

Optimization of Spent Fuel Assemblies Arrangement in Dry Storage Casks using Mixed Integer Programming and Heuristic Methods

Paulina Družijanić, Matija Zidar, Davor Grgić
University of Zagreb Faculty of Electrical Engineering and Computing
Unska 3, 10000 Zagreb, Croatia

Paulina.Druzijanic@fer.unizg.hr, Matija.Zidar@fer.unizg.hr, Davor.Grgic@fer.unizg.hr

ABSTRACT

Spent fuel dry storage (SFDS) project in Nuclear Power Plant (NPP) Krško covers transfer of spent fuel from spent fuel pool to Dry storage building in four loading campaigns. The first loading campaign was performed in 2023 according to the fuel loading plan proposed by the casks vendor Holtec International and the rest of the loading campaigns are expected to start in 2028, 2038 and 2048, respectively. In this paper, the arrangement of available spent fuel assemblies (SFA) in SFDS HI-STORM FW storage casks for future loading campaigns is proposed. In campaign two 16 casks will be filled, in campaign three 12 casks and in campaign four 18 casks. There is also an option that the last two campaigns might be merged into one, so in that case, there would be in total 3 loading campaigns and in the last campaign 30 casks would be filled. Each storage cask can accept up to 37 SFAs, divided into three spatial regions according to heat rate limit (maximum cladding temperatures during hypothetical accident) for each region. The proposed arrangement for each of the following campaigns is a result of optimization process using Mixed Integer Programming and heuristic optimization methods, both capable to comply with required technical and logistic constraints. The cost function can be either minimization or maximization of SFAs decay heat in casks depending on spent fuel pool management strategy, but it can also be defined as a uniform decay heat distribution among casks to avoid potential overheating. The SFAs decay heat used in optimization process was calculated using Origen-S module from SCALE code package using real operating history and cooling time of NPP Krško SFAs. The optimization was performed considering the number of SFAs in each campaign (both four and three loading campaigns considered), minimum cooling period of 5 years in spent fuel pool, plant operation until year 2043, region-wise heat rate casks limits, and additional constraints on cask locations allowed to accept SFAs with inserts.

Keywords: *spent fuel assembly, spent fuel dry storage, HI-STORM FW, mixed integer programming, decay heat*

1 INTRODUCTION

Nuclear Power Plant (NPP) Krško has been in operation since 1983 and in 2023 it obtained the life-time extension of 20 years. Spent fuel generated during the initial NPP lifetime is located at the spent fuel pool at the site. The spent fuel pool was designed to accommodate spent fuel during design lifetime and one of prerequisites to obtain the life-time extension was to increase spent fuel storage capacity. NPP Krško opted for spent fuel dry storage. The spent fuel dry storage in NPP Krško consists of four loading campaigns. The first campaign was loaded in 2023 according to the fuel loading plan proposed by the Holtec and the rest of the loading campaigns are expected to start in 2028, 2038 and 2048, respectively. In the first loading campaign, 16 storage casks were filled with

Spent Fuel Assemblies (SFAs) from the NPP's spent fuel pool. Each storage cask can accommodate up to 37 SFAs. In total 592 SFAs were stored in Dry Storage Building (DSB) during campaign one. In future campaigns, 16 storage casks are expected to be filled in campaign two, 12 in campaign three and 18 in campaign four.

Optimizing the arrangement of spent fuel in casks can help reduce thermal load, reduce dose rates emanating from casks or it can reduce the number of casks needed to store the spent fuel thereby minimizing overall cost of the storage. Minimization of standard deviation of the thermal load was used as an optimization criterion using mixed integer programming for a future Spanish storage, but all SFAs were considered for loading in one step, i.e. in a single loading campaign [1]. In addition, minimization of the highest heat power in casks for final disposal was done heuristically [2]. Minimization of dose rate as an optimization criterion was used for VVER-1000 SFAs using the OPOS-1000 code based on generic optimization algorithm [3]. Minimization of the number of casks needed was used as an optimization criterion using genetic algorithm [4].

In this paper, Mixed Integer Programming and heuristic optimization methods were employed to optimize future loading campaign in Nuclear Power Plant Krško using real operational history of the existing spent fuel assembly and foreseen operation of future SFAs generated during prolonged NPP lifetime. The SFAs decay heat used in optimization process was calculated using Origen-S module from SCALE6.2.4 code package. The cost function can be either minimization or maximization of SFAs decay heat in casks depending on of spent fuel pool management strategy, but it can also be defined as a uniform decay heat distribution among casks to avoid potential overheating. The optimization was performed considering the number of spent fuel assemblies in each campaign (both four and three loading campaigns considered), minimum cooling period of 5 years in spent fuel pool, plant operation until year 2043, region-wise heat rate casks limits, and additional constraints on cask locations allowed to accept SFAs with inserts (Rod Control Cluster Assembly - RCCA, Thimble Plug - TP).

2 METHODOLOGY

2.1 Spent fuel inventory and decay heat

Each SFA is described with operational parameters such as enrichment, burnup, and cooling time. For the existing spent fuel, real operational history was considered and for those yet to become SFAs, foreseen operational history was used. Origen-S module from SCALE6.2.4 **Error! Reference source not found.** was used to calculate decay heat for each SFA, with the expected number of 2294 SFAs in total. Large number of needed inputs and obtained output required preprocessing and postprocessing tool to automate the process. For each SFA, based on the time of final discharge from the reactor core, cooling time in spent fuel pool, and loading date, it was determined in which loading campaigns it can be loaded and decay heats were calculated for those loading campaigns. For example, SFA that was taken out of the reactor 20 years ago satisfies minimum cooling time of 5 years and can be placed in any loading campaign. Therefore, for such SFAs, four cooling times (each until the start date of the loading campaign) were used to calculate four decay heats in one calculation. On the other hand, for SFA that will be taken out of the reactor for example in 2027, it will not be appropriate for loading in campaign two which will start in 2028, therefore only two decay heats will be calculated based on the cooling time until 2038 and 2048 for campaign three and four, respectively.

2.2 Mixed integer programming

Linear Programming (LP) and Mixed Integer Linear Programming (MILP) are widely used in solving logistical problems in combinatorial optimization. One of the most famous is the knapsack problem [6] which can be adopted for SFA arrangement problem. Determining which SFA should be assigned to which cask and campaign respecting all technical and logistical constraints is

combinatorial optimization problem and is solved using MILP which is well studied and mature optimization technique.

MILP models were developed in open-source technologies using Python with Google OR-Tools framework [7] and open-source solvers which were a bit slower than their commercial counterparts but solving times were in low seconds for a single campaign and low minutes even for all SFA and all campaigns solved at once which is enough for this type of long-time planning problems.

The main goal of the optimization process is determining when to load SFAs, in which cask and in which campaign. As mentioned earlier, each campaign has predefined number of casks. Campaign one 16, campaign two 16, campaign three 12 and campaign four 18 casks, and each cask can accept 37 SFAs. The campaigns were optimized sequentially, first campaign 1 and last campaign four.

This optimization process has several constraints. The first one is minimum 5 years SFA cooling time in spent fuel pool. According to that, each SFA has decay heats (thermal powers) calculated for corresponding campaigns.

To help with model understanding, the following major sets and corresponding indices used in optimization model are given in Table 1. Additionally, three more subsets were defined in Table 2 for special constraints occurring in the problem.

Table 1: Indices and sets description

Index	Set	Description
i	\mathcal{J}	Fuel assemblies
k	\mathcal{K}	Campaigns
c	\mathcal{C}	Casks
z	\mathcal{Z}	Thermal regions within cask

Table 2: Indices and subsets description

Index	Subset	Description
ck	$\mathcal{C}_k \subseteq \mathcal{C}$	Subset of casks permitted in campaign k
ir	$\mathcal{J}^R \subseteq \mathcal{J}$	Subset of assemblies with RCCA
is	$\mathcal{J}^S \subseteq \mathcal{J}$	Subset of assemblies with stainless steel rods

A SFA i has thermal power Q_{ki} depending on campaign k date. If SFA is still not in the pool for campaign k (and will be available for future campaigns), it is prevented from being assigned as solution for current campaign. The total allowed decay heat in the cask Q^{cask} is limited to 42 kW, that is the second constraint.

When deciding in which casks' thermal region z should assembly be assigned there are three constraints N_z^{max} and Q_z^{max} which limit max decay heat and number of SFAs in the region. There are three spatial regions in each cask as shown in Figure 1. The number of SFAs in regions in terms of decay heat are given in Table 3. These limits correspond to the trade of between shielding

and cooling characteristics of the casks. Therefore, the lowest is the decay heat limit for region 1 which is the inner region, and the highest for region 2 which is the middle region. Region three is the outer region.

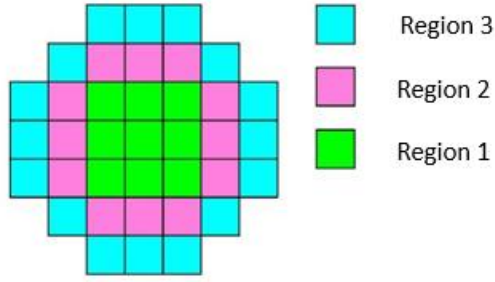


Figure 1 Three spatial regions in a cask

Table 3: Region-wise decay heat limit

Region	Max SFA decay heat	No of SFAs
1	875 W	9
2	1700 W	12
3	890 W	16

If only several casks were filled in the single campaign this would be a regular knapsack optimization problem with single decision (binary) variable $x_{i,k,c,z}$, but this multi-period optimization requires additional model expansions. Therefore, additional binary variable $y_{c,k}$ is used to assign cask to one predefined campaign and disable algorithm from assigning SFAs decay heat from other campaigns. Each campaign k has predefined number of casks C_k^{max} .

$$\sum_{k \in \mathcal{K}} \sum_{c \in \mathcal{C}} \sum_{z \in \mathcal{Z}} x_{i,k,c,z} \leq 1, \forall i \in \mathcal{J} \quad (1)$$

$$\sum_{k \in \mathcal{K}} y_{c,k} \leq 1, \forall c \in \mathcal{C} \quad (2)$$

$$\sum_{c \in \mathcal{C}} y_{c,k} \leq C_k^{max}, k \in \mathcal{K} \quad (3)$$

$$x_{i,k,c,z} \in \{0,1\}, \quad \forall i \in \mathcal{J}, \forall k \in \mathcal{K}, \forall c \in \mathcal{C}, z \in \mathcal{Z} \quad (4)$$

$$y_{c,k} \in \{0,1\}, \quad \forall c \in \mathcal{C}, \forall k \in \mathcal{K} \quad (5)$$

Those two binary variables can be combined to decrease the search space by preventing solutions which are not feasible and improve solution times. If SFA is not available for the campaign under consideration, its associated binary variable for that campaign is zero. In addition, only SFAs decay heat for campaign under consideration are allowed. In other words, all binary variables related to SFAs which are not available for the cask assigned for certain campaign are automatically set to zero. For example, a cask in campaign two cannot store SFAs with decay heats related to campaign one, three or four.

Each cask has multiple technical constraints. It is divided into three spatial regions (zones) and each region has limited number of slots and maximum allowed SFA decay heat as given in Table 3.

$$\sum_{i \in \mathcal{J}} \sum_{k \in \mathcal{K}} x_{i,k,c,z} \leq N_z^{\max}, \quad \forall c \in \mathcal{C}, z \in \mathcal{Z} \quad (6)$$

$$Q_{k,i} x_{i,k,c,z} \leq Q_z^{\max}, \quad \forall i \in \mathcal{J}, k \in \mathcal{K}, c \in \mathcal{C}, z \in \mathcal{Z} \quad (7)$$

The total decay heat in the cask should be under 42 kW (Q^{cask}) as modelled in the following constraint.

$$\sum_{i \in \mathcal{J}} \sum_{z \in \mathcal{Z}} Q_{k,i} x_{i,k,c,z} \leq Q^{\text{cask}} y_{c,k}, \quad \forall c \in \mathcal{C}, k \in \mathcal{K} \quad (8)$$

In addition to aforementioned constraints, SFAs with inserts such as RCCA or TP are allowed only in region 1 and SFAs with stainless steel rods are allowed only in regions 1 and 2.

$$x_{i,k,c,z} = 0, \quad \forall i \in \mathcal{J}^R, k \in \mathcal{K}, c \in \mathcal{C}, z \in \{2,3\} \quad (9)$$

$$x_{i,k,c,z} = 0, \quad \forall i \in \mathcal{J}^S, k \in \mathcal{K}, c \in \mathcal{C}, z \in \{3\} \quad (10)$$

Algorithm can use any kind of linear objective function, but in this case decay heat minimization is used as follows:

$$\min \sum_{i \in \mathcal{J}} \sum_{k \in \mathcal{K}} \sum_{c \in \mathcal{C}} \sum_{z \in \mathcal{Z}} Q_{k,i} x_{i,k,c,z} \quad (11)$$

For most objective functions (e.g. heat minimization) used in the analysis, there are many combinations that provide the same result. For example, assemblies in one thermal region within a cask can be freely reordered within the same region without changing objective function value. Only one of those combinations is provided as a final result.

2.3 Heuristic methods

Three heuristic methods, namely Differential Evolution (DE) [8], Particle Swarm Optimization (PSO) [9], and Sine Cosine Algorithm (SCA) [10] were adopted to the SFA arrangement optimization problem.

DE 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:

$$v_{i,G+1} = x_{r_1,G} + F(x_{r_2,G} - x_{r_3,G}) \quad (12)$$

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:

$$u_{i,G+1} = \begin{cases} v_{ji,G+1} & \text{if } (\text{randb}(j) \leq CR) \text{ or } j = \text{rnbr}(i) \\ x_{ji,G} & \text{if } (\text{randb}(j) > CR) \text{ or } j \neq \text{rnbr}(i) \end{cases} \quad j = 1,2, \dots, D \quad (13)$$

$$u_{i,G+1} = (u_{1i,G+1}, u_{2i,G+1}, \dots, u_{Di,G+1})$$

where D is the dimension of the vector, $randb(j)$ is the j th 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:

$$u_{i,G+1} = \begin{cases} u_{i,G+1} & \text{if } f(u_{i,G+1}) < f(x_{i,G}) \\ x_{i,G} & \text{else} \end{cases} \quad (14)$$

PSO 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:

$$v_i^{k+1} = \omega v_i^k + c_1 r_1 (p_i^k - x_i^k) + c_2 r_2 (g_i^k - x_i^k) \quad (15)$$

$$x_i^{k+1} = x_i^k + v_i^{k+1} \quad (16)$$

where k denotes k th iteration, i denotes i th 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 $(-v_{max}, v_{max})$.

SCA 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:

$$X_i^{t+1} = \begin{cases} X_i^t + r_1 \sin(r_2) |r_3 P_i^t - X_i^t|, r_4 < 0.5 \\ X_i^t + r_1 \cos(r_2) |r_3 P_i^t - X_i^t|, r_4 \geq 0.5 \end{cases} \quad (17)$$

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:

$$r_1 = a - t \frac{a}{T} \quad (18)$$

where T is the maximal number of iterations, and a is a constant. Coefficient r_2 is randomly selected in the interval $[0, 2\pi]$. 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 RESULTS AND DISCUSSION

3.1 Optimization of the existing campaign one

Results comparison between MILP, heuristic methods and real Holtec Internation (HI) solution is given in Table 4 for decay heat minimization and in In decay heat maximization optimization, heuristic methods obtained better results than MILP. Theoretically available maximum without technical constraints is 408.307 kW and PSO obtained best result, then MILP and SCA. DE converged in suboptimal solution.

Holtec used some other parameters (some of them based on the experience) besides cask technical constraints and heat optimization so real campaign results are somewhere in between.

Table 5 for decay heat maximization criteria. Holtec results are optimized by the company and are there just for comparison with presented optimization results. MILP run time is around 6 seconds.

LP problems are convex and always give global optimum as solution, but MILP has discrete search space and found solutions are close to global optimum, but their optimality is not always guaranteed. The same is true for heuristic optimization where found solution is based on initial conditions and solution space search vectors which can result in local optimum solution.

In decay heat minimization optimization MILP and SCA provided the same optimal solution. In direct comparison between heuristic methods the best one from the point of convergence and obtained results is SCA.

Table 4: Optimization results comparison for campaign one using decay heat minimization criterion

Cask	Decay heat [kW]				
	HI	MILP	DE	PSO	SCA
1	17.846	14.188	14.014	13.923	13.954
2	19.465	14.141	15.066	13.772	13.986
3	21.377	14.095	16.037	14.100	14.016
4	20.759	14.182	14.648	14.005	14.030
5	17.789	14.389	15.067	14.067	14.057
6	22.969	14.013	16.857	14.186	14.079
7	22.610	13.424	16.134	14.265	14.104
8	23.694	13.909	15.067	14.085	14.129
9	19.331	14.035	15.763	14.097	14.147
10	23.083	14.398	15.091	14.287	14.176
11	22.525	14.299	17.100	14.227	14.189
12	20.332	14.308	14.871	14.245	14.212
13	18.142	14.401	14.328	14.177	14.240

Cask	Decay heat [kW]				
	HI	MILP	DE	PSO	SCA
14	16.078	13.904	15.758	14.222	14.313
15	20.821	14.201	15.734	14.355	14.339
16	23.942	14.443	14.079	14.332	14.359
Sum	330.763	226.331	245.615	226.346	226.331

In decay heat maximization optimization, heuristic methods obtained better results than MILP. Theoretically available maximum without technical constraints is 408.307 kW and PSO obtained best result, then MILP and SCA. DE converged in suboptimal solution.

Holtec used some other parameters (some of them based on the experience) besides cask technical constraints and heat optimization so real campaign results are somewhere in between.

Table 5: Optimization results comparison for campaign one using decay heat maximization criterion

Cask	Decay heat [kW]				
	HI	MILP	DE	PSO	SCA
1	17.846	25.464	23.651	26.554	25.145
2	19.465	25.750	23.726	26.385	25.166
3	21.377	25.375	23.372	25.940	25.196
4	20.759	25.457	24.674	25.519	25.231
5	17.789	25.858	22.056	25.386	25.286
6	22.969	25.436	23.570	25.702	25.307
7	22.610	24.821	26.209	25.293	25.338
8	23.694	25.633	22.485	25.618	25.374
9	19.331	24.345	23.208	25.345	25.395
10	23.083	25.687	24.088	25.465	25.428
11	22.525	25.835	24.638	25.254	25.537
12	20.332	25.887	23.820	25.180	25.558
13	18.142	25.794	26.725	25.198	25.596
14	16.078	24.996	24.262	25.332	25.617
15	20.821	25.004	22.755	25.233	25.643
16	23.942	25.971	24.293	24.776	25.679
Sum	330.763	407.315	383.531	408.183	406.495

3.2 Optimization of the future campaigns

For the optimization of the future campaigns, two cases are considered. Case A is optimization of the future campaigns two, three and four, whereas in Case B only campaigns two and three are optimized. Recall, in Case B original campaign three and four are merged into one and loading date of that campaign is the same as for original campaign four.

For the optimization of the future campaigns, SFA data of the original campaign loading was removed from the dataset. Optimization results for heat minimisation after the initial campaign are given in Table 6. Each campaign was optimized separately by including previous campaigns results. For comparison, SCA results are provided in the table since that method gave the best results initially. Both methods provide similar results, especially in last campaign for which identical results are obtained, even though different solutions were obtained in previous campaigns. This can be explained by the fact that campaign four consists mostly of SFAs generated after campaign three and their cooling time is lower so their decay heat is higher and dominate in final sum. The specific thing in this optimization problem is that the number of SFAs is finite and all of them must be stored during those four campaigns. That means that in the last campaign there is no place for optimization since all the remaining SFAs must be stored. That means that they can only be rearranged among the casks and compliance with technical constraints can be verified.

Table 6: Case A future campaigns optimization results comparison using decay heat minimization criterion

Cask	Decay heat [kW]					
	Campaign two		Campaign three		Campaign four	
	MILP	SCA	MILP	SCA	MILP	SCA
1	16.821	16.169	21.167	21.949	25.427	25.241
2	16.512	16.200	22.317	21.979	25.956	25.282
3	16.703	16.239	22.485	21.995	25.970	25.337
4	16.941	16.271	22.493	22.018	25.235	25.380
5	16.607	16.312	22.457	22.050	25.594	25.412
6	16.717	16.341	22.068	22.075	25.413	25.524
7	16.866	16.373	21.390	22.099	25.489	25.694
8	16.794	16.406	22.394	22.112	25.600	25.715
9	16.273	16.432	22.267	22.138	25.697	25.733
10	16.423	16.469	21.941	22.158	25.939	25.629
11	16.395	16.511	22.455	22.176	25.679	25.653
12	16.234	16.543	22.098	22.197	25.865	25.821
13	15.697	16.582	-	-	25.865	25.698
14	16.696	16.631	-	-	25.803	25.867
15	16.515	16.703	-	-	25.526	25.763
16	15.944	16.733	-	-	25.014	25.791

Cask	Decay heat [kW]					
	Campaign two		Campaign three		Campaign four	
	MILP	SCA	MILP	SCA	MILP	SCA
17	-	-	-	-	25.793	25.955
18	-	-	-	-	25.646	26.016
Sum	264.139	262.915	265.534	264.945	461.512	461.512

Decay heat distribution for three regions in the casks are shown in Figure 2. All thermal constraints regarding region and cask decay heat are satisfied. Additional constraint was used to produce uniform decay heat distribution without affecting obtained optimal solution.

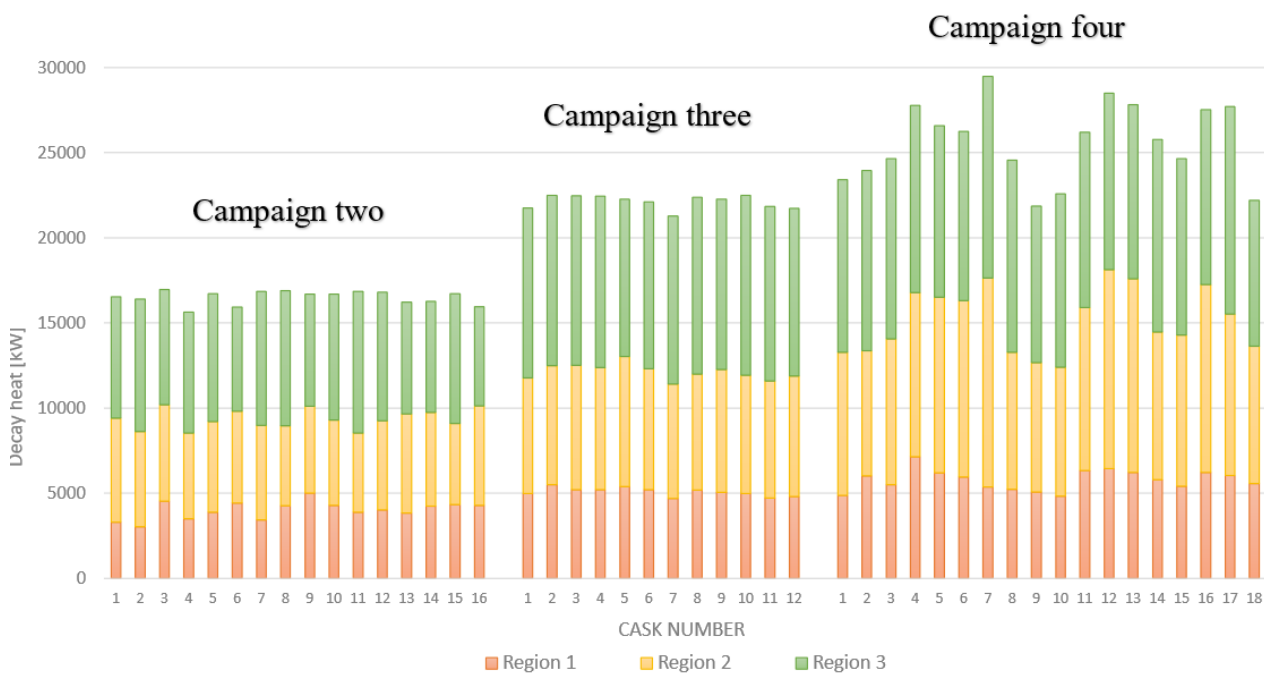


Figure 2 MILP optimization results – further campaigns (Case A)

Decay heat maximization results are presented in Table 7. For comparison, results of PSO method are provided since that method gave the best results among heuristic methods initially. MILP outperforms PSO in all campaigns, even though initially PSO obtained better results.

Using the decay heat minimization as an optimization criterion results in lower thermal load in casks in earlier campaigns, and higher thermal load in the spent fuel pool left to decay until the next campaign loading. Later campaigns have higher thermal load, but each cask is always filled with SFAs with the lowest decay heat and the ones with the highest decay heat were left to cool further. Still, one must have in mind that this optimization approach is dynamic since not all SFAs are available at the beginning but SFAs are generated during real NPP lifetime and are stored in casks during real loading campaigns. That is why results can sometimes be misleading, especially in the case with decay heat maximization. One would expect that if SFAs with the highest decay heat are filled in campaign two, that in later decay heat would be lower. That is to some degree true, but we

have to have in mind that new SFAs are generated from the time of campaign two until the time of campaign three, and those will have higher decay heat due to lower cooling time if selected.

Table 7: Case A future campaigns optimization results comparison using decay heat maximization criterion

Cask	Decay heat [kW]					
	Campaign two		Campaign three		Campaign four	
	MILP	PSO	MILP	PSO	MILP	PSO
1	23.989	25.678	25.824	26.144	21.372	20.892
2	25.984	24.744	25.907	25.928	21.459	20.687
3	25.598	25.505	25.253	26.048	21.248	20.409
4	25.384	25.257	25.771	25.640	21.573	20.559
5	25.717	25.427	25.411	25.780	20.337	21.139
6	25.795	25.346	25.920	25.375	20.606	21.334
7	25.370	24.712	25.935	25.238	21.673	21.803
8	25.735	25.010	25.401	25.203	19.751	21.899
9	24.159	25.075	25.696	25.056	21.960	21.907
10	24.823	25.137	24.624	25.454	20.214	21.066
11	25.511	24.923	25.569	25.233	21.467	22.271
12	25.829	25.097	24.929	24.747	20.899	21.769
13	25.678	25.428	-	-	21.741	21.271
14	24.254	24.850	-	-	20.831	21.223
15	25.271	24.795	--	-	21.714	21.758
16	23.908	24.732		-	21.625	20.275
17	-	-	-	-	21.675	20.653
18	-	-	-	-	21.611	20.797
Sum	403.005	401.715	306.242	305.847	381.758	381.712

The results of Case B using MILP are given in Table 8. Campaign two is the same as in Case A, but campaign three differs. It is interesting to notice that minimization criterion results in higher decay heats than maximization criterion in campaign three. This is because minimization algorithm extracts minimum decay heat in campaign two, and the remaining decay heat for campaign three is higher, and vice versa for maximization criterion. The total decay heat in all campaigns is 991.185 kW in minimization case and 1,091.005 kW in maximization case.

Table 8: Case B MILP future campaigns optimization results for decay heat minimization and maximization criterion

Cask	Decay heat [kW]			
	Campaign two		Campaign three	
	Min	Max	Min	Max
1	16.821	23.989	22.346	21.970
2	16.512	25.984	23.688	20.130
3	16.703	25.598	23.518	21.650
4	16.941	25.384	22.162	21.935
5	16.607	25.717	21.554	17.132
6	16.717	25.795	22.229	21.246
7	16.866	25.370	22.114	21.676
8	16.794	25.735	22.444	20.798
9	16.273	24.159	23.982	17.930
10	16.423	24.823	22.638	19.715
11	16.395	25.511	22.216	22.416
12	16.234	25.829	23.808	18.440
13	15.697	25.678	22.336	20.740
14	16.696	24.254	22.520	20.018
15	16.515	25.271	20.663	19.394
16	15.944	23.908	20.086	20.754
17			23.632	20.435
18			23.906	18.747
19			22.794	21.855
20			21.599	19.052
21			23.575	19.988
22			23.301	19.401
23			23.362	22.351
24			23.185	20.494
25			20.897	18.069
26			22.416	20.465
27			22.449	17.694
28			23.080	20.943
29			22.615	21.084
30			23.119	22.379
Sum	264.139	403.005	678.234	608.902

Finally, an example of the optimized loading plan for cask one in campaign two using maximization criterion (Case A) is given in Table 9.

Table 9: Optimized fuel loading plan for cask one in campaign two (Case A) using maximization criterion

Campaign	Cask	Position	Name	Burnup [MWd/tU]	Enrichment [%]	Cooling time [years]	Decay heat [W]
2	1	1.01	M04	40377	3.90	29.74	502.13
2	1	1.02	AB50	50766	4.70	17.30	767.76
2	1	1.03	M03	40948	3.90	29.73	509.22
2	1	1.04	W03	43083	4.10	21.81	518.73
2	1	1.05	AE56	34670	4.80	12.83	476.08
2	1	1.06	L05	46095	3.90	31.65	478.14
2	1	1.07	AE44	47956	4.70	12.81	707.52
2	1	1.08	ZZ21	39147	4.20	9.80	611.31
2	1	1.09	ZZ48	47636	4.60	9.83	778.03
2	1	2.01	AG12	39322	4.20	11.26	582.34
2	1	2.02	S02	44902	4.00	24.71	519.67
2	1	2.03	AD43	47716	4.70	14.33	676.25
2	1	2.04	R12	45868	4.00	26.69	515.64
2	1	2.05	ZZ19	36130	4.20	9.82	553.83
2	1	2.06	ZZ180	34659	4.20	5.35	774.61
2	1	2.07	ZZ10	39593	4.20	9.77	620.77
2	1	2.08	ZZ49	48497	4.60	9.77	798.91
2	1	2.09	EMPTY4	47692	4.60	9.83	779.24
2	1	2.10	AG24	53058	4.60	8.28	977.65
2	1	2.11	ZZ201	45214	4.60	5.33	1065.81
2	1	2.12	ZZ117	51933	4.70	6.79	1061.58
2	1	3.01	AE12	38299	4.20	12.78	539.50
2	1	3.02	X14	50820	4.70	20.34	648.14
2	1	3.03	AE29	44713	4.70	12.77	647.57
2	1	3.04	U08	41307	4.10	24.75	468.57
2	1	3.05	N34	41798	4.00	29.75	519.02
2	1	3.06	Y42	52303	4.70	20.31	673.21
2	1	3.07	K46	40047	3.90	30.67	491.90
2	1	3.08	AC08	35866	4.20	15.73	466.40

Campaign	Cask	Position	Name	Burnup [MWd/tU]	Enrichment [%]	Cooling time [years]	Decay heat [W]
2	1	3.09	N04	43616	4.00	25.73	573.81
2	1	3.10	G27	39279	3.40	37.21	445.69
2	1	3.11	N35	41445	4.00	29.75	514.65
2	1	3.12	AG27	45020	4.60	11.35	682.72
2	1	3.13	ZZ78	36453	4.20	8.32	603.47
2	1	3.14	ZZ97	47483	4.60	8.33	836.88
2	1	3.15	ZZ32	44997	4.60	9.77	723.94

4 CONCLUSION

This paper presents a systematic optimization framework for the arrangement of spent fuel assemblies in HI-STORM FW dry storage casks for the future loading campaigns at NPP Krško. Two complementary approaches were employed: MILP and three heuristic methods (DE, PSO and SCA), all formulated to respect the full set of technical and logistical constraints, including region-wise decay heat limits, minimum cooling time requirements, and insert-specific placement restrictions.

Campaign one was optimized using minimization and maximization criteria and the results were compared to the existing solution. MILP and SCA achieved identical optimal solutions for heat minimization, while PSO demonstrated the best performance for heat maximization, approaching the theoretical unconstrained maximum. Existing solution differs significantly since Holtec used other parameters (some of them based on the experience) besides cask technical constraints and heat optimization.

Further campaigns were optimized for two cases, Case A and Case B, using minimization and maximization criteria. In Case A, both MILP and SCA provided similar results using minimization criterion. Optimization results revealed some specifics about this case. First, optimization was feasible in the first two campaigns, and in the last campaign there was no place for optimization since all the remaining SFAs had to be stored in remaining casks. That means that they were only rearranged among those casks. Other specific thing is that decay heat decreases over time so minimization as an optimization criterion results in lower thermal load in casks. However, since the generation of SFAs is dynamic, later campaigns result in higher thermal load per cask due to lower cooling time of SFAs.

Case B, in which campaigns three and four are merged into a single 2048 campaign, yielded the counterintuitive result of a higher total cask decay heat in the minimization scenario compared to the maximization scenario, attributable to the distribution of decay heat from preceding campaigns.

The developed MILP model provides a robust, computationally tractable tool for dry storage optimization, while the heuristic methods offer competitive solutions and valuable cross-validation. The framework is directly applicable to future loading campaign planning at NPP Krško and is readily adaptable to other PWR dry storage configuration. Proposed optimization framework can be easily expanded to include additional technical and logistic constraints.

REFERENCES

- [1] J. Bautista-Valhondo, L. Batet, M. Mateo, Minimizing the Standard Deviation of the Thermal Load in the Spent Nuclear Fuel Cask Loading Problem, *Energies*, 13, 4869, 2020
- [2] V.P. Eronen, T. Ranta, J. A.S. Huttunen, M. M. Mäkelä, Loading optimization algorithm for solving assembly assignment problem in the final disposal of spent nuclear fuel in Finland, *Nuclear Engineering and Design*, Volume 402, 2023, 112105, <https://doi.org/10.1016/j.nucengdes.2022.112105>
- [3] M. Lovecký, J. Závorka, OPOS-1000: Advancing the efficiency of VVER-1000 spent nuclear fuel cask loading, *Nuclear Engineering and Design*, Volume 431, 2025, 113723, <https://doi.org/10.1016/j.nucengdes.2024.113723>
- [4] Gomes, Ian B., Saldanha, Pedro L. Cruz, Alvim, Antonio Carlos M., A Methodology for Optimizing the Management of Spent Fuel of Nuclear Power Plants Using Dry Storage Casks, *Science and Technology of Nuclear Installations*, 2019, 4309545, 13 pages, 2019. <https://doi.org/10.1155/2019/4309545>
- [5] Oak Ridge National Laboratory, SCALE: A Comprehensive Modeling and Simulation Suite for Nuclear Safety Analysis and Design, Version 6.2.4, Tech. Rep. ORNL/TM-2005/39, Oak Ridge, TN, USA, 2016
- [6] V. Cacchiani, M. Iori, A. Locatelli, and S. Martello, "Knapsack problems — An overview of recent advances. Part I: Single knapsack problems," *Computers & Operations Research*, vol. 143, p. 105692, 2022, doi: 10.1016/j.cor.2021.105692.
- [7] <https://developers.google.com/optimization>, accessed 8/5/2026
- [8] R. Storn, K. Price, "Differential Evolution-A Simple and Efficient Heuristic for Global Optimization over Continuous Spaces," *Journal of Global Optimization*, Vol. 11, pp. 341-359, 1997.
- [9] G. Ren, S. Wen, Z. Yan, R. Hu, Z. Zeng, Y. Cao, "Power Load Forecasting Based on Support Vector Machine and Particle Swarm Optimization", 12th World Congress on Intelligent Control and Automation (WCICA), June 12-15, 2016, Guilin, China.
- [10] S. Li, H. Fang, X. Liu, "Parameter optimization of support vector regression based sine cosine algorithm", *Expert Systems With Applications*, Vol. 91, pp. 63-77, 2018.