Original Article

Electromagnetism Mechanism for Enhancing the Refueling Cycle Length of a WWER-1000

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ABSTRACT

Increasing the operation cycle length can be an important goal in the fuel reload design of a nuclear reactor core. In this research paper, a new optimization approach, electromagnetism mechanism (EM), is applied to the fuel arrangement design of the Bushehr WWER-1000 core. For this purpose, a neutronic solver has been developed for calculating the required parameters during the reload cycle of the reactor. In this package, two modules have been linked, including PARCS v2.7 and WIMS-5B codes, integrated in a solver for using in the fuel arrangement optimization operation. The first results of the prepared package, along with the cycle for the original pattern of Bushehr WWER-1000, are compared and verified according to the Final Safety Analysis Report and then the results of exploited EM linked with Purdue Advanced Reactor Core Simulator (PARCS) and Winfrith Improved Multigroup Scheme (WIMS) codes are reported for the loading pattern optimization. Totally, the numerical results of our loading pattern optimization indicate the power of the EM for this problem and also show the effective improvement of desired parameters for the gained semi-optimized core pattern in comparison to the designer scheme.

1. Introduction

The searching of an optimum fuel assembly (FA) arrangement or a loading pattern (LP) in the reload reactor core design of a nuclear power plant amounts to a multiobjective constrained optimization problem. Given the number of fresh FAs, the primary goal of the core pattern design in most reactor reload problems is to maximize the operation cycle length while satisfying all safety constraints [1].

The loading pattern optimization (LPO) is a complex problem by containing huge possible fuel arrangements (solution vectors). For solving this problem, the metaheuristics approaches can be used. From such optimization methods, that up to now have been implemented in the fuel management optimization of the nuclear reactors core, we can point to artificial intelligence techniques like genetic algorithms [2], artificial neural networks [3], continuous particle swarm optimization [4], interval bound algorithm [5], differential harmony search algorithm [6], self-adaptive global best harmony search algorithm [7], simulated annealing algorithm [8], discrete firefly algorithm [1], bat algorithm [9], cross entropy [10], strength Pareto evolutionary algorithm [11], etc.

One of the optimization methods which have been utilized for various problems is the electromagnetism mechanism

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(EM). This approach has been recently developed for the global optimization treatment by Birbil and Fang [12]. The EM is a flexible and efficient nature-based method for optimization problems. EM originates from the electromagnetism theory of physics by assuming potential solutions as electrically charged particles which spread around the solution space. The charge of each particle depends on its objective function value. This algorithm employs a collective attraction repulsion mechanism to move the particles towards optimality [13].

In this current work, the EM is exploited for the fuel reload design of Bushehr WWER-100 core during its first operation cycle. It is notable that in previous research papers such as [1] and [11], optimization calculations have been done for only the beginning of the cycle (BOC) state of reactors core, but in this research, a more real and complicated problem is modeled and solved by checking the neutronic behavior of the reactor throughout its operation cycle. In order to calculate the neutronic parameters, PARCS v2.7 and WIMS-5B, which have been linked together, are used and by utilizing the EM, the core pattern optimization is performed for the Bushehr reactor. A fitness function is defined in regards of achieving a longer cycle time and maintaining the radial power peaking factor (PPF) below a constraint during the cycle. At last, the LPO results using EM for the Bushehr reactor test case show the acceptable and suitable performance of the prepared package.

2.   EM

Recently, the EM metaheuristic approach has been developed by Birbil and Fang [12]. The EM is a forceful algorithm, which can solve nonlinear global optimization problems converging rapidly to an optimum. EM is a stochastic optimization method based on the electromagnetism theory of physics. The main idea of this population-based metaheuristic method is to utilize the interaction between solutions, similar to attraction-repulsion of the charged particles in the electromagnetism theory [14].

In the EM, each particle is considered as an electrical charge. Afterwards, the movement of attraction and repulsion is defined by Coulomb's law, (i.e., the force is inversely proportional to the distance between the particles and straightly proportional to the product of their charges). Similar to various multiple point approaches, a set of sample points (population) of the feasible region is considered for the EM and the location of a sample point in sequential iterations is dependent on the computational experience of the other points in the population. The principle of superposition states that the "electromagnetic force on a charged particle caused by any number of other particles can be calculated by adding together the forces from any of the other particles calculated distinctly". The EM algorithm begins by sampling a set of points from the possible region, which is an n-dimensional hypercube. A sample point (solution vector) in the EM method is treated analogous to a charged particle. For determining the charge of a special point, the fitness function value at that point is utilized. This evaluated charge essentially determines the magnitude of attraction or repulsion of the point over the population. For instance, if our optimization problem is to be a minimum search of fitness, points which have less objective function values are emphasized to be highly attractive within the population. We are induced by the concept that the points with better objective values indicate the other points for converging to the global or local minima. In addition, the points in the near neighborhood of steeper regions expectantly dissuade the other members of the population by repulsion. Thus, the attraction performance guides the points towards better regions, whereas repulsion treatment enables particles to exploit the unvisited regions [15].

In respect to the above explanations, here is an example for more clarification. In Fig. 1, there are three particles and their own fitness values are 20, 10, and 15, respectively. Because Particle 1 is worse than Particle 3 while Particle 2 is better than Particle 3, Particle 1 indicates a repulsion force by the notation of F_{13} and Particle 2 encourages Particle 3, which moves to the neighborhood region of Particle 2. As a result, Particle 3 moves by the total force F, according to Fig. 1 [16].

Now if our optimization case is the minimizing search of fitness, we have the following form of the problem:

$$\text{Minimizing } f(x) \quad \text{s.t } x \in S \tag{1}$$

where $S = \{x \in \Re^n | l_k \leq x_k \leq u_k; l_k, u_k \in \Re, k = 1, 2, \ldots n\}$, and also by the parameters definitions as follows: n, dimension of the problem; u_k, upper bound in the kth dimension; l_k, lower bound in the kth dimension; and $f(x)$, the fitness function which is minimized.

In the EM approach, four main steps are considered including initialization, local search, calculation of total force, and movement along the total force. In the initialization step, m sample points are created in the feasible region by generating random numbers. For the following stage (i.e., local search), the searches around the neighborhood points are performed in order to get better solutions. Also, the calculations of the total force steps are defined for finding the total force of any point. Lastly, movement along the total force stage is considered for moving the sample points along the total force direction [17]. The principal steps of the EM method are summarized by the pseudo code which is represented in Fig. 2 [15]. In the current section, a brief presentation of the main steps for the proposed method, EM, is given.
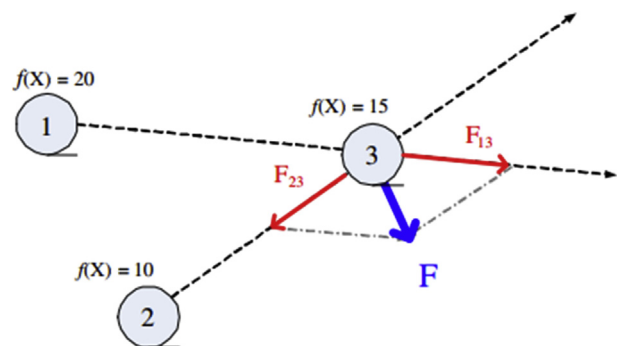

Fig. 1 – **An example for attraction and repulsion of particles.**

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ALGORITHM  EM(m, MAXITER, LSITER, δ )
m: number of sample points
MAXITER: maximum number of iterations
LSITER: maximum number of local search iterations
δ: local search parameter, δ∈[0,1]
1:  Initialize()
2:  iteration ← 1
3:  while iteration < MAXITER do
4:      Local(LSITER, δ)
5:      F ← CalcF()
6:      Move(F)
7:      iteration ← iteration +1
8:  end while
```

Fig. 2 – The pseudo code of electromagnetism mechanism (EM) algorithm.

2.1. Step 1: Initialization

In the initialization step, m sample points from the possible domain are generated by randomizing in n dimensional. Each coordinate value for a sample point is supposed to be randomly distributed between the corresponding upper and lower bounds. The fitness function of f(x) is utilized for calculating the objective function value after a point is sampled to the space. When m points are considered, the process is ended, and the point with the best fitness value is signed by x^{best} [12].

2.2. Step 2: Local search

The neighborhood information is gathered for every sample point in the local search step. In this way, a new possible point y moves in the direction of a sample point x^i limited by the maximum feasible random step length which is defined by $\delta \in$ [0, 1]. It should be mentioned that the notation of x^i specifies the i^{th} point of the population. Now if the new point y earns a better point (with better fitness value) in any iteration, the sample point x^i is substituted by the new point y. This process is stopped after all sample points have found a neighborhood position to achieve a better fitness function or finished because the considered limit cycle is met. By this procedure, the current best point is updated. Actually, the EM is a simple random line search algorithm, but it is also rapid and efficient. This is because the algorithm does not need any gradient information for performing the local search, which is distinctive from other local search methods [17].

2.3. Step 3: Calculation of total force

The total force is computed for any particle using a method which is similar to Coulomb's Principle. In this approach, the charge of each point, q^i, delineates its force of attraction or repulsion. As presented in Eq. (2), the charge of each sample point, x^i, is appraised by employing the value of the corresponding fitness function, in comparison to the fitness function value of the current best point.

$$q^i = \exp\left\{ -n \times \frac{f(x^i) - f(x^{best})}{\sum_{k=1}^m [f(x^k) - f(x^{best})]} \right\}, \quad i = 1, 2, \ldots .m. \qquad (2)$$

When the charge of each point, i.e., q^i is determined, the total force F^i can be attained by the following equation [12]:

$$F^i = \begin{cases} \sum (x^j - x^i) \cdot \dfrac{q^i q^j}{\left\| x^j - x^i \right\|^2}, & \text{if } f(x^j) < f(x^i) \\[3mm] \sum (x^j - x^i) \cdot \dfrac{q^i q^j}{\left\| x^j - x^i \right\|^2}, & \text{if } f(x^j) \geq f(x^i) \end{cases} \quad , \quad \forall i. \qquad (3)$$

2.4. Step 4: Movement along the total force

In the last step of algorithm, the point is moved along the force direction using a random step length and also the calculated total force, F^i, from the previous step. For considering a diversification effect in the proposed approach, the step length is chosen randomly. In the following equation, Eq. (4), the movement procedure of the point x^i is given. In this equation, λ is the random step length that is uniformly distributed between 0 and 1 and also the RNG is a vector whose components denote the allowed possible movement towards the current upper bound, u_k, or the lower bound, 1_k, for the corresponding dimension [17].

$$x^i = x^i + \lambda \frac{F^i}{\| F^i \|} (RNG), \quad i = 1, 2, \ldots m. \qquad (4)$$

3. Developed package for the neutronic simulation

For examining the neutronic treatment of a fuel arrangement for the Bushehr reactor core, a solver package has been prepared. This program includes two modules containing PARCS v2.7 and WIMS-5B codes. Purdue Advanced Reactor Core Simulator (PARCS) is a three-dimensional reactor core simulator, which can solve the steady-state neutron diffusion using coarse meshes by dimensions of an FA in orthogonal and nonorthogonal geometries [18]. PARCS v2.7 code is utilized in this work for calculating the reactor core neutronic parameters. Two-group neutron homogenized cross sections are used in PARCS code in which these cross sections are earned by WIMSD-5B. The WIMSD-5B code [19] is a general lattice cell program that exploits the transport theory to gain the neutron flux as a function of energy and position in the cell. The Winfrith Improved Multigroup Scheme (WIMS) code can calculate the homogenized cross sections of assemblies in order to use in the PARCS code for neutronic computations of the core.

As cross sections are changed from the bottom to the top of the core, the Bushehr reactor core was simulated in three dimensions. Each FA was divided into 20 sections in the axial direction and a WIMS input was prepared independently for any axial section of an assembly existing in the core. Fuel burn up for each FA was also calculated by the WIMSD-5B code and macroscopic cross sections were obtained by this code for any axial mesh of each FA during the operation cycle. The algorithm of calculations from the BOC to the EOC states for any LP

is described by the following stages: (1) run WIMS code for calculating the homogenized cross sections (X.S.) of all meshes are defined in the core for the current time step of the cycle by assuming a boron concentration in the coolant; (2) execute the PARCS code for estimating K_{eff} and power values of FAs by using cross sections calculated from Step 1; (3) if $K_{eff} = 1$, go to Step 4; otherwise, increase or decrease the boron concentration in the coolant for keeping the system in the critical state. Afterwards, by going to Step 1, repeat all of the above steps until the new calculated $K_{eff} = 1$; (4) if the obtained critical boron concentration is near zero, go to Step 7; otherwise, calculate the burn up values (in megawatt day/ton of uranium) of all fuel assemblies for the new time step; (5) enter the amount of burn up values from the previous stage in the POWERC card of the WIMS code and then run the WIMS code for obtaining new isotopes densities; (6) substitute the new atomic density values of all isotopes from Step 5 in the WIMS code input for the new time step of operation cycle and then go to Step 1; and (7) the end of calculations by printing values of the refueling cycle length (in day) and the maximum FA relative power in order to acquire the fitness (which will be given in a later section).

For more clarification of the approach, the above procedure for any LP is illustrated in Fig. 3.

4. Validation of neutronic calculations for the original LP of Bushehr WWER-1000

Prior to implementing the EM in the fuel management optimization of Bushehr WWER-1000 core, we should assure that the developed solver, including coupled WIMS and PARCS, performs neutronic calculations correctly and simulates neutronic behavior of the core by an acceptable precision in order that it can be used for our purpose (i.e., applying to the LPO problem as a solver). In this section, for verification

purposes, numerical results of the developed package during the first cycle of the primary (designer) fuel arrangement, are given and compared with the Final Safety Analysis Report (FSAR) [20] of Bushehr WWER-1000.

The Bushehr reactor is a WWER-1000 type with the nominal output thermal power of 3000 MWth. The core of this reactor was loaded by 163 FAs with different fuel enrichments. An FA appertained to the Bushehr reactor core can include the control absorber rods and protection system, burnable absorber, rod boundless, spring-loaded head, fuel rod bundle, and a tail-piece. Also, the FA has the shape of a hexahedron in the cross section with the maximum dimension sides of 235.1 mm. In addition, the FA comprises 311 fuel rods, 18 guiding channels for arrangement of control and protection system absorber rod or burnable absorber rod, and the central channel. However, the representation of Bushehr reactor core model in a 60° symmetry sector is given in Fig. 4 and various kinds of FAs are also introduced in Table 1 [20].

The process of neutronic calculations for any LP has been explained in a previous section. In this regard, the neutronic solver has been run for the primary core pattern, as for the approach shown in Fig. 3, from the BOC to the end of the cycle (EOC), states. Table 2 gives PPF_{max} (maximum FA relative power along the cycle), cycle length (in a day) and critical boron concentration (in g/kg) of the BOC state for both the simulated scheme and the reference (i.e., FSAR [20]). According to Table 2, one can realize the tolerable accuracy of results relative to the reference. In addition, the radial relative power distribution of the FAs, which belonged to the designer core pattern, is given in Fig. 4 for the BOC state without xenon poisoning in which it is also compared with the reference values of FSAR [20], and for the EOC state, the FAs power scheme is illustrated in Fig. 5. It is remarkable that the results are achieved without any thermohydraulic modeling of the core. Thus, these errors between results and FSAR [20] can be natural and logical. Moreover, the obtained values of critical boron concentration for various time steps during the cycle
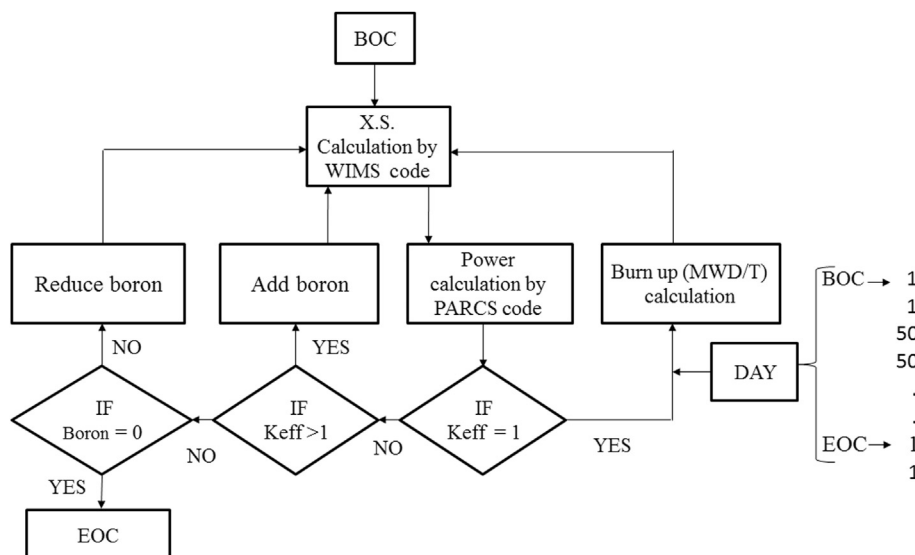

Fig. 3 − The flowchart of neutronic calculations from beginning of the cycle (BOC) to end of the cycle (EOC) states.
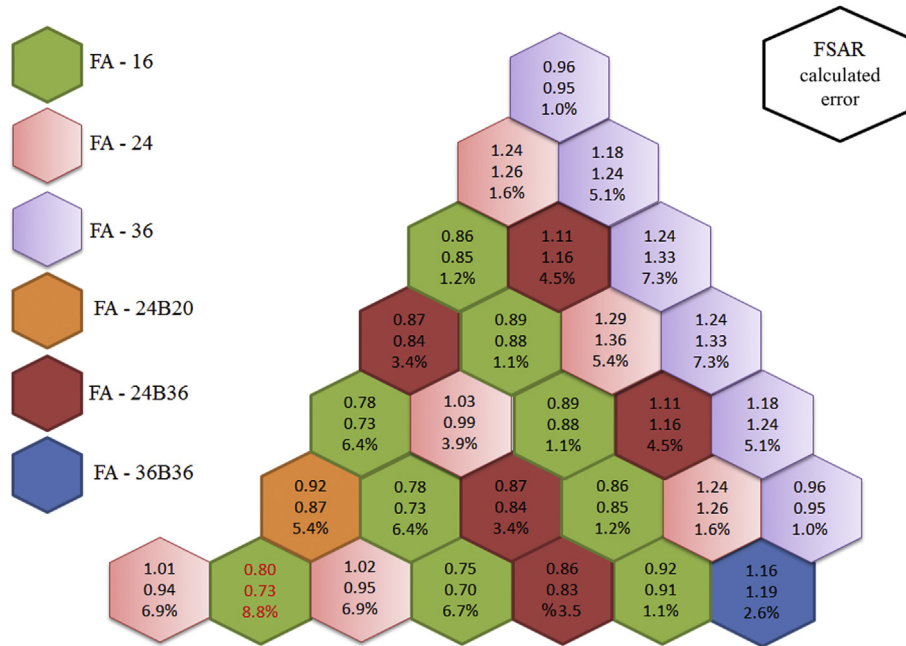
Fig. 4 − The radial relative power distribution of fuel assemblies for the designer scheme of the Bushehr reactor core in the beginning of the cycle (BOC) state.

associated with FSAR diagram [20], are shown in Fig. 6. As mentioned before, calculations during the cycle time is ended and the operation of core should not be continued when the critical boron concentration obtained is near zero. In this case, the calculated time length is considered as the operation cycle length or refueling time of the reactor core. According to the presented results, it is found that the developed simulator can be exploited for the LPO problem.

5. Determination of a fitness function for the core pattern optimization

This study aimed to find a new core pattern according to selected parameters which must be optimized. Hence, we should determine a fitness function that is optimized during the optimization process in regard of the chosen objectives. Several goals can be considered as optimization objectives for the LPO problem. In this work, two goals are elected, including maximizing the refueling cycle time of the core, along with taking the radial PPF during the cycle below a prescribed value

in order to observe the safety constraint on the PPF. Thus, we define the following equation, Eq. (5), to embrace the above goals:

$$F_t = \begin{cases} \dfrac{100}{RCL} & if \ PPF_{max} < PPF_a \\ \dfrac{100}{RCL} + PPF_{max} - PPF_a & if \ PPF_{max} \geq PPF_a \end{cases} \quad (5)$$

In Eq. (5), RCL is the refueling cycle length (in a day), PPF_{max} is the maximum value of radial relative power in all time steps of the cycle, and PPF_a is the admissible value of FA radial relative power value that can be during the operation cycle time. In this study, PPF_a is selected as 1.35. As noted before, RCL is defined as the passed time in a day until the obtained critical boron concentration is near to zero. With regard to the above optimization purposes, it is apparent that the minimum value of fitness function (F_t) defined in Eq. (5) should be sought. By reaching the higher RCL, the F_t value is less; thus, our optimization problem is a minimum searching process of F_t. However, it must be noted that the second term is added to Eq. (5), because we do not want the maximum value of PPF during the cycle to be greater than a permissible value (i.e.,

Table 1 − The number of fuel assembly (FA) types in the one-sixth of Bushehr reactor core.

FA type	16	24	24B20	24B36	36	36B36
Fuel enrichment (%)	1.6	2.4	2.4	2.4	3.6	3.6
No. of BAR	−	−	20	36	−	36
No. at 1/6th of the core	9	6	1	5	6	1

BAR, burnable absorber rod.

Table 2 − Results of developed package and reference for the original fuel arrangement of Bushehr WWER-1000 core.

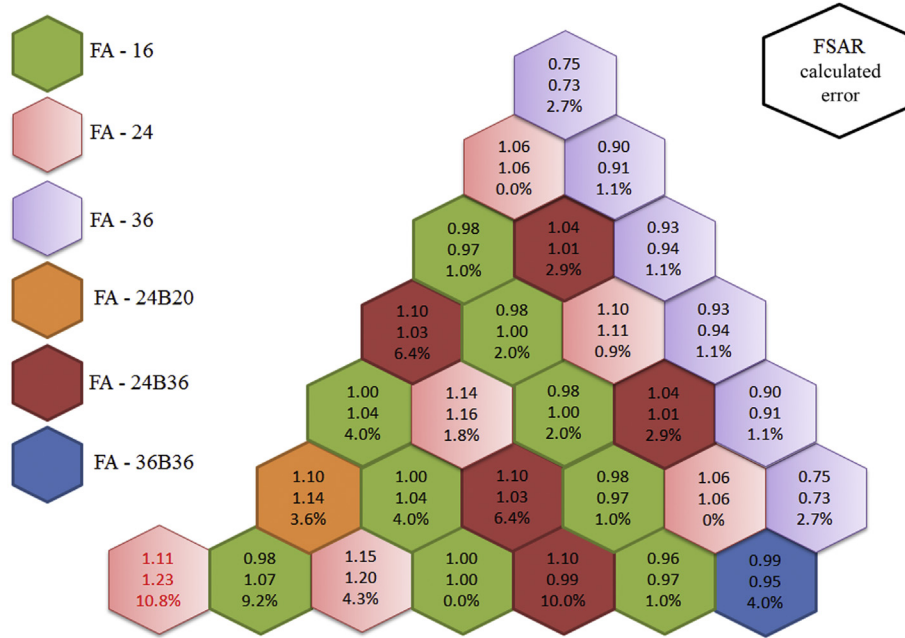| Parameter	Final Safety Analysis Report	Result
PPF_{max}	1.29	1.36
Cycle length (d)	289.7	287
Concentration of H_3BO_3(BOC) (g/kg)	6.64	6.62

Fig. 5 – The radial relative power distribution of fuel assemblies for the designer scheme of Bushehr reactor core in the end of the cycle (EOC) state.

PPF_a) due to the safety restriction which should be attended. In this way, the fitness (F_t), with the greater PPF_{max} than PPF_a will have a large value; as a result, the corresponding core pattern is identified as an infelicitous LP and automatically will be rejected from the optimization process.

6.   Simulation results of EM approach

In this section, the implementation results of EM algorithm in two optimization problems are given. In the first test case, there was a problem with a distinctive solution that is used for
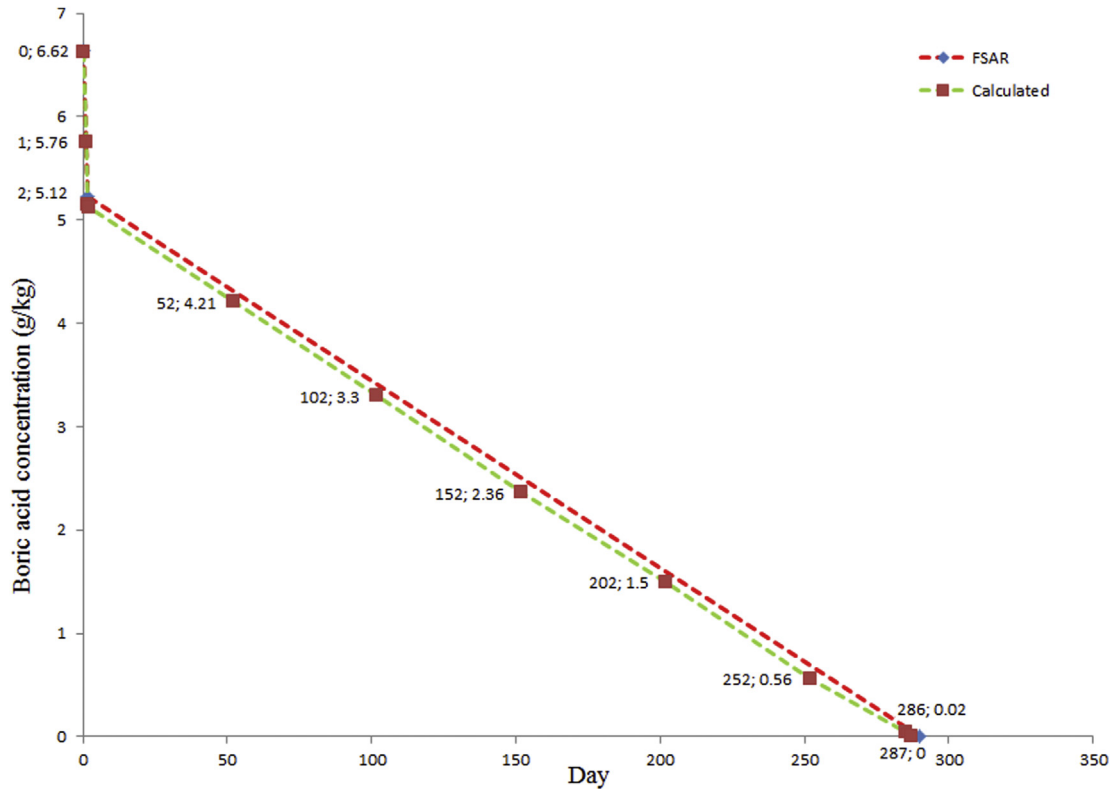

Fig. 6 – Calculated critical boron concentrations along the time for the original loading pattern (LP) of Bushehr WWER-1000.

the validation of the developed method, EM, and afterwards, the results of fuel arrangement optimization problem using EM for the Bushehr WWER-1000 core are reported and examined.

6.1.   First case study: Rastrigin function for the validation

The generalized Rastrigin test function is a nonconvex, multimodal, and additively separable problem which has usually been used for the validation of optimization algorithms. This function has several local optima arranged in a regular lattice, but it has only a global optimum located at the point x = 0 where f(x) = 0. The search range for the Rastrigin function is [−5.12, 5.12] in each variable. The Rastrigin test case is a fairly difficult problem due to its large search space and its large number of local minima [21]. The general form of the function is displayed by the following equation:

$$f(x) = 10*n + \sum_{i=1}^{n}\left[x_i^2 - 10\cos(2\pi x_i)\right], \quad x_i \in [-5.12 \ , \ 5.12],$$

$$i = 1, 2, ..., n.$$

(6)

Fig. 7 demonstrates the Rastrigin function in a two-dimensions (n = 2) view and also the parameters which have been set for the EM algorithm are given in Table 3. Results of the Rastrigin function simulation using EM are represented in Table 4 for five subsequent and independent runs. In Table 4, optimized fitness values along with point's situations in two dimensions are indicated for all five runs. However, numerical results exhibited in Table 4 confirm that the EM can reach the near exact optimum point with the minimum fitness. So, this case presents the intensity and efficient function of the developed EM approach. As a result, earned results can validate the prepared EM solver against the exploited problem in order that we can use it for the following test case (i.e., the LPO of Bushehr WWER-1000). Lastly, Fig. 8 illustrates the global optima gained by the EM along the number of iteration for the successive independent five runs. This example proves this
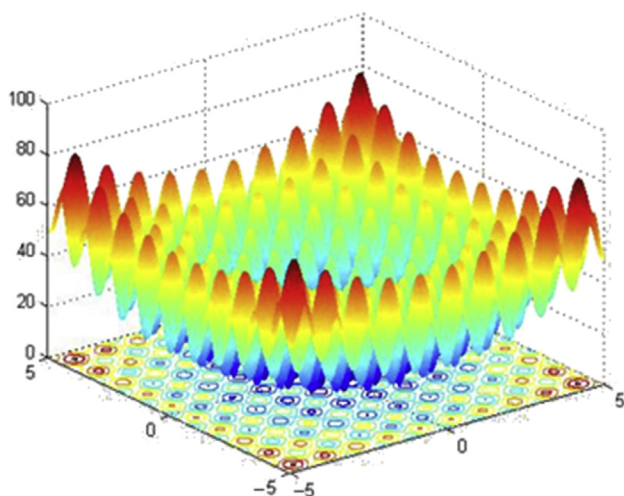
Table 3 – Parameters setting for the electromagnetism mechanism (EM) optimization algorithm.

Parameter	Notation	Value
No. of particles	m	40
Maximum no. of iterations	MAXITER	50 (20[a])
Maximum no. of iterations in local search	LSITER	10
Local search parameter	δ	0.005

[a] for the LPO problem.

Table 4 – Optimization results of Rastrigin test function obtained by the electromagnetism mechanism (EM) method.

Experiment	(X,Y)	Fitness	Iteration
1	(0.00019,−0.00091)	0.00017	33
2	(0.00158,−0.00018)	0.00050	15
3	(0.00017,0.00096)	0.00019	25
4	(−0.00055,−0.00107)	0.00029	28
5	(0.00203,−0.00103)	0.00103	26
Average (fitness)		0.00044	
Maximum (fitness)		0.00103	
Minimum (fitness)		0.00017	
Average (iteration)		25.4	

fact that the EM algorithm has a good performance in solving difficult optimization problems.

6.2.   Second case study: Bushehr reactor core

For another simulation problem (i.e., Bushehr WWER-1000 core), the LPO was done for one-sixth symmetry of the core. In this section, there are 28 FAs according to Fig. 9. Each solution vector (position vector), which is produced in the LPO process using the EM, must include integer and non-repeated numbers and it corresponds to an LP. The size of this vector is equaled to the number of FAs that can be shifted in the core. In this research paper, the FA including control rods associated with the central FA in the core are located and fixed in the primary positions with respect to the original LP of the Bushehr reactor, and also FAs with the enrichment of 3.6% in the exterior of the core are fixed. Hence, any generated solution vector is a vector with the length of 19 for one-sixth section of the core (see Fig. 9).

However, as is evident from a previous section, the real numbers were created in the generation process of a new solution vector by the EM. As noted above, the real numbers should be decoded to an integer and to the nearest unique number. For this purpose, we apply the single machine scheduling problem approach. In this scheme, the program first identifies the minimum element number in the position vector (solution vector) and replaces it with the first FA position number. Then, the second minimum element number of the position vector is substituted by the next FA number; this procedure is carried until the end. Fig. 10, for example, indicates this approach explicitly for a position vector with the length that is equal to six. As represented in Fig. 10, first the position vector is sorted, then using the new sorted vector, we decode the vector to a final one which includes integer and
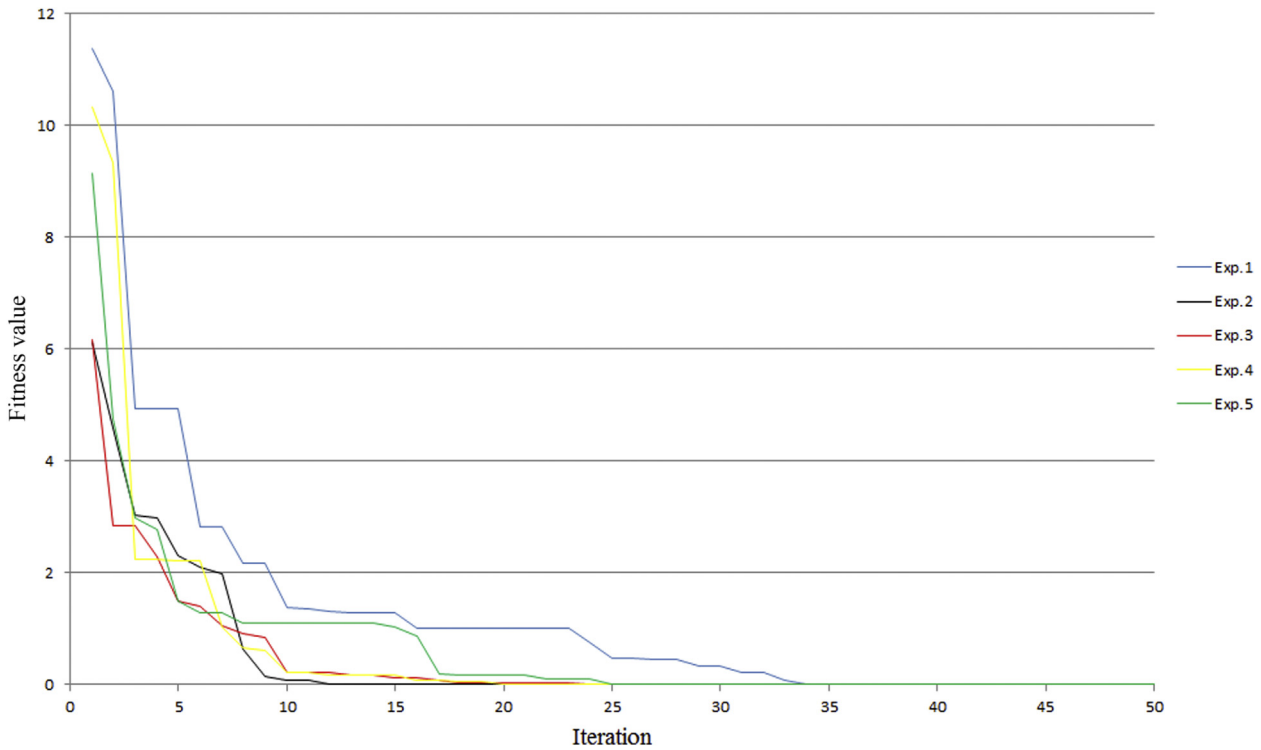

Fig. 7 – The schematic view of Rastrigin test function.

Fig. 8 − Rastrigin fitness value along the iteration earned by the electromagnetism mechanism (EM).

nonrepeating numbers. For instance, 4.3 is decoded to 4, due to occupation of the fourth position in the sorted vector. This process is continued to fill all elements of the solution vector. However, for learning more details in converting a solution (position) vector to the corresponding LP, the interested reader is referred to [22].

The EM module linked with the WIMS and PARCS codes have run three times for the LPO of the Bushehr WWER-1000 core independently and subsequently. The selected EM parameters for the LPO operation are noted in Table 3. The progress of searching better fitness for runs during 20

iterations is displaced in Fig. 11. With respect to Fig. 11, it is realized the relatively near and convergent fitness of runs in obtaining better result (less fitness) during the optimization process. Some desired parameters, including best fitness, RCL, and PPF_{max} for three runs, are given in Table 5. Results shown in Table 5 show that in all of the runs, parameters of RCL, PPF_{max}, and fitness were improved in comparison to the original scheme, especially for the operation cycle length which increased to 295 days relative to 287 days of Bushehr designer LP. However, as seen in Table 5, the best result is appertained to the run of No. 2 with less fitness value relative to other runs. In this regard, some calculated parameters for the best core pattern are compared in Table 6 with the original scheme results. According to Table 6, the improvement of parameters can be apperceived. However, the best fuel arrangement earned by the EM algorithm for Bushehr reactor core is illustrated in Fig. 12. Furthermore, the radial relative power distributions of FAs for the proposed LP are given in
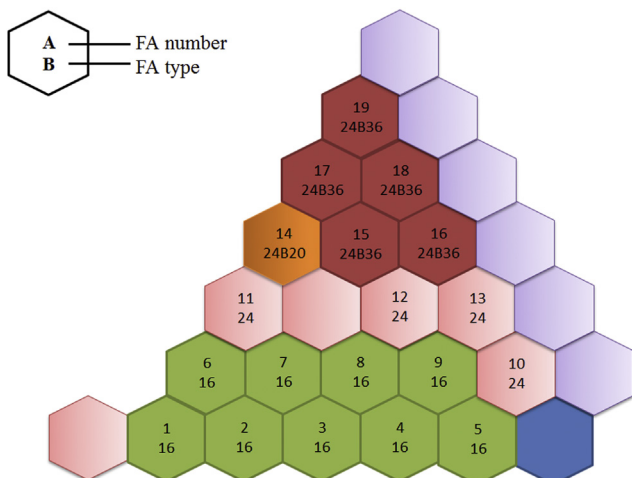

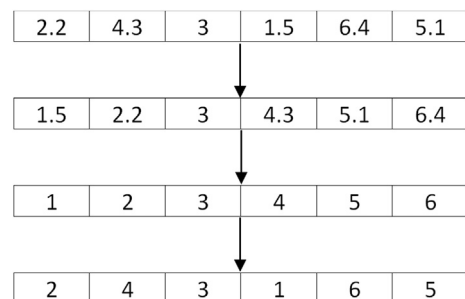Fig. 9 − Primary (original) core pattern of Bushehr WWER-1000.

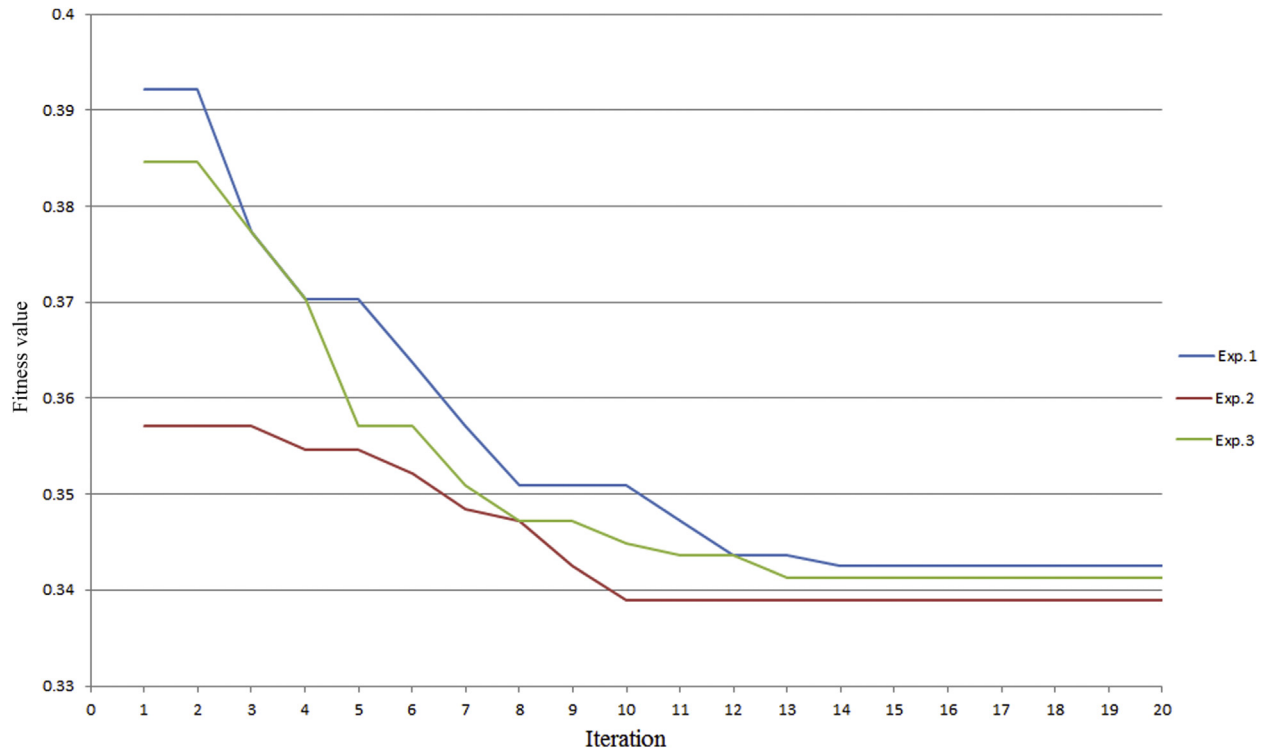Fig. 10 − Earning a position vector with length equals six.

Fig. 11 – Fitness value obtained by the electromagnetism mechanism (EM) for the loading pattern optimization (LPO) of the Bushehr reactor problem.

Table 5 – Calculated desired parameters for runs from the loading pattern optimization (LPO) of Bushehr reactor core using the electromagnetism mechanism (EM).

	RCL (day)	PPF_{max}	F_{best}
Exp. 1	292	1.31	0.342
Exp. 2	295	1.29	0.339
Exp. 3	293	1.32	0.341
Best result (fitness)			0.339
Worst result (fitness)			0.342
Average (fitness)			0.341

Fig. 12 for the BOC state without poisoning and also for the end of the cycle (EOC) (i.e., 295th day) of the core operation time. In addition, the graph of critical boron concentrations along the cycle for different time steps belonging to the proposed LP is

Table 6 – Comparison of results for the obtained best loading pattern (LP) and designer scheme of Bushehr WWER-1000.

Parameter	Designer (BNPP Core)	Optimized pattern
PPF_{max}	1.36	1.29
RCL (d)	287	295
Concentration of H_3BO_3 (BOC) (g/kg)	6.62	6.82
K_{eff} (BOC)	1.150	1.154

demonstrated in Fig. 13. According to above reported results, it is understood that the EM has been the appropriate function in solving the fuel management optimization problem of a test case (i.e., Bushehr WWER-1000).

7.　Conclusion

The main purpose of the current study was the development of a new optimization method, EM, for the LPO problem of a nuclear reactor core. In this work, the EM was applied to a complex and great time consuming LPO problem, by simulating the neutronic behavior of any produced LP during the operation cycle of the core. For calculating desired neutronic parameters during the cycle, a program was prepared using the WIMS and PARCS codes in which these solvers coupled with the EM algorithm could execute the LPO process of the Bushehr WWER-1000 case study. First, the results of the developed program were presented and analogized with the reference for the first cycle LP of the Bushehr reactor, and then, by defining an objective function containing the targets of maximizing the cycle time and maintaining the maximum PPF below a safety constraint, the LPO operation was performed using the EM approach. Altogether, the results of core pattern optimization reveal that the EM method can be reliable and also compared with other optimization algorithms in future works for solving more complicated LPO problems of nuclear reactors core.
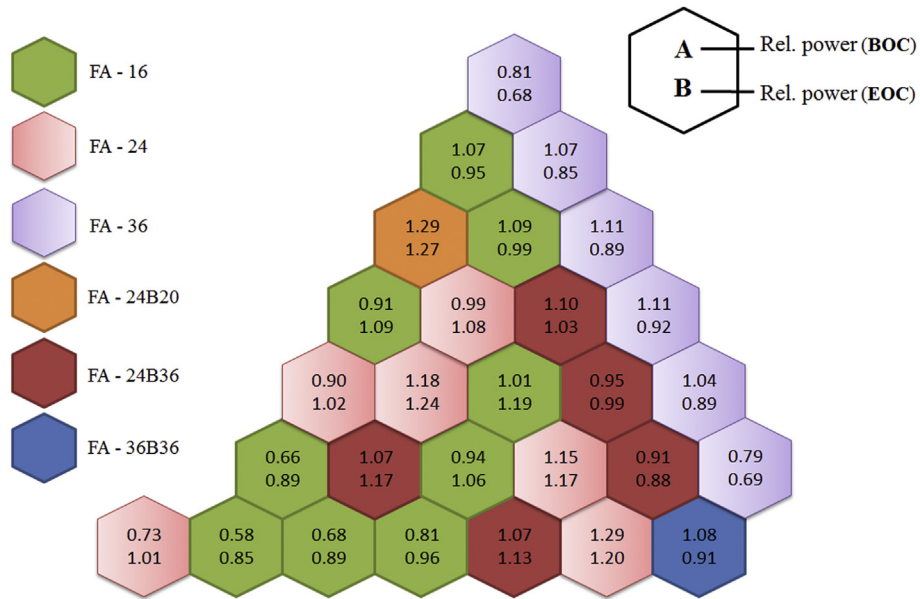
Fig. 12 − Radial relative power distributions of fuel assemblies for the proposed loading pattern (LP) of the Bushehr reactor core in beginning of the cycle (BOC) and end of the cycle (EOC) states.
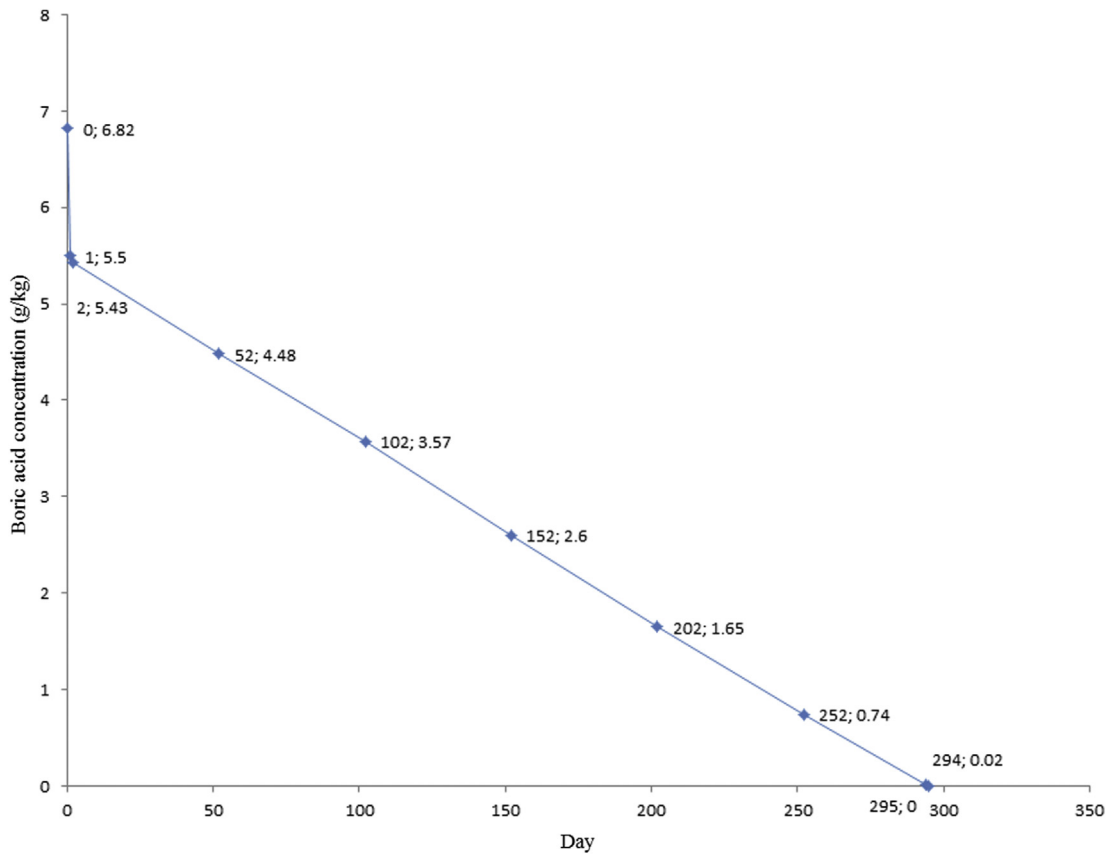

Fig. 13 − Calculated critical boron concentrations along the time for the proposed loading pattern (LP) of Bushehr WWER-1000.

Conflicts of interest

All contributing authors declare no conflicts of interest.

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