CHAPTER

4

SUSTAINABLE NUCLEAR POWER THROUGH PARTICLE SWARM OPTIMISATION

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4.1 INTRODUCTION

Nuclear energy has emerged as a potential option for fulfilling the high energy demand and achieving the net-zero carbon emission. A nuclear reactor core is the central component of a nuclear power plant, where the critical process of nuclear fission occurs. Within the core, fuel assemblies containing fissile materials such as uranium-235 (^{235}U) or plutonium-239 (^{239}Pu) undergo fission, releasing substantial amounts of heat energy. This heat is then transferred to the reactor's coolant, which is used to generate steam and, ultimately, electricity. The design and operation of the reactor core are essential for maintaining a controlled and sustained chain reaction, ensuring both safety and efficiency. Key components within the core, such as control rods and moderators, play a vital role in regulating the fission process and managing the reactor's power output. Achieving an optimal fuel arrangement is crucial for maximising fuel cycle length and minimising the use of fissionable materials, all while meeting safety and economic constraints (Chham et al., 2021).

However, optimising fuel arrangements is a time-consuming and computationally intensive task due to the numerous factors influencing the system. For instance, the PUSPATI Triga Mark-II Research Reactor (RTP) contains 112 fuel rods with varying uranium enrichments, resulting in a vast search space of 112! combinations. Analysing every possible combination to find the optimal arrangement is impractical. To address this combinatorial optimisation problem (COP), metaheuristic algorithms can be employed, offering efficient solutions for optimising fuel arrangements.

In this study, particle swarm optimisation (PSO) is applied to determine the optimal fuel arrangement in the RTP core. The main objective is to maximise the effective multiplication factor (k_{eff}) while minimising the power peaking factor, ensuring enhanced neutron economy and reactor safety.

Particle swarm optimisation (PSO) was selected over other conventional optimisation methods such as genetic algorithm (GA) due to its relatively simple implementation, faster convergence, and reduced computational overhead. Unlike GA, which relies on complex operations such as crossover and mutation, PSO uses velocity and position updates based on individual and group experiences, making it well-suited for high-dimensional, continuous optimisation problems like reactor core configuration.

4.2 PARTICLE SWARM OPTIMISATION

The term "metaheuristics" originates from the Greek words "meta" (meaning 'beyond' or 'at a higher level') and "heuristic" (meaning 'to find'). Metaheuristics encompass a class of approximate algorithms that are designed to generate near-optimal solutions within a relatively short runtime compared to exact algorithms. Unlike exact methods, which may require impractical amounts of time for large problem spaces, metaheuristics are problem-independent and can be applied to a wide range of COPs. One prominent example of a metaheuristic is the PSO method.

The PSO method is a type of swarm intelligence algorithm inspired by the collective behaviour observed in flocks of birds, first introduced by Kennedy and Eberhart in 1995. Researchers observed that the coordinated movement of birds is maintained by each individual adjusting its position based on optimal distances relative to its neighbours. Similarly, in PSO, each particle representing a potential solution adjusts its velocity based on both its own previous best position (personal best, $p\text{best}$) and the best positions discovered by the entire swarm (global best, $g\text{best}$). This mirrors the human decision-making process, where individuals draw upon their past experiences as well as those of others around them. In PSO, these particles interact and are influenced by the current optimal solutions, guiding the swarm toward finding the most favourable overall solution. The continuous nature of particle positions in PSO, when combined with a suitable encoding scheme, can explore the solution space more smoothly than the discrete crossover or mutation operations of a GA, potentially avoiding premature convergence to suboptimal solutions.

A swarm of N particles search for the optimal position in a D-dimensional search space. At the $\text{j}-\text{th}$ iteration and $\text{j}-\text{th}$ dimension, the position of the $\text{i}-\text{th}$ particle can be represented by Equation (4.1), while the velocity of the $\text{i}-\text{th}$ particle can be represented by Equation (4.2). The evolution of the velocity and position of particle i from the $\text{t}-\text{th}$ iteration to the $(\text{t}+1)-\text{th}$ iteration is updated according to Equation (4.3) and Equation (4.4), respectively. Here, w is the inertia weight, c is the acceleration coefficient, r is a uniform random number in the range of (0,1), $p\text{best}$ is the personal best position, and $g\text{best}$ is the global best position.

$$x_{ij}(t) = [x_{i1}, x_{i2}, x_{i3}, \dots\dots\ x_{iD}], i = 1,2, \dots, N \tag{4.1}$$

$$v_{ij}(t) = [v_{i1}, v_{i2}, v_{i3}, \dots\dots\ v_{iD}], i = 1,2, \dots, N \tag{4.2}$$

$$v_{ij}(t+1) = wv_{ij}(t) + c_1 r_1 \left(p\text{best}_{ij} - x_{ij}(t)\right) + c_2 r_2 \left(g\text{best}_{ij} - x_{ij}(t)\right) \tag{4.3}$$

$$x_{ij}(t+1) = x_{ij}(t) + v_{ij}(t+1) \tag{4.4}$$