Evaluating Island-based EAs on Unstable Networks with Complex Failure Patterns

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ABSTRACT

The performance of island-based evolutionary algorithms is studied on unstable networks whose nodes exhibit complex correlated failures. Simple EAs have a significant performance degradation with respect to networks with uncorrelated failures, but the use of self-⋆ properties allows the EA to increase its resilience in this scenario.

CCS CONCEPTS

• **Computing methodologies → Randomized search**; **Distributed algorithms**; *Self-organization*; • **Networks** → *Network performance analysis*;

KEYWORDS

Island-based EAs, unstable networks, resilience, sandpile model

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1 INTRODUCTION

Recent times have witnessed an increasing interest in the use of EAs in novel computational scenarios such as cloud computing (a paradigm that provides computing resources on demand), P2P networks (where interconnected computers share computing resources in a non-centralized way), or volunteer computing (in which computers donate computing resources when are idle), just to cite a few. A common theme in some of these scenarios is the dynamic nature of the underlying computational substrate (e.g., consider a P2P network in which nodes enter or leave the system subject to external factors). A sensible solution to this issue may be to construct intermediate layers to hide this dynamicity. However, such a solution is not exempt of difficulties, in particular if the computational substrate is composed of many low-power nodes just providing brief, ephemeral bursts of computation [2]. The alternative is making the algorithm cognizant of the volatile environment, reacting and self-adapting to the fluctuations in the computational substrate. Fortunately, EAs are resilient techniques that can withstand to some extent the sudden loss of part of the population [5], even more so if endowed with self-⋆ properties [1]. Recent work has precisely studied the use of self-scaling [7] and self-healing [6] techniques in this context, and shown that the robustness of the algorithm is notably improved. Previous studies have however only considered simple network models in which each node has its own dynamics, independent of the rest of the network. We consider here a more general situation in which the availability sequence of computing nodes is not independent of other nodes, but follows complex correlation patterns [4], thus putting to test the robustness and resilience of the EA, and providing a broader perspective on the usefulness of self-⋆ mechanisms to cope with computational instability.

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2 ALGORITHMIC SETTING

We consider an island-based EA running on a simulated unstable environment. Each island runs on a computational node of the system, whose topology is that of a scale-free network (as it is often the case in P2P networks). These nodes are volatile, and may abandon the system and re-enter it at a later time, over and over again. To model this instability we consider two scenarios:

- independent failures: each node can switch from active to inactive or vice versa independently of other nodes, after a fixed number of micro-failure events taking place with some probability $p(t)$ that depends on the time it has been in its current state. Following previous work and the commonly observed behavior of these systems [8], $p(t)$ is assumed to follow a Weibull distribution.
- correlated failures: node failures will be influenced by neighboring nodes [4]. This can be accomplished in different ways. In this work we have considered a variant of the sandpile model in order to induce cascading failures [3]. Much like in the previous case, we consider micro-failure events happening on each node with a certain probability $p(t)$. When the number of such micro-failures equals the number of active neighbors of a node, it is disconnected from the system; in this case, each of the active neighbors of the former node will have one active neighbor less (which can in turn produce node disconnections in cascade if these had previously accumulated a large enough number of micro-failures). As to node reactivation, a single event is required (identically to the independent scenario).

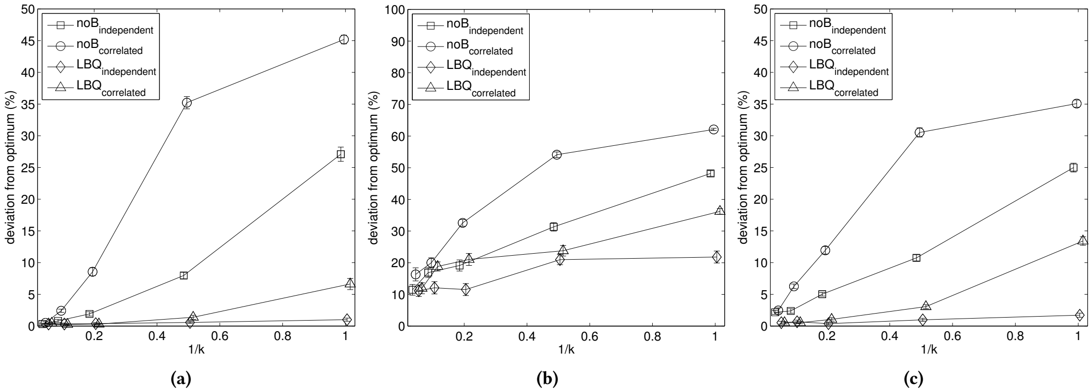

Figure 1: Average deviation from the optimal solution for each algorithmic variant and network failure model. (a) Trap function (b) HIFF function (c) MMDP function

Two variants of the island-based EA are considered: (i) a basic one (termed noB) in which every island has a fixed size and random reinitialization is used whenever a new node enters the system, and (ii) a self-$\star$ EA (termed LBQ) that uses self-scaling and self-sampling to re-size each island individually in response to fluctuations in the number of active neighbors and in the population sizes of these – see [6] for details.

3 EXPERIMENTAL RESULTS

The experiments have been done with an island-based EA composed of $n_\iota = 64$ islands of $\mu = 32$ individuals initially. Each island runs a basic steady-state EA using one-point crossover ($p_X = 1.0$), bit-flip mutation ($p_m = 1/\ell$, where ℓ is the genotype length), tournament selection, replacement of the worst parent and migration of randomly selected individuals with probability $p_{\text{mig}} = 1/(5\mu)$. We consider micro-failures distributed according to a Weibull distribution with shape parameter $\eta = 1.5$ and different scale parameters controlled by an external parameter $k \in \{1, 2, 5, 10, 20\}$ that takes values from 1 (very high volatility) to 20 (very low volatility). Three test problems are used, a trap function (32 traps of 4 bits), the hierarchical if-and-only-if function (HIFF with 128 bits) and the massively multimodal deceptive problem (MMDP with 24 blocks of 6 bits).

Figure 1 shows the results. Increasingly volatile scenarios are found to the right of the X-axis and, obviously, higher degradation of the results. Not all algorithms degrade at the same rate though: noB is very affected by these correlated failures, and has a marked degradation profile as instability increases; on the contrary, LBQ is much more resilient. A statistical analysis (ranksum test, $\alpha = 0.05$) indicates the performance of LBQ is significantly reduced in the presence of correlated failures only for $k \leqslant 1$ (trap), $10 \geqslant k \neq 2$ (HIFF) and $k \leqslant 5$ (MMDP), whereas noB exhibits significantly degraded performance with respect to the uncorrelated scenario for all values of k except $k = 20$ (for trap and MMDP) and $k \geqslant 10$ (for HIFF). Furthermore, LBQ is superior in both scenarios to its noB counterpart for all test problems and for all values of k, except $k = 20$ for trap and $k = 10$ for HIFF in the correlated scenario.

4 CONCLUSIONS

Correlated failures pose a hard challenge to island-based EAs. Self-$\star$ properties seem to be essential to boost the resilience of the algorithm in such scenarios. We are currently working on other models of correlated failures and network types in order to confirm these findings and analyze more in depth the effect they cause in the search process.

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