A Preliminary Study on Core Loading Pattern Optimization Techniques Based on a 2D Spatial Allocation Model

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1. Introduction

As the global expansion of renewable energy to achieve carbon neutrality necessitates flexible resources within the power grid, nuclear power plants, traditionally operated as base-load power sources, are now strictly required to have flexible operation capabilities that allow them to adjust their output in response to grid demands. Securing this technology is also an urgent task to maintain the export competitiveness of domestic nuclear reactors on the global market. However, implementing flexible operation exponentially increases the complexity of core design due to issues such as frequent control rod manipulations and xenon oscillation. Currently, Loading Pattern (LP) design heavily relies on manual processes guided by the designer's experience and intuition, with a focus on full-power operation. Manually searching for an optimal LP that satisfies both economics (cycle length) and safety constraints (peaking factor, etc.) under flexible operation condition is highly time-consuming, costly, and inherently limited by significant quality differences depending on the designer's proficiency.

To address these technical limitations, this study ultimately aims to develop an "AI-based, user-friendly optimal core loading pattern generation tool" applicable to APR1400 and APR1000 reactors. As a first step in this research, this paper conducted a performance analysis of probabilistic optimization techniques to be utilized for optimal LP exploration. Given the current absence of reference sample designs specific to flexible operation, a temporary 2D spatial allocation problem model—which mimics the physical characteristics and adjacency effects of fuel assembly layouts in a reactor core—was constructed. Based on this proxy model, representative metaheuristic algorithms and their hybrid algorithms were applied to comparatively analyze the optimization performance and convergence efficiency of each technique.

2. Methods

2.1. 2D Spatial Allocation Problem

Optimizing a practical reactor core LP considering flexible operation involves numerous constraints and highly non-linear physical interactions. In this study, prior to integrating a full-scale core simulator, a "Directional 2D Spatial Allocation Problem" was defined as a surrogate model. This proxy problem mimics the spatial layout characteristics of nuclear fuel assemblies to verify the search performance of the proposed metaheuristic algorithms.

As shown in Fig. 1, this model consists of a 5×5 grid array where 5 different types of items are allocated into 25 available spaces. These 5 item types represent fuel assemblies with varying enrichments and burnups. Generally, fresh fuel with high enrichment provides a longer cycle length (Value) but simultaneously induces higher local peaking and reduces thermal margins (Cost). To simulate this, a trade-off relationship is established in which items with higher values inherently possess higher costs. Furthermore, each item possesses one of four directions (Up, Down, Left, Right). Depending on the type of adjacent item it points to, it receives an additional Synergy or Penalty value. This mathematically simulates the neutronic coupling between adjacent fuel assemblies and the asymmetrical power distribution changes caused by control rod positions in the core.

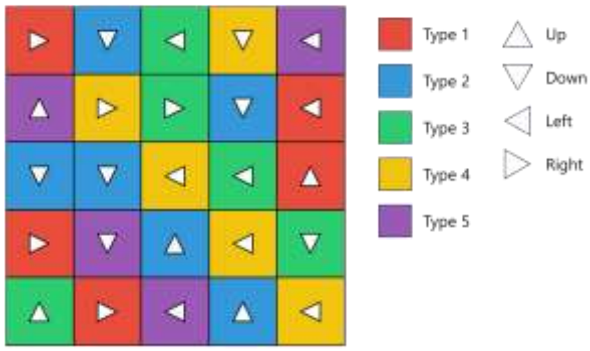


Fig. 1. Example 5×5 Grid Structure of the Directional 2D Spatial Allocation Problem

This 5×5 grid-based surrogate model focuses on simulating the inherent combinatorial difficulty of actual core LP optimization, specifically the trade-off between fuel value and cost, as well as the non-linear interactions between adjacent assemblies. However, practical core design involves much stricter and more complex constraints, such as octant or quadrant core symmetry, fixed inventory of fresh and reloaded fuel assemblies, and continuous neutronic feedback based on the diffusion equation. In this preliminary study, to benchmark the pure search efficiency and local optima escape capabilities of each metaheuristic algorithm prior to coupling with computationally expensive actual core analysis codes, these physical constraints were intentionally simplified or abstracted into discrete matrix formats. In future research, the optimization engine verified through this surrogate model will be directly coupled with a commercial core simulator by incorporating constraints for actual core symmetry and fixed fuel inventory.

2.1.1. Item Properties and Adjacent Interactions

The properties of the five items defined in this problem are presented in Table 1. Items with higher values are configured to have exponentially higher costs, reflecting the fundamental characteristics of the Knapsack Problem, which requires achieving maximum efficiency within limited resources. This simulates the physical trade-off phenomenon in core design, where highly enriched fresh fuel provides a longer cycle length but simultaneously induces high local peaking and reduced thermal margins.

Table I: Base Value and Cost by Item Type

Item Type	Value	Cost
Type 1	10.2	5
Type 2	12.1	6
Type 3	14.0	7
Type 4	15.9	8
Type 5	17.8	9

Furthermore, the Synergy Matrix in Table 2 defines the incremental value that is added based on the types of neighboring item placed in the direction each item points. The rows represent the subject item possessing directionality, while the columns represent the targeted adjacent item. A positive score implies synergy (an increase in value), while a negative value indicates antagonism (a decrease in value). This mathematically implements the neutron flux interference and power distortion phenomena that occur when specific types of fuel assemblies are next to each other in the reactor core.

Table II: Synergy Matrix between Adjacent Items according to Directionality

Target / Subject	Type 1	Type 2	Type 3	Type 4	Type 5
Type 1	0.3	3.2	-1.4	1.6	-3.1
Type 2	-2.5	1.2	3.3	-1.8	1.2
Type 3	2.3	-2.4	0.4	4.1	-3.3
Type 4	-3.4	1.2	-1.2	0.1	3.2
Type 5	4.1	-1.8	-0.2	-2.9	1.1

The values within the synergy matrix (Table II) applied in this study were not merely assigned at random; rather, they were designed with two strategic intentions to ensure a balanced search space and enable a clear performance comparison among the algorithms.

First, to prevent the extreme bias of layouts toward specific item types during the optimization process, the synergy and penalty values occurring between items were evenly distributed to allow for mutual counterbalance.

Second, to minimize the occurrence of tied solutions where different spatial layout combinations yield the exact same total value, the synergy matrix was formulated using floating-point numbers to one decimal place instead of integers. While an integer-based matrix often results in multiple local optima sharing the same fitness, making it difficult to distinguish the superiority of the algorithms, the introduction of floating-point values finely segmented the fitness landscape. This approach significantly enhanced the discriminative power to clearly evaluate the differences in the fine-tuning capabilities of each optimization algorithm.

2.1.2. Mathematical Modeling

Let the row and column of each cell in the 5×5 array be r and c $(1 \leq r, c \leq 5)$. The decision variables are defined as follows:

- $x_{r,c} \in \{1, 2, 3, 4, 5\}$: The type of item placed at position (r, c).
- $d_{r,c} \in \{U, D, L, R\}$: The direction of the item at position (r, c).

Let $V(i)$ and $C(i)$ be the base value and base cost of item type i, respectively. Let $y_{r,c}$ be the type of the adjacent item pointed to by direction $d_{r,c}$. The synergy matrix $S(i, j)$ represents the additional value generated when item type i looks at item type j. (If the direction points outside the grid boundary, $S = 0$).

Therefore, the total value (V_{total}) and total cost (C_{total}) for a given spatial configuration are determined as follows:

$$V_{total} = \sum_{r=1}^{5} \sum_{c=1}^{5} \left(V(x_{r,c}) + S(x_{r,c}, y_{r,c}) \right)$$

$$C_{total} = \sum_{r=1}^{5} \sum_{c=1}^{5} C(x_{r,c})$$

2.1.3. Mathematical Modeling

The ultimate goal of this optimization problem is to find the optimal combination of allocations ($x_{r,c}$) and directions ($d_{r,c}$) that maximizes the total value (V_{total}) within the maximum allowable cost limit (C_{max}). To apply metaheuristic algorithms which typically perform unconstrained optimization, an exterior penalty function method was introduced. This imposes a severe penalty on the objective function value if the constraints are violated. The final fitness function (F) is formulated as follows:

$$Maximize\ F = V_{total} - \alpha \cdot \max(0, C_{total} - C_{max})$$

Here, α is a penalty coefficient, set as a sufficiently large constant to ensure that solutions violating the cost limit are eliminated during the exploration process.

2.2. Metaheuristic Optimization Algorithms and Hybrid Techniques

Combinatorial optimization problems with numerous constraints and vast search spaces, such as nuclear core LP design, are categorized as NP-hard problems, making it exceedingly difficult to find an optimal solution within polynomial time. To address this, rather than evaluating all possible combinations, metaheuristic algorithms—inspired by natural phenomena or biological evolution—are widely utilized to derive excellent global optima or near-optimal solutions within a reasonable timeframe. In this study, representative single-solution-based search techniques, Simulated Annealing (SA) and Tabu Search (TS), along with a population-based search technique, Genetic Algorithm (GA), were introduced. Furthermore, hybrid techniques combining their strengths were constructed to comparatively analyze search performance.

2.2.1. Simulated Annealing

Simulated Annealing is a probabilistic optimization technique that mimics the annealing process in metallurgy, where a solid material is slowly cooled to form a stable crystal structure with minimized energy.

The most significant characteristic of SA is its adherence to the Metropolis acceptance criterion. During the search process, it unconditionally accepts solutions that improve the objective function. However, even if a solution degrades the objective value, it is conditionally accepted based on a probability $P = exp(-\Delta E/T)$, determined by the current temperature parameter (T). When the initial temperature is high, the algorithm broadly explores the search space to prevent entrapment in local optima. As the temperature gradually cools, it secures convergence and performs detailed exploitation.

2.2.2. Genetic Algorithm

The Genetic Algorithm is a population-based search technique that combines Darwin's principle of survival of the fittest with genetics. To apply it to the 2D spatial allocation problem in this study, the entire 5×5 grid array was defined as a single chromosome. GA simultaneously evaluates multiple solutions and selects superior solutions with high fitness as parent generations. Through the crossover operation, useful traits of the parents (excellent spatial layout structures) are inherited by the offspring generation. Additionally, mutation operations are performed with a certain probability to randomly change the type or direction of items, thereby maintaining population diversity and exploring new search areas.

2.2.3. Tabu Search

Tabu Search is a memory-based search technique that mimics the human memory process to prevent cycling phenomena during exploration and efficiently pioneer new paths.

TS evaluates various neighborhood solutions derived from the current solution and moves to the best one. During this process, it operates a short-term memory device called a Tabu List, which prohibits returning to recently visited states for a specific period (Tabu Tenure). This forcibly prevents the algorithm from hovering around local optima and induces it to explore new regions.

2.2.4. Hybrid Optimization Techniques

Each metaheuristic algorithm has unique strengths and weaknesses regarding global exploration and local exploitation capabilities. This study proposes two hybrid techniques to overcome the limitations of single algorithms and generate complementary synergy.

- GA + SA: This utilizes GA's population-based search to establish the global structure of superior solutions across a broad domain. Subsequently, a brief SA is applied to the generated offspring to perform fine-tuning, maximizing local adjacency effects and synergy.
- SA + TS: This structure combines the probabilistic search process of SA with the Tabu List memory of TS. When the temperature drops and SA's capacity for random escape diminishes, the Tabu List blocks past paths. This prevents meaningless repetitive calculations and induces forced local escape, thereby enhancing both convergence speed and solution quality.

3. Analyses & Results

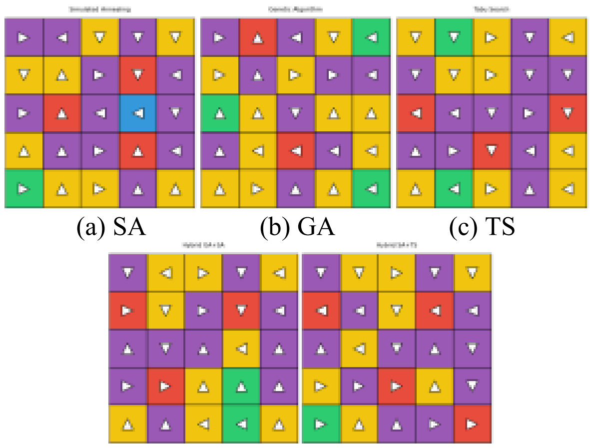
3.1. Experimental Setup and Parameter Configuration

To analyze the optimization performance of the proposed metaheuristic and hybrid algorithms, a 2D spatial allocation problem was evaluated in a Python environment. All algorithms searched an identical 5×5 array (25 cells in total), with a total cost limit (C_{max}) of 200. When constraints were violated, a penalty of 100 per unit of excess cost was imposed to the fitness calculation. To ensure a fair comparison, the convergence behavior was observed by setting the maximum number of objective function evaluations to a consistent level across all algorithms.

To quantitatively evaluate the optimization performance of the proposed single metaheuristic (SA, GA, TS) and hybrid (GA+SA, SA+TS) approaches 100 independent search runs were conducted for each algorithm. Table 3 summarizes the average value, average cost, average generation, and the metrics for the best solution discovered across all 100 runs. Furthermore, the final 2D spatial layouts of the best solutions obtained by each algorithm are graphically depicted in Fig. 2.

Table III: Comparison of 100 Independent Runs for Metaheuristic and Hybrid Algorithms

	SA	GA	TS	GA+SA	SA+TS
Average value	469.99	465.49	468.19	468.79	469.31
Average cost	199.08	199.42	198.83	199.31	198.99
Average Generations	8207.79	8078.9	6825.5	9038	8523.69
Best value	476.6	473.2	473.8	475.4	474.7
Cost of best	200	200	200	200	199
Generations for best	10140	8993	2100	9000	7312



(a) SA (b) GA (c) TS

(d) GA+SA (e) SA+TS

Fig. 2. Final Layouts of the Best Solutions for the 2D Spatial Allocation Problem Derived by Each Optimization Algorithm

3.2. Analysis of Optimization Performance and Search Behavior

The analysis of the experimental data clearly highlighted the unique search characteristics of each algorithm and the synergistic effects of the hybrid techniques.

First, SA achieved the best optimization performance in terms of average value (469.99) and best value (476.6). This suggests that SA's probabilistic acceptance mechanism is very good at undertaking deep and detailed local exploitation in a landscape with numerous local optima caused by adjacent interactions. However, it required the most evaluations (10,140) to determine the optimal solution, resulting in the highest computing cost.

Second, the GA recorded the lowest average (465.49) and best values (473.2). This is likely due to premature convergence, in which excellent building blocks are disrupted during the crossover operation in spatial layout problems, or when the diversity within the population is lost early on, trapping the algorithm in local optima.

Third, TS demonstrated an overwhelmingly fast convergence speed, identifying its best solution after 2,100 generations. The TS mechanism, which blocks redundant searches using the Tabu List and forces movement into uncharted territories, contributed to rapidly deriving an excellent approximate solution with low computational effort.

Fourth, the GA+SA effectively addressed GA's critical flaw of premature convergence. When compared to pure GA, both the average value (465.49 → 468.79) and best value (473.2 → 475.4) increased significantly. Furthermore, the generation that reached the best solution (9,000) outperformed pure SA (10,140). This demonstrates that SA successfully fine-tuned the local synergies based on the macroscopic optimal layout structures explored by GA, striking a balance between global exploration and local exploitation.

Fifth, the SA+TS hybrid algorithm maintained strong search reliability comparable to pure SA, with an average value of 469.31, while demonstrating outstanding efficiency by reducing the generations to find the best solution (7,312) by approximately 28% when compared to pure SA. Interestingly, it produced a high value of 474.7 at a cost of 199, making the only best solution among all algorithms that did not hit the maximum cost limit (200). This indicates that the Tabu List effectively intervened in the late stages of search to suppress meaningless cycling, maintain a cost margin, and forcibly pioneer new search paths.

4. Conclusions

This study conducted foundational research for the development of an automated core LP optimization tool to meet the demands for flexible operation of nuclear power plants amid the expansion of renewable energy. A 'directional 2D spatial allocation problem' was constructed as a surrogate model to mathematically simulate the complex physical characteristics and constraints of actual core design. Based on this model, the search performances of representative metaheuristic algorithms (SA, GA, TS) and hybrid algorithms (GA+SA, SA+TS) were comparatively analyzed.

According to the preliminary performance analysis, SA demonstrated excellent fine-tuning capabilities by deriving the highest peak value, albeit with high computational costs. The GA recorded relatively lower performance due to premature convergence. TS showed an overwhelmingly fast convergence speed by suppressing redundant queries. Notably, the hybrid GA+SA algorithm overcomes the shortcomings of pure GA to derive excellent solutions by balancing global exploration and local exploitation. Furthermore, the SA+TS hybrid demonstrated the most stable and efficient optimization performance by securing a cost margin within the limit while simultaneously attaining a high value comparable to pure SA and reducing the search time.

While this study utilized a 2D spatial allocation problem as a preliminary step to explore optimal loading patterns, future research plans to perform optimization under flexible operation conditions by directly applying core analysis codes to actual nuclear reactor core loading patterns. In addition, to address the constraint of the large computational time required by physical core analysis codes, we will introduce state-of-the-art Artificial Intelligence (AI) machine learning techniques to develop a surrogate model that predicts core behavior fast and accurately. Future study will focus in-depth on how this AI-trained surrogate model can innovatively accelerate the optimization process.

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