A HYBRID NICHED-ISLAND GENETIC ALGORITHM APPLIED TO A NUCLEAR CORE OPTIMIZATION PROBLEM

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ABSTRACT

Diversity maintenance is a key-feature in most genetic-based optimization processes. The quest for such characteristic, has been motivating improvements in the original genetic algorithm (GA). The use of multiple populations (called islands) has demonstrating to increase diversity, delaying the genetic drift. Island Genetic Algorithms (IGA) lead to better results, however, the drift is only delayed, but not avoided. An important advantage of this approach is the simplicity and efficiency for parallel processing. Diversity can also be improved by the use of niching techniques. Niched Genetic Algorithms (NGA) are able to avoid the genetic drift, by containing evolution in niches of a single-population GA, however computational cost is increased. In this work it is investigated the use of a hybrid Niched-Island Genetic Algorithm (NIGA) in a nuclear core optimization problem found in literature. Computational experiments demonstrate that it is possible to take advantage of both, performance enhancement due to the parallelism and drift avoidance due to the use of niches. Comparative results shown that the proposed NIGA demonstrated to be more efficient and robust than an IGA and a NGA for solving the proposed optimization problem.

1. INTRODUCTION

Genetic Algorithms (GA) are searching methods based upon the biological principles of natural selection and evolution. They were rigorously introduced by Holland [1]. GAs consist of a population of individuals that are possible solution candidates and each one of these individuals receives a reward, known as “fitness”, that quantifies its suitability to solve the problem. Individuals with better than average fitness receive greater opportunities to cross. On the other hand, low fitness individuals will have less chance to reproduce until they are extinguished. Consequently, the good features of the best individuals are disseminated over the generations. In other words, the most promising areas of the search space are explored, making the GA converge to the optimal or near optimal solution.
Genetic Algorithms have proven to be efficient in a great variety of domains, as the population of candidate solutions converge to a single optimum. However, in multimodal domains, it may be interesting not only to find a single optimum, especially in functions with equal optima. The convergence to a single optimum in this case is the result of the phenomenon known as genetic drift [2].

Diversity maintenance is a key-feature in most genetic-based optimization processes. The quest for such characteristic, has been motivating improvements in the original genetic algorithm (GA) [2]. The use of multiple populations (also called islands) has demonstrating to increase diversity, delaying the genetic drift. Island Genetic Algorithms (IGA) [3] have demonstrating to be more efficient and robust leading to better results when comparing to the standard GA. Several applications of IGA in nuclear optimization problems corroborate this affirmative [4, 5]. By using IGA, however, the drift is not avoided, only delayed. An important advantage of this approach is the simplicity and efficiency for parallel processing.

Diversity can also be improved by the use of niching techniques. Niched Genetic Algorithms (NGA) [1]. NGAs are able to avoid the genetic drift, by containing evolution in niches of a single-population GA, however, computational cost is increased. An application of a NGA to a nuclear core optimization problem, found in literature, demonstrated its superiority over the standard GA [6].

The main objective of this work is to investigate the use of a hybrid Niched Island Genetic Algorithm (NIGA) in a nuclear core optimization problem. To accomplish that, it was chosen a reactor core optimization problem found in literature [4, 6]. Then, the optimization problem has been modeled into the Genetic Niched Island System (GenNIS), developed in Instituto de Engenharia Nuclear (IEN).

Computational experiments demonstrate that it is possible to take advantage of both, performance enhancement due to the parallelism and drift avoidance due to the use of niches. Comparative results shown that the proposed NIGA demonstrated to be more efficient and robust than an IGA and a NGA for solving the proposed optimization problem.

In next section, the NIGA, as well as the main aspects of island and niched GAs are discussed. Section 3 describe the computational experiments and obtained results, while section 4 shows several concluding remarks.

2. THE NICHED-ISLAND GENETIC ALGORITHM

2.1. Island Topology

The Island Genetic Algorithm (IGA) is a multi-population approach for parallel GAs. Each population is located into a processor (island) which have their own independent evolution process. In order to promote cooperation between islands, a new operator, called migration is created. According to some predefined strategy, individuals migrate from one island to another. Many topologies for IGAs are possible. In this work we used an 8-islands ring topology, illustrated in Figure 1. Each island search procedure starts from its own initial
population, and, during some generations, may be exploring some part of the search space. As migration occurs, information about different regions of the search space is exchanged between islands, providing more diversity in the search. In the present work, the best individual migrates every multiple of 50 generations. According to Cantú-Paz [3], IGAs have been demonstrating to be more robust and efficient than the SGA. In the proposed NIGA, islands alternate standard GA (SGA) and NGA, as shown in Figure 2.

![Island Genetic Algorithm with ring topology.](image)

Considering the amount of communication required for each model, the Island GA is the one that requires less (very much less) communication. Therefore it is the most indicated model to run on distributed systems.

### 2.2. Niching Technique

In NGAs, the analogy with nature is straightforward, as in an ecosystem there are different subsystems (niches) that contain many diverse species. The number of elements in a niche is determined by its resources and by the efficiency of each individual in taking profit of these resources.

Using this analogy, it is possible to maintain the population diversity in a GA. Each peak of the multi-modal function can be seen as a niche that supports a number of individuals directly proportional to its “fertility”, which is measured by the fitness of this peak relatively to the fitnesses of the other peaks of the domain. The difficulty in implementing niching methods lies on the fact that the peaks are obviously not known beforehand. This complicates the process of populating each niche correctly according to its fitness. Various niching formation methods have been proposed, in this work, “sharing function”, the most disseminated niching paradigm have been used.

Fitness sharing was introduced by Goldberg and Richardson [7], consisting of the reduction of the fitness of an individual proportionally to the number of nearby individuals. As selection occurs after the fitness correction, sharing does affect this mechanism. The shared fitness $f_i'$ of the $i$-th individual is given by
\[ f_i' = \frac{f_i}{m_i} \]  \hspace{1cm} (1)

where \( f_i \) is the original fitness of the \( i \)-th individual.

\[ m_i' = \sum_{j=1}^{N} s h(d_{ij}) \]  \hspace{1cm} (2)

is the niche count, that takes into account the whole population in relation to the \( i \)-th individual, derating the fitness of this individual according to the nearness of the others. Variables \( N \) and \( d_{ij} \) are, respectively, the population size and the distance between individuals \( i \) and \( j \). The function that quantifies this proximity is the following:

\[
sh(d) = \begin{cases} 
1 - \left( \frac{d}{\sigma_{bare}} \right)^{\alpha}, & \text{if } d < \sigma_{bare} \\
0, & \text{otherwise}
\end{cases}
\]  \hspace{1cm} (3)

where \( \sigma_{bare} \) and \( \alpha \) are user defined constants. The first constant is of difficult estimation, requiring knowledge of the search space to be properly chosen. Generally it is estimated on a trial and error basis, in this work, it was used \( \sigma_{bare} = 0.5 \). The second constant, \( \alpha \), is generally set to 1.0 [7] so that the function is linear.

### 3. METHOD APPLICATION

#### 3.1. Optimization Problem

As the main objective of this work is to compare the GA with niching method (NGA) with the Standard GA (SGA), we address the same problem, described in previous [4, 6]. In order to provide a complete understanding of this work, we will briefly describe it here. Consider a cylindrical 3-enrichment-zone PWR, with typical cell composed by moderator (light water), cladding and fuel. Figure 2 illustrates such reactor.

![Figure 2](image)

**Figure 2** – (a) The reactor and (b) its typical cell.
The design parameters that may be changed in the optimization process, as well as their variation ranges are shown in Table 1.

### Table 1. Parameters range

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Symbol</th>
<th>Range</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fuel Radius (in.)</td>
<td>R_f</td>
<td>0.2 to 0.5</td>
</tr>
<tr>
<td>Cladding Thickness (in.)</td>
<td>∆c</td>
<td>0.01 to 0.1</td>
</tr>
<tr>
<td>Moderator Thickness (in.)</td>
<td>R_e</td>
<td>0.01 to 0.3</td>
</tr>
<tr>
<td>Enrichment of Zone 1 (%)</td>
<td>E_1</td>
<td>2.0 to 5.0</td>
</tr>
<tr>
<td>Enrichment of Zone 2 (%)</td>
<td>E_2</td>
<td>2.0 to 5.0</td>
</tr>
<tr>
<td>Enrichment of Zone 3 (%)</td>
<td>E_3</td>
<td>2.0 to 5.0</td>
</tr>
<tr>
<td>Fuel Material</td>
<td>M_f</td>
<td>{U-Metal or UO_2}</td>
</tr>
<tr>
<td>Cladding Material</td>
<td>M_c</td>
<td>{Zircaloy-2, Aluminum or Stainless-304}</td>
</tr>
</tbody>
</table>

The objective of the optimization problem is to minimize the average peak-factor, \( f_p \), of the proposed reactor, considering that the reactor must be critical (\( k_{eff} = 1.0 \pm 1\% \)) and sub-moderated, providing a given average flux \( \phi_0 \). The objective function used is written in Eq. 4.

\[
f_p, \quad \Delta k_{eff} \leq 0.01; \Delta \phi \leq 0.01 \phi_0; \frac{\Delta' k_{eff}}{\Delta Vm} > 0
\]

\[
f_p + r_1 \Delta k_{eff}, \quad \Delta k_{eff} > 0.01; \Delta \phi \leq 0.01 \phi_0; \frac{\Delta' k_{eff}}{\Delta Vm} > 0
\]

\[
f_p + r_2 \Delta \phi, \quad \Delta k_{eff} \leq 0.01; \Delta \phi > 0.01 \phi_0; \frac{\Delta' k_{eff}}{\Delta Vm} > 0
\]

\[
f_p + r_1 \frac{\Delta' k_{eff}}{\Delta Vm}, \quad \Delta k_{eff} \leq 0.01; \Delta \phi \leq 0.01 \phi_0; \frac{\Delta' k_{eff}}{\Delta Vm} < 0
\]

\[
f_p + r_1 \Delta k_{eff} + r_2 \Delta \phi, \quad \Delta k_{eff} > 0.01; \Delta \phi > 0.01 \phi_0; \frac{\Delta' k_{eff}}{\Delta Vm} > 0
\]

\[
f_p + r_1 \Delta k_{eff} + r_3 \frac{\Delta' k_{eff}}{\Delta Vm}, \quad \Delta k_{eff} > 0.01; \Delta \phi \leq 0.01 \phi_0; \frac{\Delta' k_{eff}}{\Delta Vm} < 0
\]

\[
f_p + r_2 \Delta \phi + r_3 \frac{\Delta' k_{eff}}{\Delta Vm}, \quad \Delta k_{eff} \leq 0.01; \Delta \phi > 0.01 \phi_0; \frac{\Delta' k_{eff}}{\Delta Vm} < 0
\]

\[
f_p + r_1 \Delta k_{eff} + r_2 \Delta \phi + r_3 \frac{\Delta' k_{eff}}{\Delta Vm}, \quad \Delta k_{eff} > 0.01; \Delta \phi > 0.01 \phi_0; \frac{\Delta' k_{eff}}{\Delta Vm} < 0
\]

where \( V_m \) is the moderator volume and the \( min \) and \( max \) subscript refers to the lower and upper limits of the parameters ranges, given in Table 1. The values of penalty constants \( r_1, r_2, r_3 \) were set to 10 as in previous work [4].
The genotype was modeled such that each gene comprises a search parameter. A fixed length binary encoding has been used. Dimensions and enrichments were encoded with 7 bits. For fuel and cladding materials 1 and 2 bits have been used respectively.

3.2. Experiments and Results

In order to evaluate the performance and robustness of the proposed NIGA, several experiments using different genetic parameters (random seeds, crossover and mutation rates) have been made. The number of generations was set to 500.

The NIGA as well as the IGA have adopted an 8-island ring topology with 50 individuals each. Synchronous migration of the best individual at each 50 generations was used. The NGA an unique island of 400 individuals.

Table 2 shows the results obtained by the NIGA, as well as those obtained by an IGA and a NGA for each set of genetic parameters.

<table>
<thead>
<tr>
<th>Experiment</th>
<th>Mutation</th>
<th>Crossover</th>
<th>NGA</th>
<th>IGA</th>
<th>NIGA</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.002</td>
<td>0.6</td>
<td>1.3494</td>
<td>1.2790</td>
<td>1.2786</td>
</tr>
<tr>
<td>2</td>
<td>0.002</td>
<td>0.6</td>
<td>1.3092</td>
<td>1.2887</td>
<td>1.2895</td>
</tr>
<tr>
<td>3</td>
<td>0.002</td>
<td>0.6</td>
<td>1.2963</td>
<td>1.3296</td>
<td>1.2888</td>
</tr>
<tr>
<td>31</td>
<td>0.001</td>
<td>0.6</td>
<td>1.3092</td>
<td>1.3046</td>
<td>1.2855</td>
</tr>
<tr>
<td>32</td>
<td>0.001</td>
<td>0.6</td>
<td>1.3198</td>
<td>1.3139</td>
<td>1.2933</td>
</tr>
<tr>
<td>51</td>
<td>0.01</td>
<td>0.8</td>
<td>1.3143</td>
<td>1.2777</td>
<td>1.2804</td>
</tr>
<tr>
<td>52</td>
<td>0.01</td>
<td>0.8</td>
<td>1.3094</td>
<td>1.2782</td>
<td>1.2792</td>
</tr>
</tbody>
</table>

| Average     | 1.3154   | 1.2960   | 1.2850 |
| Std. Dev.   | 0.0166   | 0.0205   | 0.0058 |

It could be clearly observe that the IGA, is more susceptible to be trapped by local optima than the NIGA, as occurred in Experiment 3, shown in Table 2. The lower average in NIGA demonstrated a gain in terms of efficiency. Observing the standard deviation, it can be seen that robustness in NIGA is enhanced. The NGA, in this work, found the worst results. It occurs because, by using niches, the convergence process slows down stop the process in 500 generations is too premature. This fact ratifies the importance of using niches together with islands.

4. CONCLUSIONS

This work demonstrated that it is possible to take advantages of both, islands and niching techniques hybridizing an IGA and a NGA. In the proposed core optimization problem, NIGA has outperformed the NGA and the IGA, demonstrating to be more robust and efficient.
Some more investigations should, however be done regarding topology, migration strategies and genetic parameter. Future work should also include the use of other niching techniques and application of NIGA to other nuclear engineering problems.

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REFERENCES