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

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Introduction

- **Need for Flexible Operation:** The expansion of renewable energy requires nuclear power plants to adopt flexible operation capabilities to adjust their output in response to power grid demands.
- **Limitations of Current LP Design:** Flexible operation exponentially increases core design complexity, making the current manual, experience-driven Loading Pattern (LP) optimization highly time-consuming, costly, and subject to inconsistent quality.
- **Ultimate Goal:** To address these technical limitations, this study aims to develop an "AI-based, user-friendly optimal core loading pattern generation tool" applicable to APR1400 and APR1000 reactors.
- **Scope of This Study:** As a preliminary step, a 2D spatial allocation proxy model that mimics the physical characteristics of fuel assembly layouts was constructed to comparatively analyze the performance and convergence efficiency of various metaheuristic and hybrid optimization algorithms.

Methods

2D Spatial Allocation Surrogate Model

- **Model Structure:** A 5 × 5 grid surrogate model was designed, allocating 5 item types (representing fuel assemblies) and 4 directions to simulate actual core layouts.

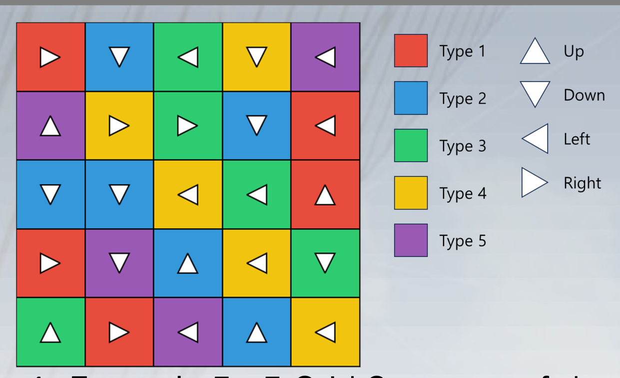

Fig. 1. Example 5×5 Grid Structure of the Directional 2D Spatial Allocation Problem

- **Value-Cost Trade-off (Table I):** Modeled the physical reality where fresh fuel provides longer cycles but reduces thermal margins. High-value items were configured to have exponentially higher costs, mimicking a Knapsack Problem.
- **Adjacent Interactions (Table II):** Neutronic coupling was formulated as directional synergy (+) and penalty (−) values. The synergy matrix utilized floating-point numbers to balance the search space, prevent tied solutions, and enhance algorithm discriminative power.

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

Table II: Synergy Matrix between Adjacent Items

Subject \ Target	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

Mathematical Modeling

- **Objective:** To find the optimal combination of allocations and directions that maximizes the total value (V_{total}) without exceeding the maximum allowable cost limit (C_{max}).
- **Penalty Function:** An exterior penalty function was applied to impose severe penalties on solutions violating the cost limit, adapting the unconstrained metaheuristic algorithms to solve the constrained problem.

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

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

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

- $x_{r,c} \in \{1,2,3,4,5\}$: The type of item placed at position (r,c).
- $y_{r,c} \in \{1,2,3,4,5\}$: The type of the adjacent item pointed to by direction.
- $V(i)$ and $C(i)$: The base value and base cost of item type i
- $S(i,j)$: The additional value generated when item type i looks at item type j.
- α: A penalty coefficient.

Metaheuristic & Hybrid Optimization Techniques

- **Single Algorithms:** Applied Simulated Annealing (**SA**) for deep local exploitation via the Metropolis criterion , Genetic Algorithm (**GA**) for population-based global exploration , and Tabu Search (**TS**) for fast convergence using a short-term memory list.
- **Hybrid Algorithms:**
  - **GA+SA:** Combines GA's population-based search for global structures with SA's local fine-tuning capabilities.
  - **SA+TS:** Merges SA's probabilistic search with TS's tabu list memory to block past paths, preventing meaningless cycling and forcing local escape.

Analyses & Results

- Experimental Setup and Evaluation Conditions
  - Conducted 100 independent search runs for each algorithm to ensure a highly reliable and quantitative performance evaluation.
  - Applied a strict total cost limit ($C_{max} = 200$), imposing a severe penalty of 100 per excess cost unit during the fitness calculation.
- Performance Evaluation of Single Algorithms
  - **SA:** Achieved the highest best value (476.6) due to its strong capability for deep local exploitation, but required the highest computing cost (10,140 evaluations).
  - **GA:** Recorded the lowest overall performance (473.2) due to premature convergence, as excellent building blocks were frequently disrupted during crossover operations.
  - **TS:** Demonstrated an overwhelmingly fast convergence speed (2,100 generations) by effectively blocking redundant searches and forcing exploration using its Tabu List.
- Synergistic Effects of Hybrid Algorithms
  - **GA+SA:** Effectively addressed GA's critical flaw of premature convergence. It successfully balanced global exploration and local exploitation by finetuning local synergies based on the macroscopic layout structures explored by GA.
  - **SA+TS:** Reduced the generations to find the best solution by ~28% compared to pure SA, as the Tabu List effectively suppressed meaningless cycling in the late stages of search. Notably, it was the only algorithm to secure a cost margin (Cost: 199) without hitting the maximum limit while yielding a highly competitive value, proving to be the most efficient design.

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

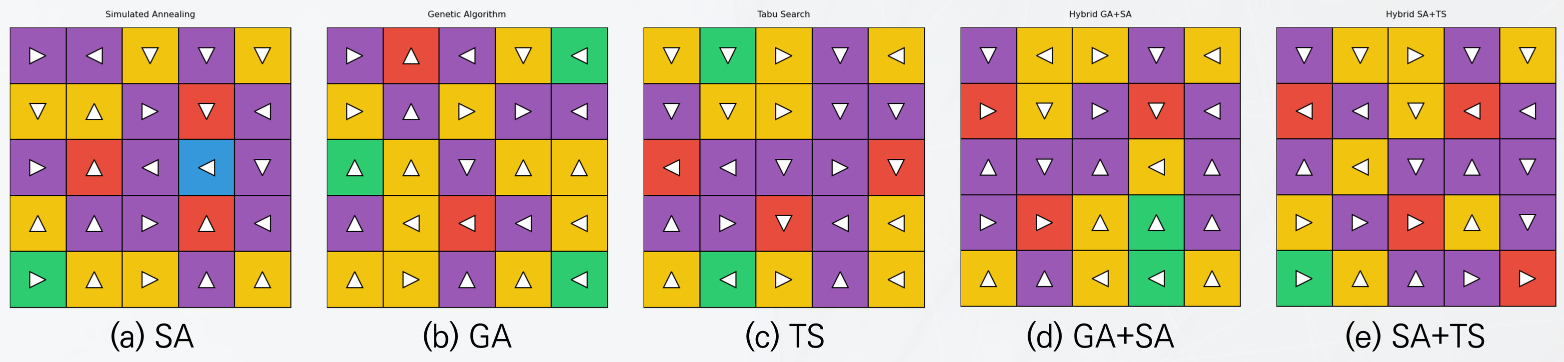

Fig. 2. Final Layouts of the Best Solutions for the 2D Spatial Allocation Problem Derived by Each Optimization Algorithm

Conclusions

- **Study Significance:** Conducted foundational research to develop an automated core LP optimization tool for flexible operation by constructing a 2D spatial allocation surrogate model that simulates complex core constraints.
- **Single Algorithm Performance:** SA showed excellent fine-tuning but high computational costs, GA suffered from premature convergence, and TS demonstrated overwhelmingly fast convergence by suppressing redundant queries.
- **Excellence of Hybrids:** GA+SA successfully balanced global and local exploration, while the SA+TS hybrid demonstrated the most stable and efficient performance by securing a cost margin, attaining high value, and reducing search time.
- **Future Work:** Future research will directly apply actual core analysis codes and introduce state-of-the-art AI machine learning to develop a surrogate model that fast and accurately predicts core behavior, innovatively accelerating the optimization process.

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