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Balancing exploration and exploitation in differential evolution via variable scaling factors: An application to practical problems

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ABSTRACT

Some optimization problems in the field of nuclear engineering, as for example the incore nuclear fuel management and a nuclear reactor core design, are highly multimodal, requiring techniques that overcome local optima, exploring the search space and promoting the exploitation of its most promising areas. The differential evolution algorithm (DE) relies mainly on the mechanism of mutation, where an individual is perturbed using the weighted difference (with the so-called "scaling factor" *F*) between two randomly chosen individuals. DE's canonical version employs a constant value of *F*. However, this parameter should be variable in order to balance the exploration and exploitation of the search space. In this work, we test some variable scaling factors from the literature and present the novel exponential scaling factor. These methods are applied to two problems: the aforementioned core design and the turbine balancing problem, which is an NP-hard (i.e. intrinsically harder than those that can be solved in nondeterministic polynomial time) combinatorial optimization problem that can be used to assess the potential of an algorithm to be applied to fuel management optimization. DE with variable scaling factors perform well in both problems, showing potential to be used in other nuclear science and engineering optimization problems.

1. Introduction

Some optimization problems in the field of nuclear engineering are highly multimodal, remaining a great challenge for most methods. The most notorious problem is the incore fuel management (Carter, 1997; Turinsky, 2010), which is a large search space problem with $\sim 10^{12}$ possible configurations and $\sim 10^{10}$ local optima (Galperin, 1995).

Another multimodal problem is a nuclear reactor core design optimization introduced by Pereira et al. (1999), which has been attacked by other researchers, as in Sacco et al. (2004) and Domingos et al. (2006), for example. In this work, we address this problem, and also a problem that belongs, as well as nuclear fuel management, to the class of combinatorial optimization problems (Papadimitriou and Steiglitz, 1998): the turbine balancing problem (Mosevich, 1986). Therefore, optimization algorithms that are successful in this problem are prone to perform well in the nuclear problem. We must add that the turbine balancing problem is NP-hard (Johnson and Garey, 1979; Atallah and Blanton, 2010), which, according to Atallah and Blanton (2010) means

> *a complexity class of problems that are intrinsically harder than those that can be solved by a Turing machine in nondeterministic polynomial time. When a decision version of a combinatorial optimization problem is proven to belong to the class of NP-complete problems, which includes well-known problems such as satisfiability, traveling salesman problem, etc., an optimization version is NP-hard.*

In these multimodal problems, the search space should be thoroughly explored and its most promising areas should be exploited, so that the optimization algorithm does not converge to a local optimum.

The differential evolution algorithm (DE) (Storn and Price, 1997) has been successfully applied in many fields (Yang et al., 2002; Ilonen et al., 2003; Onwubolu and Davendra, 2006; Babu and Munawar, 2007; Das et al., 2008; Noman and Iba, 2008; Henderson et al., 2010; Sarkar et al., 2015; Örkcü et al., 2015;

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Chen et al., 2015), including nuclear engineering (Sacco et al., 2009; Bledsoe et al., 2011). Indeed, differential evolution outperformed the more popular genetic algorithm and particle swarm optimization in extensive experiments (Vesterstrom and Thomsen, 2004). However, the canonical DE tends to converge prematurely to local optima (Das and Suganthan, 2011). This tendency is a burden in many real-world problems, including the nuclear-engineering ones mentioned above. To overcome this situation, researchers have proposed niching methods (Qu and Suganthan, 2010; Qu et al., 2012; Sacco et al., 2014), new mutation schemes (Zhang and Sanderson, 2009; Sacco et al., 2014b), parallel implementations (Tasoulis et al., 2004; Weber et al., 2011), the opposition-based learning paradigm (Rahnamayan et al., 2008), and variable scaling factors (Ali and Törn, 2004; Kaelo and Ali, 2006; Draa et al., 2015).

In this work, we test the application of variable scaling factors in order to balance exploration and exploitation in DE and try to avoid getting trapped in local optima. As the reader will see in Section 3, DE relies mainly on the mechanism of mutation, where an individual is perturbed using the weighted difference (with the so-called "scaling factor" F) between two randomly chosen individuals. DE's canonical version employs a constant value of F. However, this parameter should be variable in order to balance the exploration and exploitation of the search space (Draa et al., 2015). We use three variable scaling factors from the literature and a novel scheme, the exponential scaling factor.

The remainder of the paper is described as follows. The optimization problems are described in Section 2. The description of DE is presented in Section 3. The scaling factors tested here are explained in Section 4, including the new one. The computational experiments and their discussions are in Section 5. Finally, the conclusions are made in Section 6.

2. The optimization problems

2.1. The nuclear reactor core design problem

Let us describe the optimization problem (for a more detailed exposition, see Pereira et al. (1990)). Consider a cylindrical three-enrichment-zone reference reactor, as seen in Fig. 1a, with $R1 = 86$ cm, $R2 = 38$ cm, $R3 = 18$ cm, and $h = 63$ cm. This reactor's typical cell is composed by moderator (light water), cladding and fuel (Fig. 1b). The design parameters that may be varied in the optimization process, as well as their variation ranges, are shown in Table 1. The materials are represented by discrete variables.

The objective of the optimization problem is to minimize the average flux or power peaking factor, f_p, of the proposed reactor, allowing the reactor to be sub-critical or super critical ($k_{eff} = 1.0 \pm 1\%$), for a given average flux ϕ_0. Let $\mathbf{D} = \{R_f, \Delta_c, R_e, E_1, E_2, E_3\}$ be the vector of design variables. Then, the optimization problem can be written as follows:

Table 1
Range of parameters.

Parameter	Symbol	Range
Fuel Radius (cm)	R_f	0.508 to 1.270
Cladding Thickness (cm)	Δc	0.025 to 0.254
Moderator Thickness (cm)	R_e	0.025 to 0.762
Enrichment of Zone 1 (%)	E_1	2.0 to 5.0
Enrichment of Zone 2 (%)	E_2	2.0 to 5.0
Enrichment of Zone 3 (%)	E_3	2.0 to 5.0
Fuel Material	M_f	{U-Metal or UO_2}
Cladding Material	M_c	{Zircaloy-2, Aluminum or Stainless-304}

Minimize $f_p(\mathbf{D})$ s.t.

$$\phi(\mathbf{D}) = \phi_0; \tag{1}$$

$$0.99 \le k_{eff}(\mathbf{D}) \le 1.01; \tag{2}$$

$$\frac{dk_{eff}}{dV_m} > 0; \tag{3}$$

$$\mathbf{D}_i^l \le \mathbf{D}_i \le \mathbf{D}_i^u, i = 1, 2, \dots, 6; \tag{4}$$

$$M_f = \{\mathrm{U-Metal\ \ or\ \ UO_2}\}; \tag{5}$$

$$M_c = \{\mathrm{Zircaloy-2,\ \ Al\ \ or\ \ SS-304}\}, \tag{6}$$

where V_m is the moderator volume, and the superscripts l and u indicate respectively the lower and upper bounds (of the feasible range) for each design variable.

The HAMMER system (Suich and Honeck, 1967) was used for cell and diffusion equations calculations. It performs a multigroup calculation of the thermal and epithermal flux distribution from the integral transport theory in a unit cell of the lattice,

$$\phi(r) = \int_V \frac{e^{-\sum_t |r-r'|}}{4\pi |r-r'|^2} S(r') d^3 r'. \tag{7}$$

The integral transport equation for scalar flux $\phi(\overrightarrow{r})$ is solved for all sub-regions of the unit cell, being the neutron source $S(r)$ isotropic into the energy group under consideration. The transfer kernel in Eq. (7) is related to the collision probabilities for a flat isotropic source in the initial region. The solution is initially performed for a unit cell in an infinite lattice.

The integral transport calculation is followed by a multigroup Fourier transfer leakage spectrum theory in order to include the leakage effects in the previous calculation and to proceed with the multigroup flux-volume weighting.

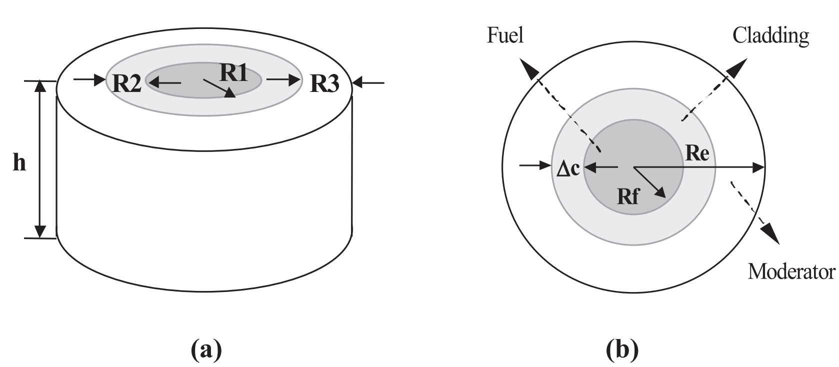

Fig. 1. (a) The nuclear reactor and (b) its typical cell.