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Spent Fuel Dry Storage Loading Plan Based on Uniform Decay Heat Distribution among Casks

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ABSTRACT

For this paper, the optimization of the SFAs arrangement in the casks was performed based on the advanced optimization algorithms such as Differential Evolution, Particle Swarm Optimization, and Sine Cosine Algorithm. The algorithms were adopted for the problem of interest and implemented in the MATLAB code. Each loading campaign was treated separately due to limitations such as minimal cooling time of 5 years in the SFP after a SFA is taken out of the reactor core. The starting time of each campaign and number of relocated elements is the same as in real NEK SFDS project. The decay heats of the SFAs were calculated based on the foreseen operational history using the ORIGEN-S from the SCALE6.2.4 code package. The optimization criterion was a uniformly distributed decay heat among the casks in each loading campaign. The constrains included SFA cooling time and limiting region heat loads. Fitness function was therefore defined as the standard deviation of the total heat loads among the casks. Except for the standard deviation minimization, the results in terms of mean, minimum and maximum cask heat load, as well as the total load in the campaign are also presented.

1 INTRODUCTION

Nuclear power plant Krsko opted for Spent Fuel Dry Storage (SFDS) to ensure place for spent fuel assemblies (SFA) in the Spent Fuel Pool (SFP) for additional 20 years of prolonged operation. The SFAs will be probably relocated from the SFP to the SFDS in four loading campaigns; in Campaign 1 16 casks will be filled; in Campaign 2 also 16 casks; in Campaign 3 12 casks, and in Campaign 4 18 casks. In total, 2294 SFAs will be placed in a dry storage building, arranged in 62 HI-STORM FW casks, 37 SFAs in each cask [1]. There is also an option of three loading campaigns, with above mentioned Campaign 3 and 4 united in one campaign, depending on the project development.

There are different constraints that must be satisfied when arranging the SFAs in the casks. The most important is decay heat since the cooling of the casks is passive by design. The layout of the cask is limited by the total decay heat per cask. That is the maximal decay heat a cask can contain to be cooled adequately. When arranging the casks, it is possible to have maximal decay heat in one cask and the other cask may be much less thermally loaded. However, it is favourable to have uniform loading in all casks to avoid maximal thermal load if there are thermally underloaded casks. This problem can be solved by using optimization algorithms to arrange the casks under desired constraints. There is a wide spectrum of the optimization techniques that can be used for that purpose [2]. However, not many research studies have been published on optimization of the SFAs in casks. Spencer et al. proposed new method for optimization of dry cask loadings called GAMMA-PC, which is based on greedy randomized adaptive search procedures embedded in a multiobjective evolutionary algorithm [3]. Solans et al. performed an optimization of the canister loading in deep geological repositories using first fit decreasing and genetic algorithm [4]. Bautista-Valhondo et al. applied a three steps approach in minimizing the standard deviation of the thermal load among casks. In the first step they used mixed integer linear programming to minimize the cost of the casks required. Then they used a deterministic algorithm to place the spent fuel assemblies in specific region of a specific casks. Lastly, they used local search algorithm to minimize the standard deviation [5].

In this paper, the application of optimization techniques such as Differential Evolution [6], Particle Swarm Optimization [7], and Sine Cosine Algorithm [8] for the SFAs arrangement in the casks was investigated. The algorithms were adopted for the problem of interest and implemented in the MATLAB code [9]. Each loading campaign was treated separately due to limitations such as minimal cooling time of 5 years in the SFP after a SFA is taken out of the reactor core. The starting time of each campaign and number of relocated elements is the same as in real NEK SFDS project [1]. The decay heats of the SFAs were calculated based on the foreseen operational history using the ORIGEN-S from the SCALE6.2.4 code package [10]. The optimization criterion was a uniformly distributed decay heat among the casks in each loading campaign. The constrains included SFA cooling time and region heat load limits.

2 OPTIMIZATION TECHNIQUES

Three optimization techniques were considered as a potential optimization tool for arranging SFAs into casks: Differential Evolution, Particle Swarm Optimization and Sine-Cosine Algorithm. In the following subchapters a brief description of these techniques is provided.

2.1 Differential Evolution

Differential Evolution (DE) [6] is a population based parallel direct search optimization method. The DE uses evolution operator crossover, selection, and mutation, and it is based on real encoding. The algorithm starts with uniformly and randomly chosen initial population, covering the entire search space.

The population size NP is arbitrarily determined by the user, as well as the crossover and mutation factor, CR and F respectively. In the mutation phase, the next generation mutant individual is obtained by adding the weighted difference between two vectors in a population to a third vector:

$$v_{i,G+1} = x_{r1,G} + F(x_{r2,G} - x_{r3,G}) \tag{1}$$

where $r_1, r_2, r_3 \in \{1,2,\dots,NP\}$ are random indexes mutually different and different from i. The diversity of the next generation population is achieved by introducing crossover:

$$u_{i,G+1} = \begin{cases} v_{ji,G+1} & if\ (randb(j) \leq CR)\ or\ j = rnbr(i) \\ x_{ji,G} & if\ (randb(j) > CR)\ or\ j \neq rnbr(i) \end{cases} \Bigg\}\ j = 1,2,..,D$$
$$u_{i,G+1} = (u_{1i,g+1}, u_{2i,g+1}, \dots, u_{Di,g+1}) \tag{2}$$

where D is the dimension of the vector, $randb(j)$ is the jth evaluation of uniform random number generator in the range of (0,1), $rnbr(i)$ is a random index in the range (1, D), ensuring that at least one parameter from $v_{ji,G+1}$ is inherited.

In the selection process, one should decide if the next generation population vector $u_{i,G+1}$ is going to replace the current generation population vector $x_{i,G}$ by evaluating the fitness of the vectors:

$$u_{i,G+1} = \begin{Bmatrix} u_{i,G+1} & if\ f(u_{i,G+1}) < f(x_{i,G}) \\ x_{i,G} & else \end{Bmatrix}. \tag{3}$$

2.2 Particle Swarm Optimization

Particle Swarm Optimization (PSO) [7] is an optimization method inspired by the social behaviour of birds that maintain swarm actions. Each particle in the swarm depends on the actions of a swarm, i.e., the entire swarm is moving through the search space according to the best particle's actions. At the beginning, it is important to assign initial position and velocity of each particle in a swarm. The optimization process is iterative so in each iteration the position and velocity of a particle is update according to the equations:

$$v_i^{k+1} = \omega v_i^k + c_1 r_1 (p_i^k - x_i^k) + c_2 r_2 (g_i^k - x_i^k) \tag{4}$$

$$x_i^{k+1} = x_i^k + v_i^{k+1} \tag{5}$$

where k denotes kth iteration, i denotes ith particle in a swarm, r_1 and r_2 are random and independent variables uniformly distributed in the range (0,1), c_1 and c_2 are positive acceleration coefficients which control maximum step size, ω is inertial weight. To prevent particles from flying out of the solution area the velocities are conditioned by $(-v_{max}, v_{max})$.

2.3 Sine-Cosine Algorithm

Sine – Cosine Algorithm (SCA) [8] is a population based optimization algorithm which uses a sine and cosine function to search through the domain of parameters being optimized. The population in the next generation (iteration) is obtained according to:

$$X_i^{t+1} = \begin{cases} X_i^t + r_1 \sin(r_2)\, |r_3 P_i^t - X_i^t|, r_4 < 0.5 \\ X_i^t + r_1 \cos(r_2)\, |r_3 P_i^t - X_i^t|, r_4 \geq 0.5 \end{cases} \tag{6}$$

where X_i^t is the current solution, i is the i-th member of population, t is the t-th iteration, P_i^t is best solution so far, r_1 is the coefficient which determines the direction of the movement through the domain, r_2 determines the length of the movement towards or from the best solution so far, r_3 is used to stochastically assign weight to the best solution so far and r_4 determines whether sine or cosine function will be used.

Coefficient r_1 is calculated as follows:

$$r_1 = a - t\frac{a}{T} \tag{7}$$

where T is the maximal number of iterations, and a is a constant. Coefficient r_2 is randomly selected in the interval [0, 2π]. If the coefficient r_3>1, the influence of the best solution so far is emphasized, while for r_3<1 the influence of the best solution so far is diminished. Coefficient r_4 is randomly selected in the interval [0, 1].

3 METHODOLOGY

The optimization of SFA layout in casks was performed for two cases. In Case A four loading campaigns were considered: in the first campaign 16 casks; in the second also 16 casks; in the third 12 casks; and in the last one 18 casks. For the Case B three campaigns were considered with the last two campaigns from Case A merged in one campaign in which 30 casks will be loaded. In both cases 62 casks will be loaded. Each cask can hold up to 37 SFA. The starting date of each campaign loading for both cases is given in Table 1.

Table 1: Start dates of campaigns in case A and B

Campaign	Start date	
	Case A	Case B
1	01.01.2022	01.01.2022
2	01.01.2028	01.01.2028
3	09.01.2038	29.12.2048
4	29.12.2048	-

In this paper, the foreseen characteristics of SFAs according to original SFDS project design [1] were considered. There are 2294 SFAs with foreseen discharge date, burnup and enrichment specific for each element. These characteristics were based on the existing operating experience and existing spent fuel in the SFP in the Krsko NPP.

There are three criteria set by the SFDS project design that have to be taken into account during the arrangement of the SFAs in the casks. The first is the minimum cooling time of 5 years in the SFP set to facilitate the manipulation of the SFAs with decreased decay heat during that time. The second is a region-wise decay heat limit (Figure 1). Each cask is divided into three spatial regions with decay heat limits as follows:

- Region 1 < 875 W
- Region 2 < 1700 W
- Region 3 < 890 W

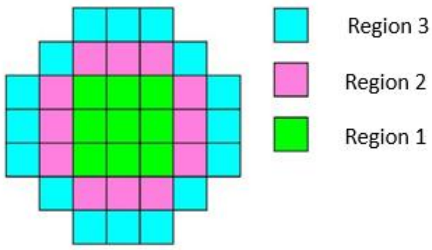

Figure 1: Spatial regions

This region-wise division is introduced to balance shielding and cooling properties of casks. Higher neutron and gamma source intensity means higher decay heat. From the shielding point of view, it is favourable to place the SFAs with the higher source intensity in the innermost region and the ones with lower in the outermost region. On the other hand, from the thermal point of view, cooling is more efficient if the SFAs with higher decay heat are placed outwards and the ones with lower inwards. The balance between these two is to place the SFAs with higher source intensity and thus higher decay heat in the middle region. The third criterion is the limit decay heat of 42 kW per cask which was not used as a constraint in the optimization process, but the results will be checked against it.

Thus, before optimization, it was convenient to divide the data into sets taking into account the cooling limit. This resulted in four datasets corresponding to each campaign in Case A and three datasets for three campaigns in Case B. The criterion is:

$$\textit{Starting date of a campaign} - \textit{discharged date of a SFA} > \textit{5 years} \tag{8}$$

Next, the division by the second criterium of region-wise decay heat limits resulted in three subsets for each campaign. It is important to note that all the data which belong to dataset for Campaign 1 are also applicable for other campaigns since their starting date is later than campaign 1. Thus, Campaign 1 was optimized the first due and then Campaigns 2, 3 and 4. In each campaign, the SFAs in region 1 were selected, and then region 3 and 2. All the SFAs that are applicable for region 1 are also applicable for region 3 and 2 due to higher decay heat limit. Having datasets ready, the decay heat calculations were the next step in this methodology. The decay heat was calculated for each SFA using ORIGEN-S module of the SCALE6.2.3 package [10]. For the data that may be applicable for multiple campaigns, at this point the cooling times until the start of each campaign were calculated and used in ORIGEN-S. For example, a SFA that belongs to first campaign is also applicable for all next campaigns. Therefore, four cooling times were calculated according to Eq. (8) and corresponding decay heats were calculated afterwards. If this SFA is not selected for the first campaign, it is transferred to the next campaign and there is no need for another decay heat calculation since all possible decay heats were calculated at once before the optimization process has started.

The three above described optimization methods were applied for optimizing the layout of the SFAs in casks specific for the SFDS project in the Krsko NPP. The optimization criterion is uniform decay heat among the casks in each campaign. The decay heat of each cask is calculated as the sum of decay heats of all the SFAs in the that cask. Thus, the fitness function is defined as the standard deviation of the decay heats of the casks belonging to certain campaign. For example, for Campaign 1, the standard deviation of decay heats of the first 16 casks was calculated. Using the optimization techniques, through multiple iterations and multiple populations, we find the combination with the lowest standard deviation of decay heats. The number of iterations was set as maximal possible, which was calculated as the ratio of the available data and the number of casks in campaign under consideration. The number of populations is set as nPop=100. The optimization process stops when all iterations were conducted. The DE method requires user defined mutation factor F and crossover factor CR, while the SCA method requires constant a. Based on previous experience and literature references, these parameters are set as follows: F=0.8, CR=0.8 and a=2.

4 RESULTS

4.1 Case A

This section gives the results of the optimization process for the Case A. In Table 2 the comparison of the optimization techniques is provided in terms of standard deviation, mean decay heat, maximal and minimal decay heat, and the total load in the campaign. From these results it can be seen that the SCA method resulted with the lowest standard deviation of decay heats among the casks in all campaigns except Campaign 4 for which PSO method gave smaller standard deviation. This means that optimization methods select different SFAs and therefore mean decay heat is different for each optimization method. It can also be seen that the maximal decay heat is much less than the project design limit of 42 kW per cask. That means that for the data used, it is not necessary to implement the maximal decay heat per cask as a constraint in the optimization process. It is interesting, however, that the standard deviation obtained by any method increases in subsequent campaigns, and it is especially higher in the last campaign. That is because there are more SFAs in that campaign than in the others, but more importantly because in the last campaigns there is not much space for optimization since all remaining elements have to be loaded. This means that in the last campaign we cannot select which SFA to load, but what is possible to be done is maneuvering with the arrangement of the SFAs in the casks to obtain as low standard deviation as possible.

Table 2: Comparison of the optimization techniques in terms of standard deviation, mean decay heat, maximal and minimal decay heat, and the total decay heat for each campaign in Case A (four campaigns)

Campaign	Method	Std [W]	Mean decay heat [W]	Maximal decay heat [W]	Minimal decay heat [W]	Total decay heat [W]
1	DE	10.56	18971.41	18992.81	18955.04	303542.59
	PSO	20.18	17279.74	17328.70	17248.55	276475.89
	SCA	1.27	17579.34	17581.19	17577.23	281269.48
2	DE	70.78	18376.43	18511.76	18257.93	294022.90
	PSO	32.22	19297.90	19348.43	19237.98	308766.34
	SCA	2.77	18885.44	18891.00	18880.82	302167.07
3	DE	51.52	21521.13	21625.13	21434.16	258253.59
	PSO	36.78	21714.08	21758.40	21641.63	260568.99
	SCA	5.37	21477.38	21484.90	21467.90	257728.59
4	DE	430.14	22773.96	23378.45	22023.35	409931.33
	PSO	226.83	22842.59	23252.61	22493.87	411166.67
	SCA	288.46	23005.83	23801.83	22648.41	414104.96

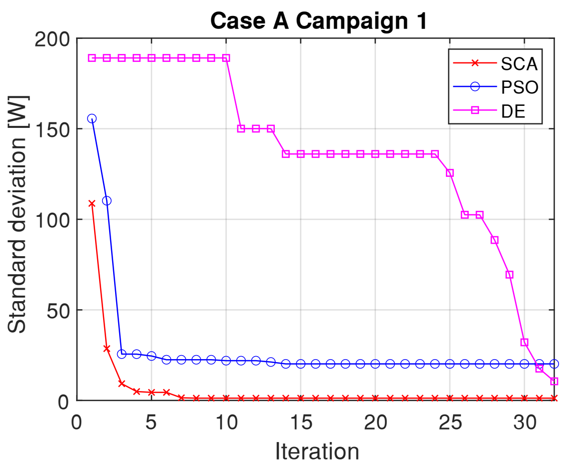

Figure 2: Optimization process for different methods Case A

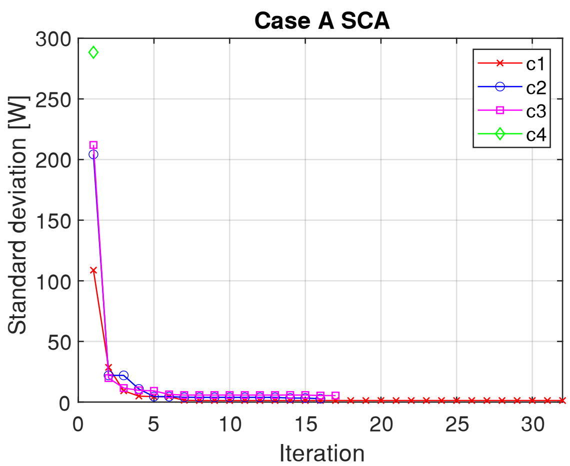

Figure 3: Optimization process for all campaigns conducted by the SCA method Case A

The optimization process, ie. the standard deviation as a function of iterations conducted for Campaign 1 in Case A for different methods is shown in Figure 2. Note that the iteration process is repeated for each element added. This figure shows results for the last added element in Region 2 of Campaign 1 in Case A. The standard deviation decreases with the number of iterations for all methods. Recall, the number of iterations was set maximal possible and the stopping criterion was all iteration conducted. It can be seen that only six iterations were required for the SCA which gave the smallest standard deviation. The optimization process for all campaigns conducted by the SCA method is shown in Figure 3. From this figure, it is clear that for the Campaign 1 there were many available data, so the number of possible iterations is higher than in other campaigns. It is also clear that the optimization process for the last SFA in Campaign 4 could not be iterated because there were no SFAs to maneuver with. An example of the optimized layout of the Casks 1 decay heat of each element is given in Figure 4.

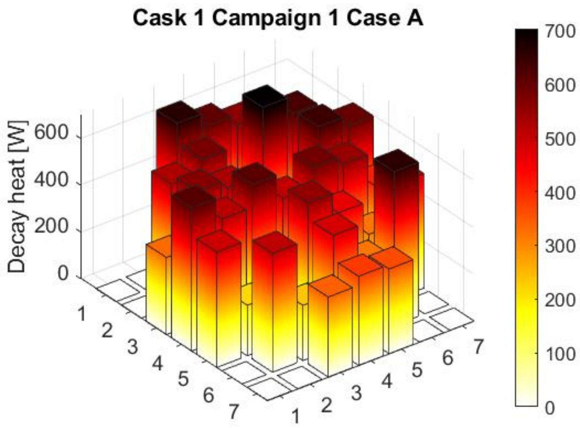

Figure 4: Decay heat layout for Cask 1 of Campaign 1 in Case A

4.2 Case B

The results for Case B are shown in Table 3 and the optimization process is shown in Figure 5 for Campaign 1 for different methods and in Figure 6 for all campaigns optimized using SCA method. It can again be observed that SCA method resulted in a significantly lower standard deviation, except for the last campaign. In this case, the maximal decay heat per cask is still lower than the limiting 42 kW. From the obtained results it can be concluded that Case B is more favourable than Case A. In case B, we obtained lower standard deviation in the last campaign, but it is also important to note that after Campaign 2 the rest of the SFAs will have longer cooling time and therefore lower decay heat and source intensity.

Table 3: Comparison of the optimization techniques in terms of standard deviation, mean decay heat, maximal and minimal decay heat, and the total decay heat for each campaign in Case B (three campaigns).

Campaign	Method	Std [W]	Mean decay heat [W]	Maximal decay heat [W]	Minimal decay heat [W]	Total decay heat [W]
1	DE	14.84	19117.84	19134.71	19083.58	305885.42
	PSO	21.37	20020.28	20048.36	19972.09	320324.52
	SCA	0.85	17644.81	17646.84	17643.37	282316.88
2	DE	70.08	18363.51	18480.81	18256.68	293816.16
	PSO	18.48	17523.08	17553.60	17490.94	280369.29
	SCA	6.61	18832.12	18838.26	18809.72	301313.88
3	DE	431.67	20820.34	21592.98	20178.65	624610.14
	PSO	191.19	20930.65	21354.69	20489.29	627919.48
	SCA	240.95	20969.93	21511.11	20433.47	629097.88

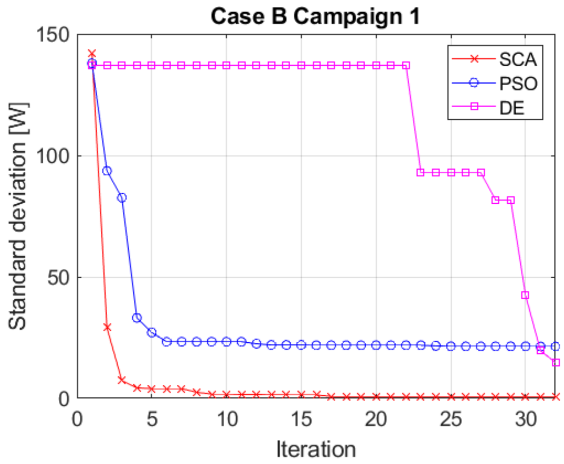

Figure 5: Optimization process for different methods Case B

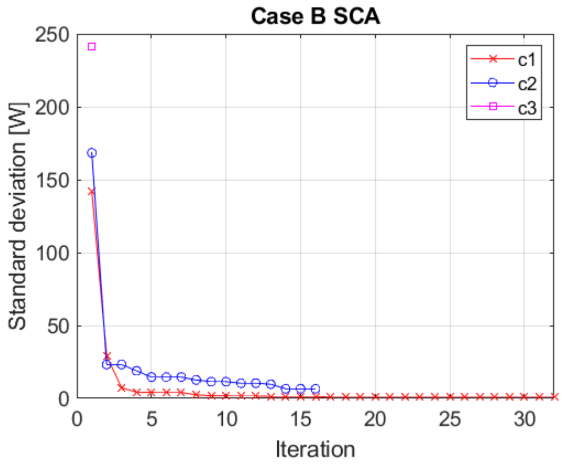

Figure 6: Optimization process for all campaigns conducted by the SCA method Case B

5 CONCLUSIONS

In this research, the optimization of the SFAs arrangement in the casks was performed for two loading cases based on the advanced optimization algorithms such as Differential Evolution, Particle Swarm Optimization, and Sine Cosine Algorithm. The results showed that in both cases the SCA method resulted with the lowest standard deviation of decay heat among the casks in all campaigns except Campaign 4. It was also showed that in both cases the maximal decay heat is much less than the project design limit of 42 kW per cask. That means that for the data used, it is not necessary to implement the maximal decay heat per cask as a constraint in the optimization process. It is interesting, however, that the standard deviation obtained by any method increases in subsequent campaigns, and it is especially higher in the last campaign. That is because there are more SFAs in that campaign than in the others, but more importantly because in the last campaigns there is not much space for optimization since all remaining elements have to be loaded. This means that in the last campaign we cannot select which SFA to load, but what is possible to be done it a maneuvering with the arrangement of the SFAs in the casks to obtain as low standard deviation as possible.

The optimization process showed that the standard deviation decreases with the number of iterations for all methods. Only six iterations were required for the SCA method, which gave the lowest standard deviation. The optimization process for different campaigns showed that there were many available data for Campaign 1 so the number of possible iterations is higher than in other campaigns. It is also clear that the optimization process for the last SFA in Campaign 4 in Case A and in Campaigns 3 in Case B could not be iterated because there were no SFAs to maneuver with.

Case B resulted in lower standard deviations, especially in the last campaign, but it is also important to note that after Campaign 2 the rest of the SFAs will have longer cooling time and therefore lower decay heat and source intensity. However, other factors may prevail in making the decision on the number of campaigns.

The purpose of this research was to illustrate the potential of advanced optimization algorithms for SFA arrangement in the casks. The obtained standard deviations by any method are way lower than the ones calculated for the vendor's proposed loading plan, which are around couple of thousands. However, there are many other criteria that were taken into account by the vendor, for example inserts.

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