Influence of the Migration Period in Parallel Distributed GAs for Dynamic Optimization

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Abstract. Dynamic optimization problems (DOP) challenge the performance of the standard Genetic Algorithm (GA) due to its *panmictic* population strategy. Several approaches have been proposed to tackle this limitation. However, one of the barely studied domains has been the parallel distributed GA (dGA), characterized by decentralizing the population in islands communicating through *migrations* of individuals. In this article, we analyze the influence of the migration period in dGAs for DOPs. Results show how to adjust this parameter for addressing different change severities in a comprehensive set of dynamic test-bed functions.

1 Introduction

Solving dynamic optimization problems (DOPs) means pursuing an optimal value that changes over time. Job shop scheduling (dealing with new arrivals), semaphores (adapting to traffic), and elevator systems (minimizing customer waiting time while receiving new calls), are some of these scenarios. These systems raise big challenges for researchers in Genetic Algorithms (GAs) [1, 2]. The reason is that GAs hardly can, once converged, to escape from old optima and adapt to the new environment.

An important weak part of the standard GA model lies in its panmictic population strategy, consisting on a single pool of individuals where any two of them can potentially mate. Consequently, a few authors have used multiple populations for specializing and tracking promising regions of the search space [1–3]. Most of these approaches perform periodical migrations of individuals among the populations. However, there is no unified and comprehensive study of the influence of the migration period in the literature.

In this article, we adopt the parallel distributed GA (dGA), which has been barely studied in this domain [3]. Many dGAs have proven effective in scenarios of high diversity requirements and computing resources, so their use should be valuable to DOPs. Our contributions are twofold: (1) we analyze the influence of the migration period in the performance of the dGA for a comprehensive set of DOP benchmarks (Section 4) and (2) we illustrate and discuss the diversity enhancement and speciation-like features of dGA models for DOPs (Section 5). Let us start by providing a brief background on DOP and dGA model.

2 Background

A dynamic optimization problem (DOP) is a real-world problems that change on time, where the fitness function is deterministic over time intervals. The goal here is to find the optimal solution for each time interval quickly and accurately, and do it by reusing information from previous time intervals rather than restarting the search from scratch. Two of the most important features of DOPs are the *change frequency* (how often the changes occur) and *change severity* (how different the environment is after a change) [1].

The dGA model [5] structures the population in demes named *islands*. Each island independently evolves, usually in parallel, and communicates with the other ones through migration of individuals. The migration period (ζ), amount of migrants to exchange (m), criteria for selecting (ω_s) or accepting (ω_r) migrants, neighborhood among islands and synchronization, form the *migration policy*.

Two main reasons drove us to use dGAs in DOPs. First, different islands can naturally evolve to different solutions (speciation), which is useful to track multiple peaks at the same time, i.e., potential optima after an environmental change. Second, the coarse grained distribution and migrations among islands, improves the population diversity due to the recombination of different genetic material. This last can be seen as a mechanism to adapt to the changes in a DOP, since both behaviors depend on the coupling degree among the islands, which is highly influenced by the migration period.

3 Experimental Setup

The behavior of algorithms is tested using two well-known benchmarks for binary and real encoding GAs, thus addressing both discrete and continuous DOPs. The first one is the technique introduced in [6] to build DOPs from a given binary-encoded stationary functions $f(x)(x \in \{0,1\}^l)$. We use that technique on three different functions: Onemax, Royal Road, and Deceptive [6]. We vary the change severity ($\rho \in \{0.05, 0.1, 0.2, 0.5, 0.7\}$) to provide a wide set of difficulty degrees. The second type of generator is the moving peaks benchmark (MPB) with the parameter setting of the first standard scenario[3] and vary the *number of peaks* ($n = \{5, 50, 200\}$) and the *step severity* ($\rho = \{0.0, 0.5, 1.0, 2.0, 3.0\}$). Since we are interested in studying the adaptation ability of the dGA, we set the same change frequency of $\tau = 50$ generations for all problem instances tested.

Our dGA consists of eight islands evolving homogenously. In every island, we use a sequential GA with generational replacement. Migrations occur synchronously on a unidirectional ring topology and the migration policies used are defined in Table 1. The migration periods used are set in number of generations and proportional to the change frequency ($\tau = 50$). Thus, we test the influence of migrations at each generation ($\zeta = 1$), four times at each stationary interval ($\zeta = \frac{\tau}{4}$), one time in the half and other after a change ($\frac{\tau}{2}$), only after a change ($\zeta = \tau$), plus other at alternating intervals ($\zeta = \frac{2\tau}{3}$), respectively.

[3] Online available at *http://people.aifb.kit.edu/jbr/MovPeaks*

Table 1: Parameter settings for GAs and migration policy.

Population Size	512 (64 × 8 islands)	ζ	$\in \{1, 12, 25, 50, 75\}$
Parent's Selection	(Binary tournament,	m	One copy
	Binary tournament)	ω_s	*Random* selection
Crossover	SPX, pc=0.6,	ω_r	Replace *if-better* than *least-fit*
	($BLX_{\alpha=0.5}$ for MPB)		
Bit Mutation	pm=1/L, L=string length		Synchronous migrations
	(Polynomial for MPB)		Unidirectional ring topology

Algorithms and benchmarks were implemented in C++, using the MALLBA library[4]. All experiments were performed in a PC with an Intel Core i7-720QM processor at 1.60GHz, 4GB of RAM, and running Ubuntu 10.10. To describe the behavior of algorithms we use the *accuracy* ($\overline{acc}$) metric, also known as *relative error*. Then, we apply the performance tool proposed in [7] based on the area below the curve defined by this population feature ($ABC_{\overline{Acc}}$). Finally, we average the results over 100 independent runs and evaluate the statistical significance with a level of confidence of 95 %.

4 Influence of the migration period on the performance

Lets us first analyze the influence of the migration period in dGAs for DOPs. Fig. 1. summarizes the $ABC_{\overline{Acc}}$ achieved with several migration periods and change severities. High values of this metric indicate a better adaptation of the algorithm to the changing optimum throughout all the run.

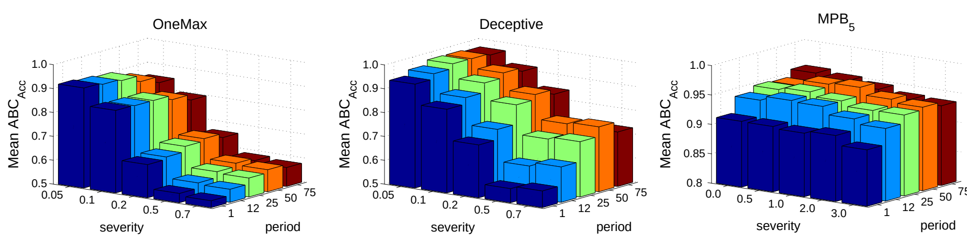


Fig. 1: Influence of the migration period in the performance of the dGA model for DOPs with different severity degrees.

As a first conclusion, you can notice that the effect of the migration period is dependent on the severity of change. The lowest migration period ($\zeta = 1$) is notably better for Onemax with low severity. This instance consists of a fitness landscape with a single optimal solution drifting slowly. Therefore, a high coupling among the islands produces an accumulation of visited solutions around the optimum which is useful to pursue small variations of it, but at the expense

[4] Online available at *http://neo.lcc.uma.es/mallba/easy-mallba*

of the global diversity. In fact, if the severity degree is higher ($\rho > 0.1$) then the algorithm hardly react and adapt to the changes in the environment (see Fig. 1a). Conversely, a high migration period ($\zeta = \tau = 50$) results beneficial for unimodal DOPs with high severity, since a loose coupling improves the global diversity of the population.

Multimodal DOPs (Deceptive or MPB) add an additional behavior due to the large number of suboptimal solutions that arise. In these scenarios, a small change in the problem can produce abrupt and discontinuous shifts of the optimum in the search space. Then, a high migration period ($\zeta = 50$ or $\zeta = 75$) produces better performance, even when the step severity is low, since in addition to the diversity enhancement it allows *speciation* for tracking several optima candidate at the same time (see next section). We can see in Table 2 the numerical results with all instances tested. For each severity value (columns in the table), the best result is marked with a star (*) character and the bold type is applied to those which are not significantly different from this one.

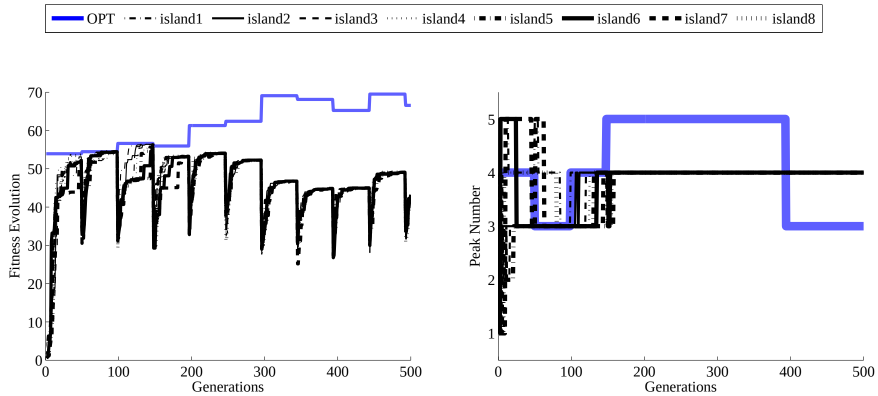
Table 2: Mean $ABC_{\overline{Acc}}$ computed for dGA with different migration periods for DOPs with several change severities.

ζ	$\rho = 0.05$	$\rho = 0.1$	$\rho = 0.2$	$\rho = 0.5$	$\rho = 0.7$	$\rho = 0.0$	$\rho = 0.5$	$\rho = 1.0$	$\rho = 2.0$	$\rho = 3.0$
	Onemax					MPB_5				
1	**0.919***	**0.845***	0.639	0.539	0.528	0.912	0.911	0.908	0.912	0.896
12	0.912	**0.843**	0.649	0.561	0.554	0.939	**0.946**	0.945	**0.932**	0.923
25	0.905	**0.842**	0.671	0.585	0.579	**0.948**	**0.952**	0.945	**0.937**	**0.937**
50	0.879	0.824	**0.681***	**0.599***	**0.592***	0.946	**0.956***	**0.959***	**0.947***	**0.942***
75	0.852	0.800	0.664	0.588	0.579	**0.958***	**0.953**	0.947	**0.938**	**0.935**
	RoyalRoad					MPB_{50}				
1	**0.734***	**0.601***	**0.306**	0.0758	0.0777	0.874	0.860	0.870	0.860	0.850
12	0.720	**0.599**	**0.313**	0.0944	0.098	**0.906**	0.898	**0.907**	**0.903**	0.887
25	0.711	**0.579**	**0.311**	0.110	0.114	**0.915**	0.903	**0.911**	**0.899**	**0.897**
50	0.661	0.562	**0.319***	**0.118***	**0.122***	**0.913**	**0.916**	**0.912**	**0.908***	**0.903***
75	0.589	0.491	0.286	0.111	0.114	**0.923***	**0.916***	**0.912***	**0.908**	**0.896**
	Deceptive					MPB_{200}				
1	0.936	0.851	0.722	0.559	0.570	0.856	0.852	0.856	0.848	0.851
12	0.957	0.877	0.765	0.631	0.648	**0.898**	0.900	**0.894**	**0.887**	**0.879**
25	**0.977***	0.917	0.846	0.723	0.732	**0.901**	**0.901**	**0.900**	**0.894**	**0.882**
50	0.976	**0.937***	**0.867***	**0.764***	**0.772***	0.897	**0.910**	**0.908***	**0.900***	**0.894***
75	0.969	0.921	0.846	0.723	0.728	**0.913***	**0.914***	**0.897**	0.886	**0.888**

Results in Table 2 corroborate the previous observations statistically. Another finding is that migrating after a change produces the best overall performance. Since it insuflates diversity into the population, through the crossbreading between individuals with different genotypes. In addition, we note that it can only be effective if islands have had enough isolation time as to promote the speciation of individuals, as we will illustrate in the next section.

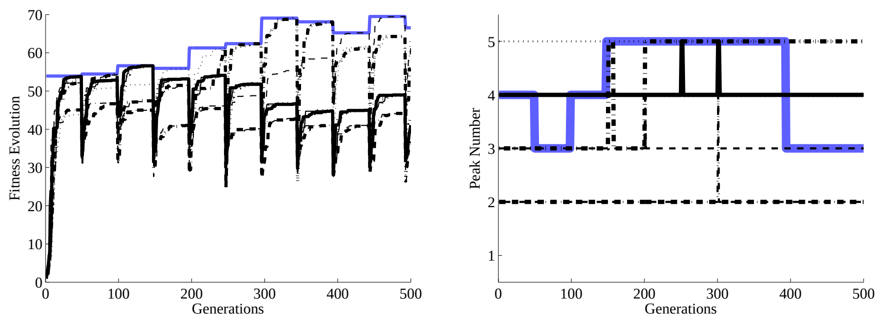
5 Benefits of Speciation for DOPs

With the aim at illustrating the speciation feature of a dGA, we use only two migration periods: a low one ($\zeta = 1$) and a high value ($\zeta = 50$), and the MPB_5 instance with change severity of $\rho = 3.0$, ensuring the same dynamic behavior throughout all the runs. Fig. 2 shows the best fitness evolution and the peak being exploited by each deme. The blue line depicts the optimum trajectory.



(a) Low Period $\zeta = 1$

(b) Low Period $\zeta = 1$



(c) High Period $\zeta = 50$

(d) High Period $\zeta = 50$

Fig. 2: Fitness evolution (left) and peak tracking (right) by each island of a dGA with low (upper half) and high (bottom half) migration periods for the MPB_5.

On the one hand (low period), the dGA losses the evolutionary potential in the Fig. 2a (curves join in a straight line), which is due to islands exploit in parallel a reduced number of promising areas converging to a single solution. Such behavior is also depicted in Fig. 2b, during the first 150 generations (peak number 4). As noted in previous section, this behavior could be useful for unimodal DOPs with continuous and drifting landscapes. However, it raises the convergence problem in the long term, since it resembles the panmictic population strategy. On the other hand, a high migration period improves the population diversity and promotes speciation by the isolated evolution of islands. Speciation process consists of the natural grouping of individuals with similar traits (species), because of the constrained mating induced by structuring the population in several demes. Note in Fig. 2c that the curves are more widely spaced than the ones obtained above with a low migration period. This behavior corresponds to the ability of the algorithm to track several peaks at the same time.

This is more clear in Fig 2c from generation 150 up to 400, where the problem changes but the optimal peak remains the same, and the two islands exploiting this peak dynamically adapt to its movement. If the optimal peak alternates, as can be seen in the remainder time intervals, a new specie is able to adapt to the new environment (track island number 4 after the third change and island number 2 after the eighth change in Fig. 2d).

6 Conclusions

In this paper we analyzed the influence of the migration period, an important parameter for dGA models, for DOPs. We used a comprehensive test environment based on unimodal and multimodal DOP benchmarks. On the one hand, results showed the benefits of a low migration period to address unimodal DOPs with small changes. On the other hand, a high migration period showed more robust to tackle a wide range of change severities in all DOP instances tested, enhancing the diversity and speciation features of the population. In particular, migrating as response to a change in the environment shown effective as a mechanism to adapt to dynamic environments.

In future works, we aim at developing adaptive or self-adaptive dGA models that exploit the main findings of this work with respect to the migration period in function of the severity of change, a unified study of all parameters governing the migration policy, and enhancing the basic behavior with other DOP techniques like memory, hypermutation, etc.

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