A Fitness-based Migration Policy for Biased Random-Key Genetic Algorithms

Mateus Boiani, Rafael S. Parpinelli, Márcio Dorn

Institute of Informatics, Federal University of Rio Grande do Sul

Abstract

Population diversity management is crucial for the quality of solutions in Evolutionary Algorithms. Many techniques require assistance to handle diverse problem characteristics and may prematurely converge in local optima. Maintaining diversity enables the algorithm to search the space and produce better results effectively. Parallel models are a common approach to preserving diversity; however, design decisions affect optimization process characteristics. For example, the Island model's migration policy affects convergence speed. This study proposes and evaluates a fitness-based migration policy for the Biased Random-Key Genetic Algorithm (`BRKGA`) and compares it to two traditional strategies. The results in continuous search spaces demonstrate that the proposed policy can enhance `BRKGA` optimization with appropriate parameters.

Proposed Method

This paper proposes and explores a new migration policy built on top of `BRKGA` algorithm for multi-population genetic algorithms.

The main features of the proposed **Fitness-based Migration Policy** (`FBMP`) are:

- It uses the `BRKGA'` population structure to rearrange individuals in the same range/position of fitness.
- Each island contains individuals from the i-th portion (batch) of all islands.
- The batch size (ω) is defined according to equation:

$$\omega = \frac{NP}{\iota}$$

- It establishes a fully-connected communication structure to exchange individuals.

Figure 1 presents the `FBMP's` behavior over time with six individuals (NP), three islands (ι), and batch size equal to two (ω). From i to $i+1$, an exploitation behavior is observed, i.e., similar individuals are gathered in the same island (indicated by λ values). Then, a new migration results in an exploration behavior (from $i+1$ to $i+2$), i.e., similar individuals are spread over the islands.

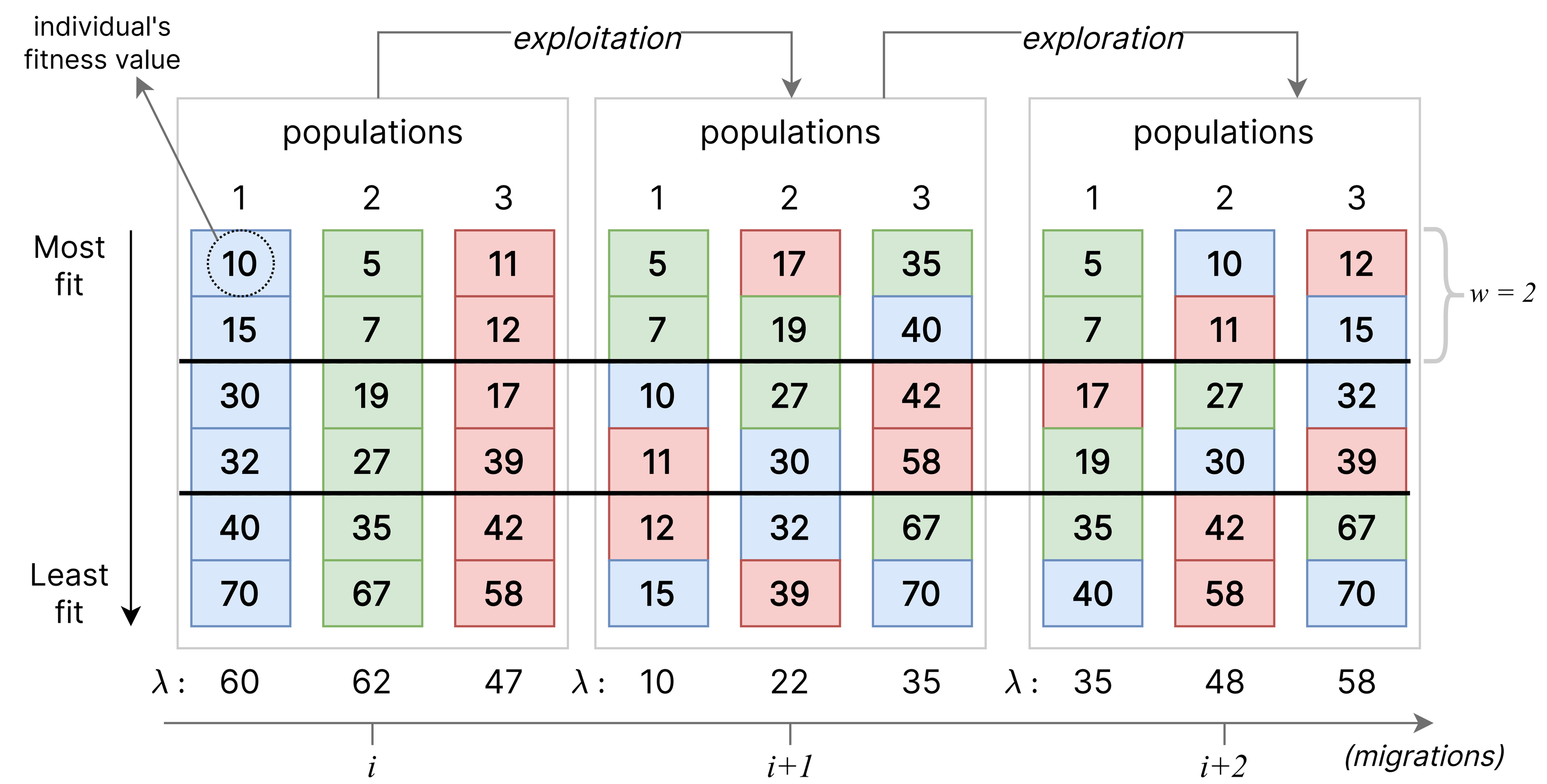

Figure 1. `FBMP's` behavior over time.

Experimental Protocols

Setup

The experiments were carried out on a computing node with 2 Intel Xeon Silver 4216 processors at 2.1 GHz, featuring 32 cores and 64 threads. The development environment is made of Ubuntu 20.04 operating system, and we use C and Python programming languages.

Benchmark Problems

The `CEC17's` single-objective real parameter numeric optimization benchmark was used to analyze algorithms' effectiveness [1]. The benchmark contains a set of 29 functions structured into four groups: **unimodal, simple multimodal, hybrid, and composition**. Regarding dimensionality, we evaluate the proposal on 10, 30, 50, and 100 dimensions. More details and functions' characteristics are available in [1].

Parameter Settings

In the experiments, some parameters were established through empirical determination, while others passed through an automated algorithm configuration package that varies values to estimate the most suitable set. Each scenario/configuration run 31 times, starting from different random seeds with a fixed population size (NP) of 100. `BRKGA` parameters follows author's recommendation [2]. The population (P) comprises an elite group (P_e) of 10%; the crossover solutions contain 70%, and 20% are reserved for mutation solutions. The elite inheritance probability (ρ_e) was fixed at 0.70.

The irace automatic algorithm configuration package [3] was used to evaluate the performance of each migration policy fairly, based on the parameters listed in Table 1:

Table 1. Parameters for automatic tuning with irace.

Parameter	Description	Type	Value range
τ	Migration frequency	Categorical	$\{32, 64, 128, 256, 512, 1024\}$
ι	Number of islands	Categorical	$\{2, 4, 5, 10\}$
η	Number of migrant individuals on ηBest policy	Integer	$[1, 10]$

Seeking a reasonable proportion between experimentation time and results quality, we focus on finding the most appropriate set of parameters for each group of functions: unimodal, simple multimodal, hybrid, and composition.

The tuning budget (number of runs) for irace varies according to the number of instances (functions) variations; we define a budget of 500 runs per function. Thus, the first group with two functions has a budget of 1000, for example. Furthermore, for the whole experimentation, each execution has $D \cdot 10^4$ function evaluations with D referring to the problem dimensionality.

Evaluation Metrics

Ranking: relatively to the Friedman test, it computes the relative ranking of each algorithm according to its mean performance on each function and reports the average ranking computed through all the functions.

Best: refers to the number of functions in which each algorithm obtains the best results compared to other algorithms.

Wins: computes the difference between the number of times each algorithm is statistically better and worse according to the Wilcoxon Signed Rank Test in a pair-wise comparison (with a degree of confidence of 95%).

Results and Analysis

Scenarios

1st Comprehends the algorithm proposed as stated

2nd Assesses the impact of turn-off the mutant group for k generations with k equals 25 (empirically defined) after each migration

3rd The third scenario assesses the same impact; however, it attaches the duration of the turn-off to the migration frequency. We consider a turn-off of 20% of the migration frequency.

Table 2. Results on each scenario (lower better).

		1st scenario			2nd scenario			3rd scenario		
D	MP	Ranking	Best	Wins	Ranking	Best	Wins	Ranking	Best	Wins
10	`FBMP`	1.80	13	3	1.44	18	10	1.82	14	3
	Ring	2.00	11	5	2.33	8	−1	1.82	10	7
	ηBest	2.20	5	−8	2.22	3	−9	2.36	5	−10
30	`FBMP`	1.62	16	12	1.50	17	19	1.52	17	17
	Ring	1.81	11	13	1.88	10	11	1.83	10	13
	ηBest	2.57	2	−25	2.62	2	−30	2.65	2	−30
50	`FBMP`	1.44	17	18	1.45	18	20	1.46	19	27
	Ring	2.17	8	2	2.10	7	−1	2.08	6	−5
	ηBest	2.39	4	−20	2.45	4	−19	2.46	4	−22
100	`FBMP`	2.35	7	−11	2.19	8	−11	1.65	15	16
	Ring	1.55	15	10	1.62	15	10	2.00	8	−5
	ηBest	2.10	7	1	2.19	6	1	2.35	6	−11

Considerations

- The `FBMP` aims to preserve population diversity, coordinating the search on multiple populations and periodically exchanging individuals with similar fitness ranks.
- The analysis demonstrates that **the proposed migration policy is highly competitive** and can enhance BRKGA's performance.
- We could reach results that point out the FBMP as the best choice among the tested alternatives.
- We observe that the parameters substantially affect the methods' performance. Thus, experiments consider offline tuning to reduce sensitivity effects.

References

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mateus.boiani@inf.ufrgs.br