Table 1), the linear power distribution is calculated as in Eq. (5):

$$P'_m = \frac{P_t \times PPF_{m,Rdial} \times PPF_{m,Axial}}{N_m \times N(FA) \times L_m} \tag{5}$$

where P'_m is the linear power for each mesh, P_t is SMART core total thermal power, $PPF_{m,Rdial}$ and $PPF_{m,Axial}$ are radial and axial PPF for each mesh, N_m and $N(FA)$ are the total number of meshes and fuel assemblies and L_m is the length of each axial mesh (Vahman et al., 2016; Hosseini et al., 2020).

The linear power for all meshes are calculated according to Eq. (5), and mapped to the corresponding mesh in the COBRA-EN input deck.

7. The COBRA-EN executable code is called, and the core thermal-hydraulic calculations are performed.
8. The convergence criteria will be activated after the second iteration and is based on power in each mesh for each iteration that is given by Eqs. (6) and (7):

$$\delta_m^i = \left| \frac{P_m^i - P_m^{i-1}}{P_m^{i-1}} \right| \tag{6}$$

where P_m^i and P_m^{i-1} are the power of mesh number m in iteration number i and $i-1$ respectively,

$$\delta_{\max}^i = \max\{\delta_1^i, \delta_2^i, \ldots, \delta_M^i\} \tag{7}$$

After checking the convergence criteria, if the iteration is converged, the coupling will be finished; otherwise, the temperature and density profiles will be read from COBRA-EN output and fed to DRAGON input again. The iteration will be continued up to the time that coupling procedure is converged according to Eq. (7). Also, DRPACO has a capability to perform burn-up calculations with the same algorithm but with the difference that the DRAGON code generates required cross sections for each time step and also criticality is checked according to the boric acid concentration during the cycle. COBRA-EN, PARCS, and DRAGON codes have been validated for the calculation of several reactor core parameters in different types of reactors (Marleau et al., 2016; Downar et al., 2006; Basile et al., 1999).

3.3. Mapping of SMART core on COA

The main objective of the present work is to optimize the core loading pattern of SMART reactor using COA. In the COA, each loading

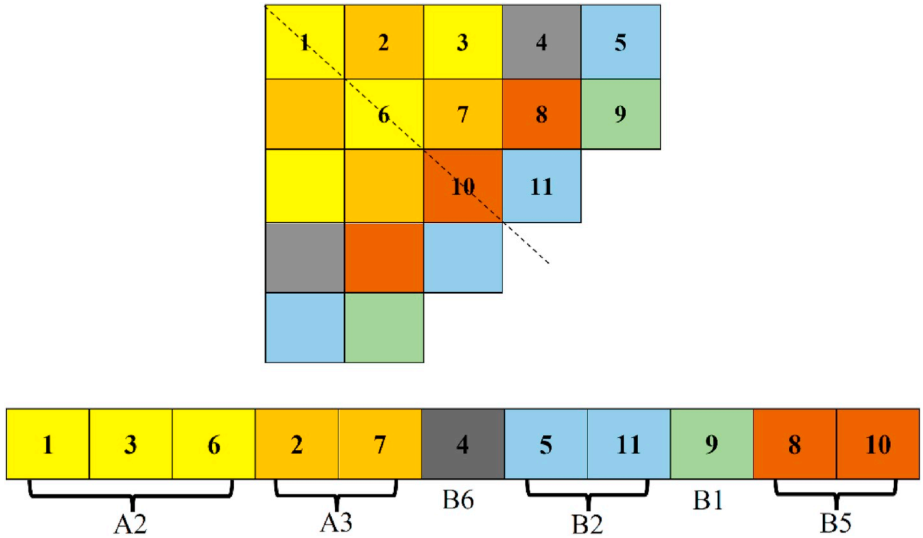

Fig. 9. Radial array of non-identical FA positions in smart.

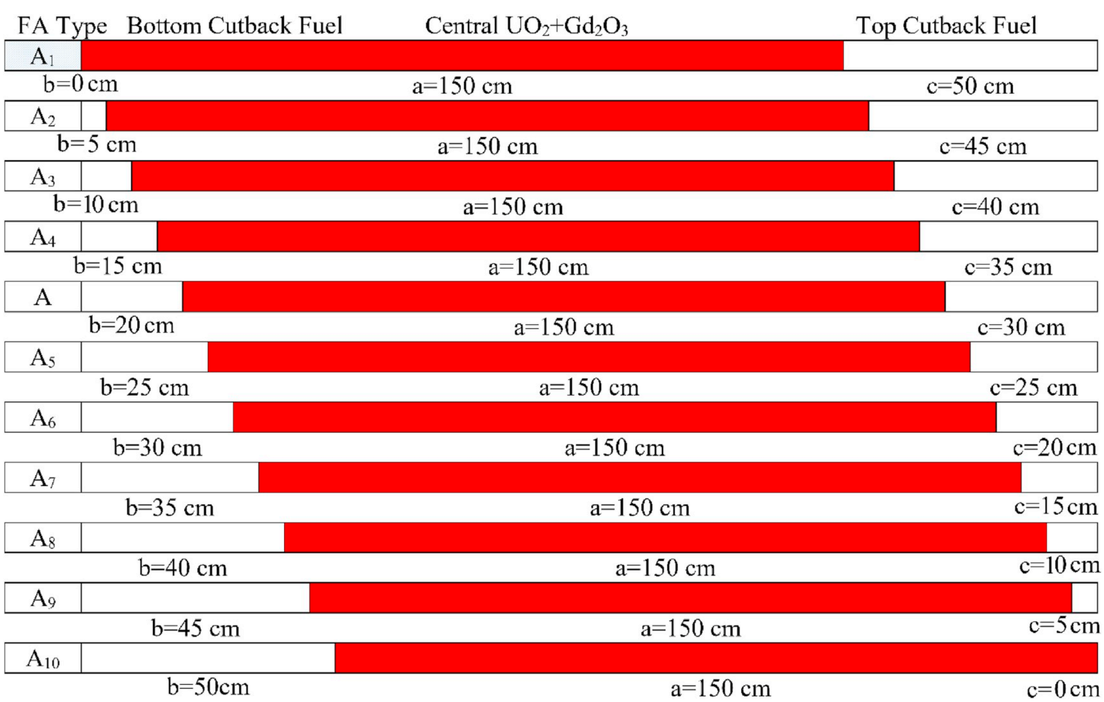

Fig. 10. The possible axial Arrangements of cutback fuel in type A FAs.

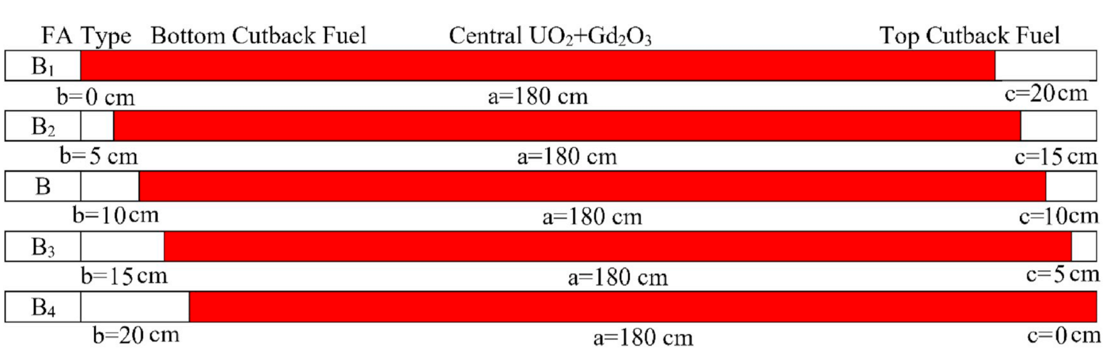

Fig. 11. The possible axial Arrangements of cutback fuel in type B FAs.

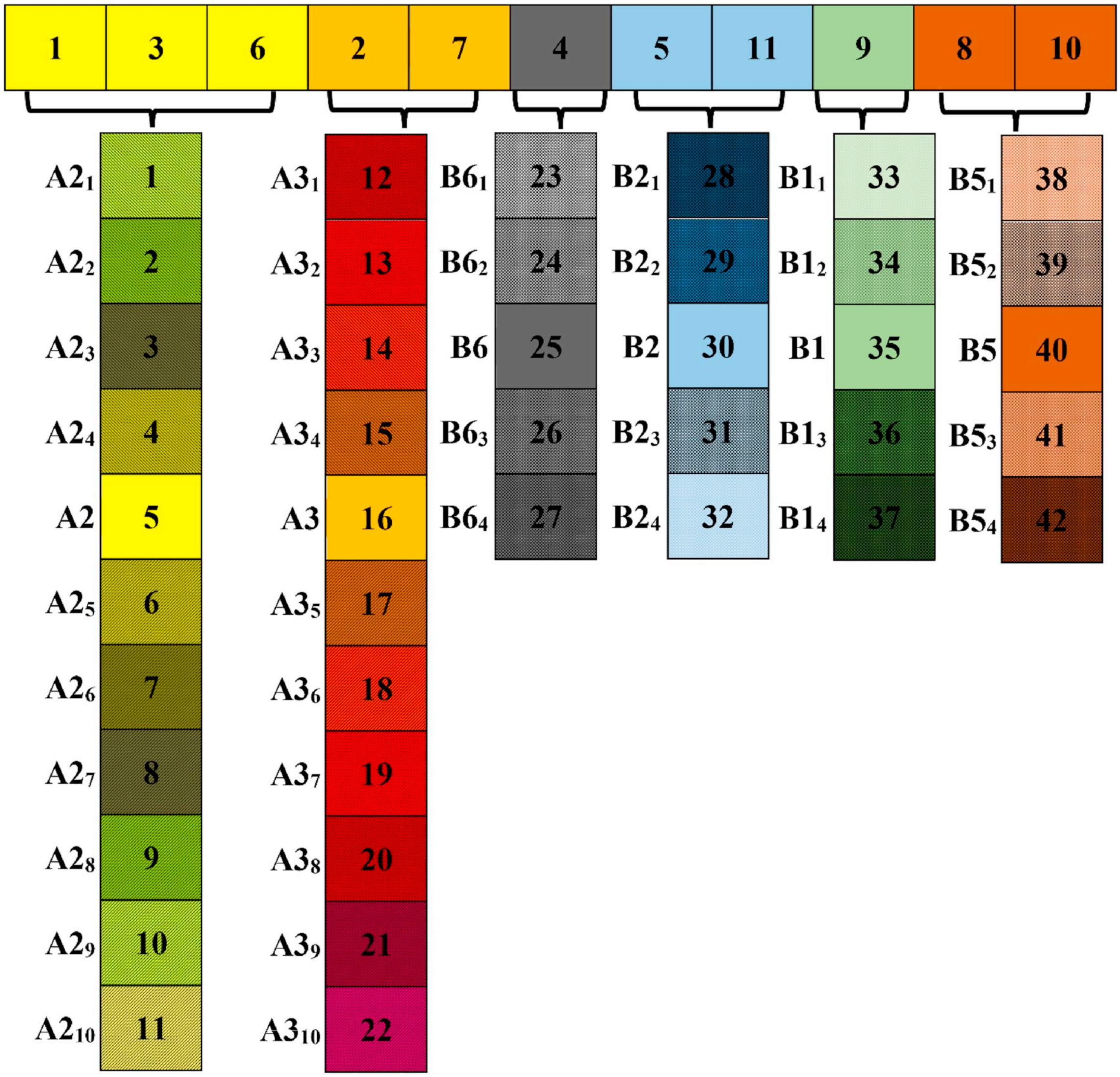

Fig. 12. The combination of radial and axial mapping of FAs as an array for COA.

pattern of reactor core could be considered as a habitat which by moving cuckoos toward the best habitat during their egg-laying and migration, the SMART core gets closer to the best core loading pattern according to the cost function. 57 FAs of SMART core with 1/8th symmetry, have 11 non-identical FA positions, that reduce the computational cost, only these non-identical FA positions have been considered in COA. According to these 11 unique positions, each loading pattern of SMART core as habitat have been allocated to a vector. The radial mapping of core in COA as an array is shown in Fig. 9. From the core design view, it is important to keep the two batch configurations of the SMART core, so in the shuffling process of FAs, this constraint has been taken into account. Thus the A-type FAs with 2.82% enrichment and the B-type FAs with 4.84% enrichment, are just placed in the central and outer region of the core, respectively.

Using cutback fuel at the top and bottom of the IFBA rods reduces the axial PPF, and also could minimize the effects of the residual burnable absorber. Most of the SMR designs have used cutback fuels at the top and bottom of the IFBA rods. In the present study, different lengths of cutback fuel at the bottom and the top of the IFBA rods have also been considered to reduce the axial PPF. In SMART design, at the top and bottom of the IFBA rods for type A and B FAs, there exist 50 cm and 20 cm cutback fuels respectively. According to Fig. 10, for the type A FAs (including A2 and A3 type FAs), besides the standard IFBA rod design, another ten axial arrangements have been considered in the COA process. Also, as shown in Fig. 11, in addition to the standard IFBA rod design of type B (including B1, B2, B5, and B6 FAs), another four axial arrangement have been considered. It should be mentioned that in this arrangement, there isn't any change in the amount of the cutback fuel and UO_2+Gd_2O_3 in comparison to the standard core design. All of these axial arrangements in combination with a radial mapping of FAs have been introduced to the COA as a discretized array, which is shown in Fig. 12.

3.4. Fitness function

During the COA calculations, the most important criteria to find the best habitat is to define a proper cost function according to the problem characteristics. For the core loading pattern of nuclear reactors, setting proper objectives to reach the best possible safe and economically competitive core is necessary. In this study, the multi-objective fitness function includes both neutronic and thermal-hydraulic parameters. This fitness function has been defined in a way to cover burn-up cycle length, axial and radial PPFs, and DNBR as the representatives for the economic and safety aspects of the reactor core. The fitness function is presented in Eq. (8):

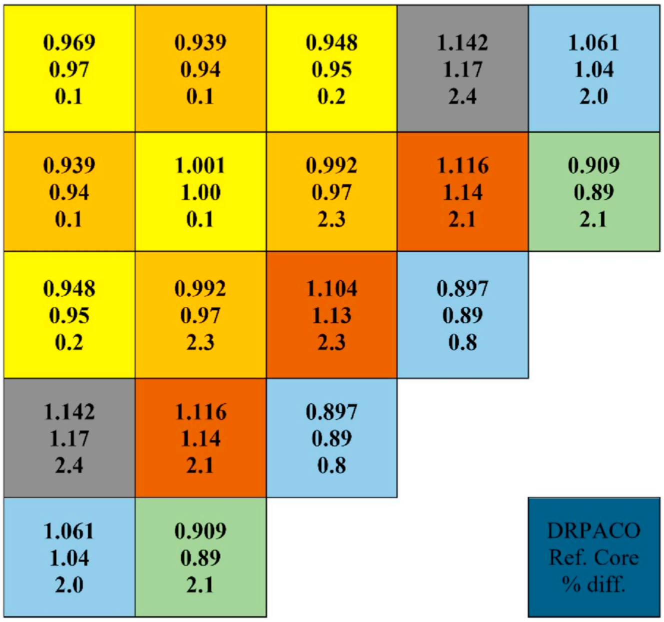

Fig. 13. Radial PPF at the BOC.

$$ff = a\frac{1}{CL} + b\frac{1}{MDNBR} + c[APPF_{Max} + RPPF_{Max}] + d[(1+\overline{AFlat}) + (1+\overline{RFlat})] \quad (8)$$

where: *ff* is the fitness function; *CL* is the time duration of the fuel cycle burn-up; *MDNBR* is the minimum DNBR through the entire cycle length; $APPF_{Max}$ and $RPPF_{Max}$ are the maximum axial and radial PPF during whole cycle length. Also, $\overline{AFlat}$ and $\overline{RFlat}$ are presented in Eqs. (9) and (10):

$$\overline{AFlat} = \frac{\sum_{i=1}^{TS} AFlat(i)}{TS} \quad (9)$$

$$\overline{RFlat} = \frac{\sum_{i=1}^{TS} RFlat(i)}{TS} \quad (10)$$

which TS is the number of time steps during cycle length and *AFlat* and *RFlat* are defined as:

$$AFlat = \frac{\sum_{j=1}^{AM} |APPF(j) - 1|}{AM} \quad (11)$$

$$RFlat = \frac{\sum_{j=1}^{N} |RPPF(j) - 1|}{N} \quad (12)$$

In Eqs. (11) and (12), *APPF* is the axial PPF; *AM* is the number of axial meshes; *RPPF* is the radial PPF and N is the number of fuel assemblies which in 1/8th symmetry of SMART core equals to 11 ($N = 11$). It should be noticed that a, b, c and d coefficients are constant weights according to importance of each objective and also to bring all parameters in a comparable numerical range.

4. Results and discussion

The results of axial and radial SMART core optimization using COA have been presented and discussed in this section. At the beginning to ensure the DRAGON/PARCS/COBRA coupling system and the data used for SMART core, the results of radial PPF of DRPACO package at the beginning of the cycle (BOC) have been compared with the reference core, which according to Fig. 13 have a maximum difference of 2.4%. This difference comes from the different cross section library used, the approximate capability of reflector modeling in deterministic codes and difference in simulation methods. The average coolant outlet temperature resulted from the thermal-hydraulic module of DRPACO package is 324 °C that in comparison to the 323 °C temperature that is reported from SMART core standard safety design has less than 0.3% difference which is acceptable. Also, the burn-up cycle length according to the DRPACO calculation is 891 Effective Full Power Days (EFPDs) that has less than 1% difference from cycle length reported in the SAR of SMART reference core (900 EFPDs) (SMART Report, 2012; SMART SSAR, 2010).

Table 4
The values of COA parameters.

COA Parameters	Value	definition
numCuckooS	10	number of initial population
minNumberOfEggs	2	minimum number of eggs for each cuckoo
maxNumberOfEggs	6	maximum number of eggs for each cuckoo
maxIter	50	maximum iterations of the Cuckoo Algorithm
knnClusterNum	3	number of clusters that we want to make
motionCoeff	9	Lambda variable in COA paper
maxNumOfCuckoos	50	maximum number of cuckoos that can live at the same time
radiusCoeff	5	Control parameter of egg-laying
cuckooPopVariance	1E-10	population variance that cuts the optimization

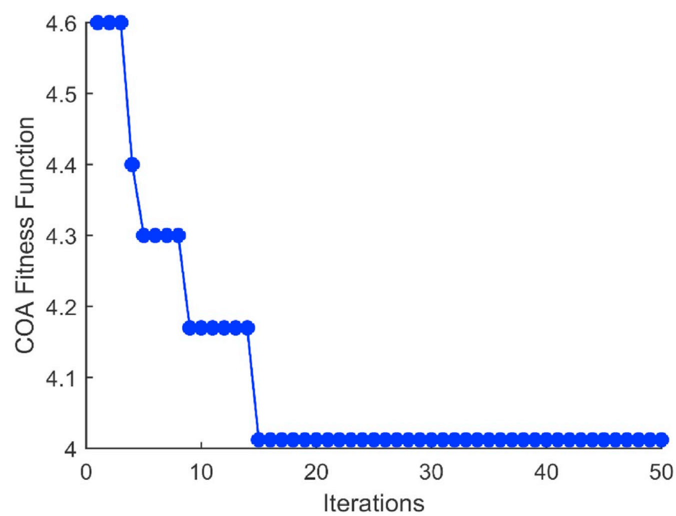

Fig. 14. The attained fitness function using COA.

For the optimization of SMART core using COA, different values of the COA parameters during the several runs have been used. According to the best cost function achieved, the nature of cuckoo living, and a trade-off between convergence speed, global optima achievement and covered optimization area, the values used for COA parameters and their definitions have been presented in Table 4. According to the given fitness function in Eq. (8), the COA cost function with Eq. (3) form has been used to minimize the objectives. The best fitness function achieved using COA for the different axial and radial FA types of the SMART, is shown in Fig. 14. The COA reaches the minimum fitness function equal to 4.012 after 15 iterations with fast convergence speed.

The proposed radial configuration for SMART loading pattern according to the COA is shown in Fig. 15. As mentioned before, the configuration of the SMART core should have two batches as a design constraint, and this constraint has been satisfied, as shown in Fig. 15. The maximum radial PPF for the proposed core during the entire cycle length is equal to 1.24, which in comparison to the reference core (1.32) is improved by 6%. Also, the maximum radial PPF distribution for

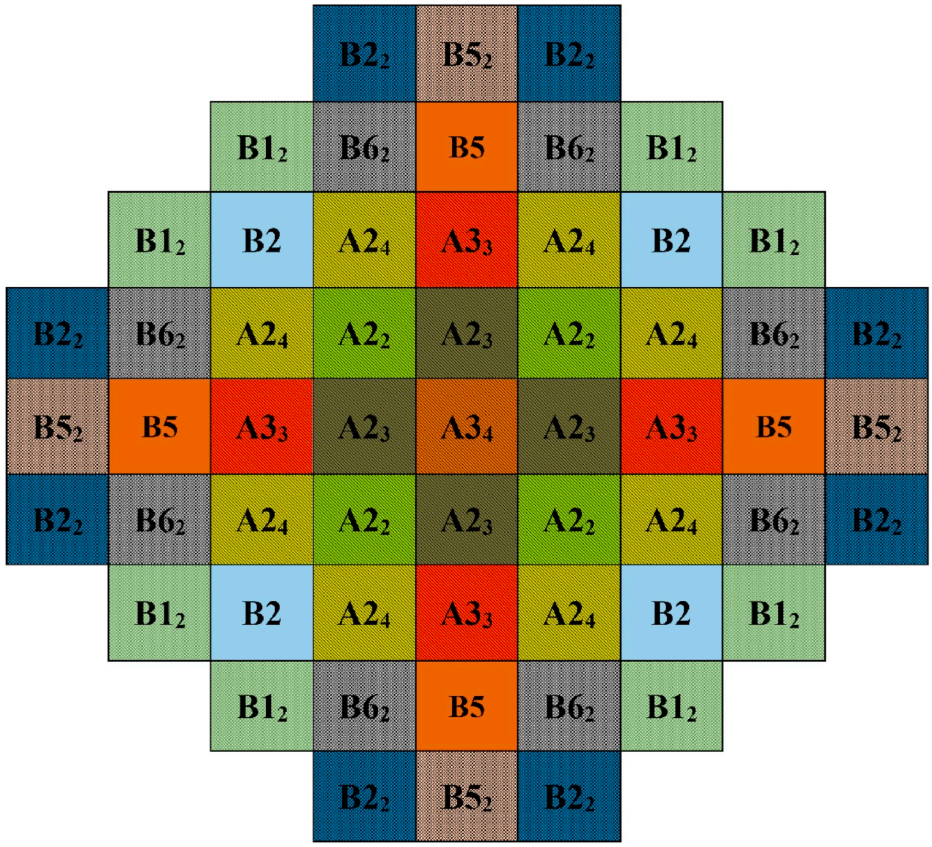

Fig. 15. The proposed SMART core loading pattern by COA.

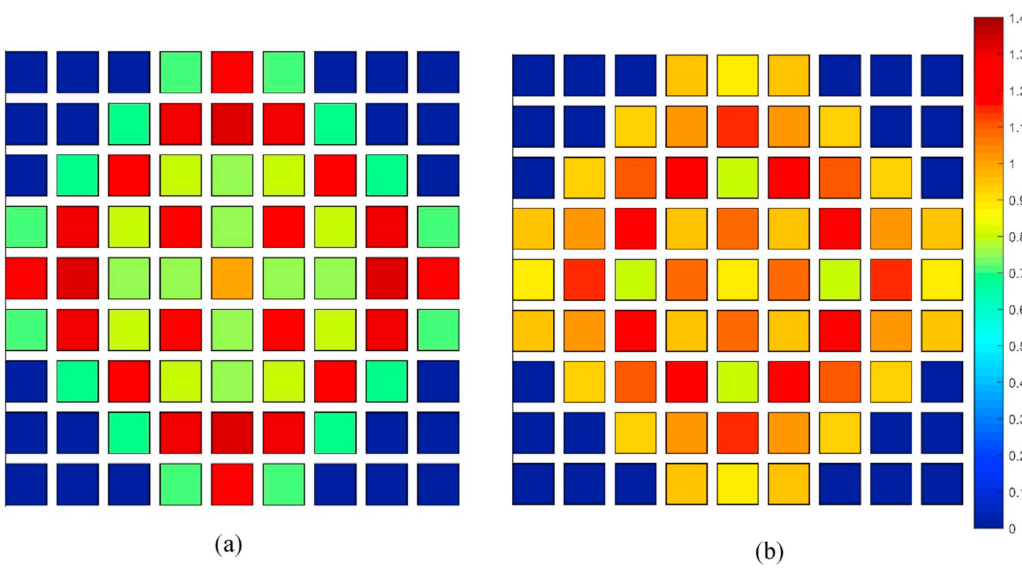

Fig. 16. The maximum radial PPF distribution for the reference core (a) and COA proposed core (b) during the cycle length.

reference core and COA proposed core is shown in Fig. 16, that shows the proposed core have been flattened properly.

In the COA proposed core, most of the FAs with more cutback fuel at the top and less in the bottom sides of the IFBA rods have been used, which shows the approach of the COA according to the fitness function to achieve an axial pattern with lower maximum axial PPF during the optimization process. Fig. 17 compares the changes of the maximum axial PPFs for the reference core and COA proposed core that clearly demonstrate the effects of the axial pattern of IFBA rods by flattening the axial PPFs. The lower slope at the bottom and higher slope at the top of the axial PPF profile of COA proposed core in comparison to the reference core profile, show the effects of using more cutback fuels at the top of the FAs.

The cycle length of the COA proposed core is 911 EFPDs that doesn't show a considerable improvement in comparison to the reference core. This is because of the weighting factor at the defined fitness function (Eq. (8)) which due to the high importance of safety factors (MDNBR and PPFs) in nuclear reactors, the cycle length have decreased by 1.5-fold. In

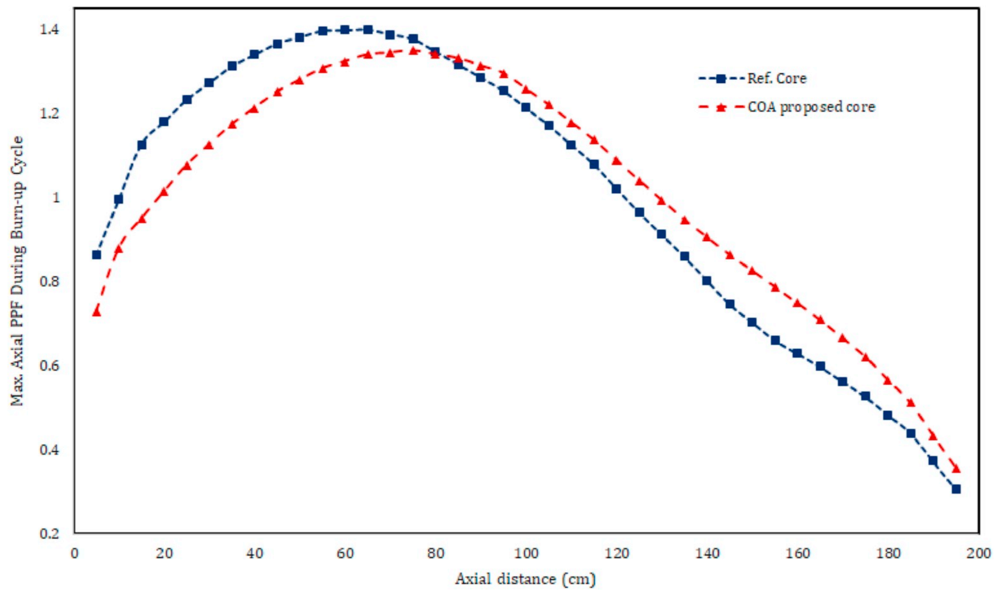

Fig. 17. The maximum axial PPFs of the reference core and COA proposed core during the cycle length.

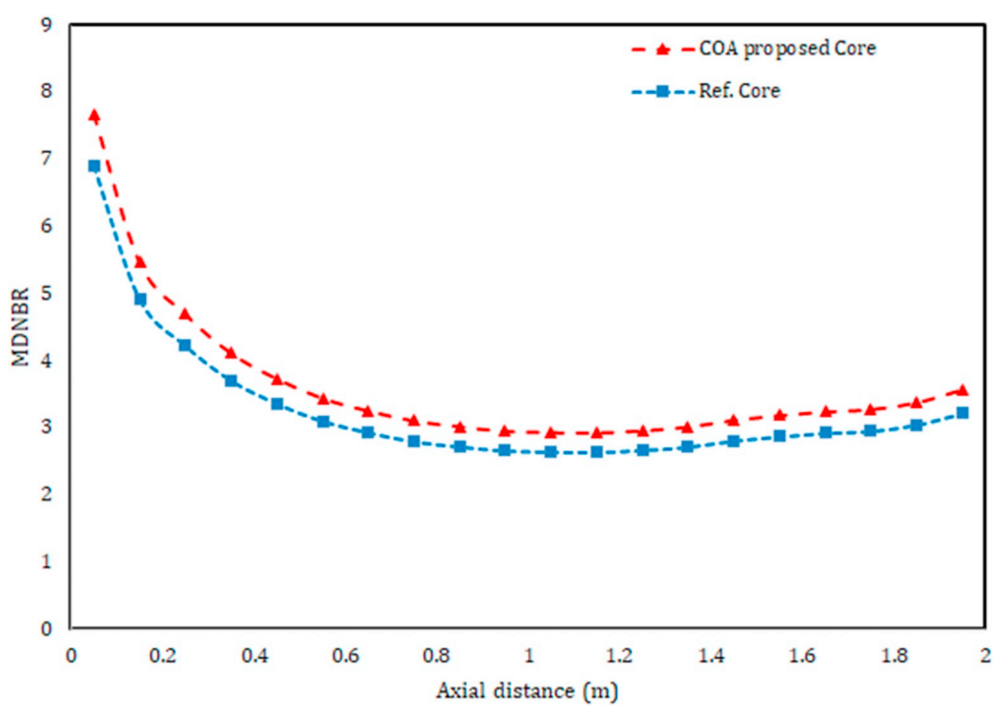

Fig. 18. The reference core and COA proposed core MDNBR profiles at the hottest channel along the cycle.

other words, in the present work, the fitness function has been defined in a way to give more importance to the safety factors in comparison to the economic factor.

The minimum DNBR profiles in the hottest channel along the cycle, for the reference core and COA proposed core, is shown in Fig. 18. The minimum DNBR has been increased to 2.928 in comparison to the reference core value (2.635), which increased the safety and reduced the two-phase state possibilities. Also, the maximum fuel temperature as one of the most important safety parameters has been reduced in the COA proposed core (1068 K) in comparison to the reference core (1093 K). The radial variation of temperatures at the hottest fuel pin axial zone, during the cycle length, is shown in Fig. 19. The lower maximum fuel centerline temperature shows better safety features of COA proposed core versus reference core axial and radial loading pattern.

5. Conclusion

Performing full thermo-neutronic calculations during the cycle for an axial and radial multi-objective core loading pattern problem is computationally very expensive, but using the high convergence speed and global optima achievement of COA helps to reduce the amount of calculations considerably. Although the small radial and axial size of SMRs make axial and radial power flattening very hard, the results of the present work show the possibility to achieve the improved core parameters using simultaneous radial and axial loading pattern optimization. Also, the role of using a multi-objective fitness function which

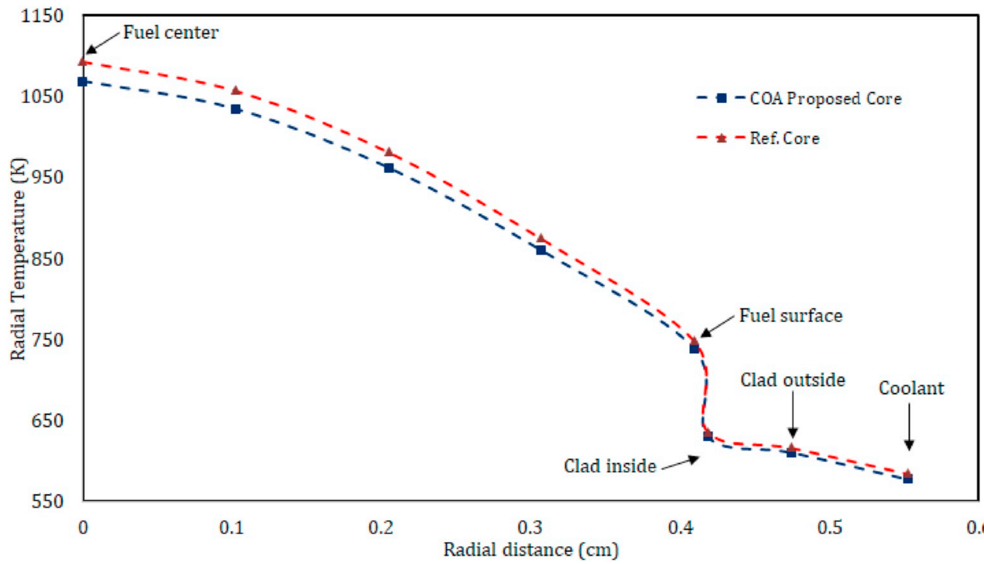

Fig. 19. The maximum radial temperature profile of the reference core and COA proposed core in hottest zone along the cycle length.

consists of both neutronic and thermal-hydraulic parameters is inevitable to reach a higher safe and economic core according to the objectives of designers and users. Finally, the results show the proper performance of the cuckoo algorithm for using in nuclear reactor fuel management problems and also the importance of performing both the axial and radial core optimization to achieve a better SMR core.

CRediT authorship contribution statement

R. Akbari: Methodology, Software, Validation, Formal analysis, Writing - original draft. **D. Rezaei Ochbelagh:** Methodology, Writing - review & editing, Supervision. **A. Gharib:** Writing - review & editing, Supervision. **J.R. Maiorino:** Supervision. **F. D'Auria:** Supervision.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.pnucene.2020.103271.

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