Self-Adaptive Operator Selection (SAOS)
A study on self-adaptive migration topologies in island models

Henning Bartsch, Andrei Furdui, Maximilian Knaller, and Julio J. Lopez Gonzalez

Abstract. Finding evolutionary algorithm (EA) parameters that perform well on one or more given problems is a remaining challenge in current research. One successful approach to control parameters during the evolution is self-adaption. However, it is mainly used to optimize numeric parameters, limiting its area of influence to EA instances. Self-Adaptive Operator Selection (SAOS) is an approach to overcome this limitation by allowing evolution to choose from more than one given symbolic operator. So far this evolution of the evolution was only proven to work successfully on operators that allow direct relative evidence. However, many symbolic parameters act on higher scopes and their relative evidence is hard or impossible to measure. Therefore this paper investigates the usage of SAOS on an symbolic parameter, using only indirect relative evidence of the evolution circle, the migration topology of an island model EA.

1 Introduction

The performance of evolutionary algorithms (EA) heavily depends on their parameterization. Nevertheless, parameters are often set by convention, ad hoc choices or "best practices". Hence, there is a lack of understanding exactly how EA parameters affect performance, and finding good parameter values is often a poorly structured, ill-defined, complex problem[1]. As EAs are known to perform well on such problems, there are efforts to find well performing parameter settings automatically during the optimization process. Self-adaption evolves algorithm parameters that are encoded in the chromosomes. Beneficial parameter values lead to fitter individuals which have a higher chance of reproduction and survival, which in turn leads to propagation of these parameters throughout the population. While widely and successfully used to adapt numeric parameters (e.g. mutation-step-sizes in CMSA-ES), self-adapting algorithms are rarely used to evolve symbolic parameters, i.e. the operator itself. Using the terminology of Eiben et al.[1], self-adaption is more often applied on the algorithm layer, optimizing an EA instance, than on the design layer optimizing the EA. This is surprising, since several papers successfully proposed **Self-Adaptive Operator Selection (SAOS)** to handle multiple crossover operators and thereby increased the EA's performance[2]. All of the authors saw SAOS as a way towards a flexible, parameter-free EA.

The Island Model (IM) approach is a well known technique for the parallelization of continuous optimization algorithms [3], much like the Schaffers F7 function problem. The main idea behind IM is to divide the population in subpopulations (islands), which evolve separately, with sparse exchange of individuals (migration). The division in islands and the sparse migration between them leads to increased algorithm performance in terms of finding a balance between exploitation and exploration. Hence, the migration policy is an essential part in the evolution circle, allowing for greater control over population diversity. A migration policy consists of three main operators: Emigration, Topology and Immigration. Emigration describes the selection of individuals, i.e. who emigrates. The **Migration Topology (MT)** determines the exchange of emigrants between islands, i.e. where they go. Immigration describes the integration into islands, i.e. if/how an immigrant is included into the subpopulation.

While research showed that SAOS works on the individual scope, not much is known about its capabilities on a more indirect one. To be more precise, variation operators like crossover affect the individual directly by changing the genotype, and thereby the individual's fitness, thus creating a direct relative evidence of the positive or negative impact of the operation. The relative evidence of more indirect operations on the population scope is harder to specify or measure directly. However, their importance to push the population towards the optimum and to create flexible EAs is undoubted. The interpretation of the scope of an operator can depend heavily on the implementation and the point of view [1], e.g. change in the mutation-step-size might be seen as a change on a gene, the chromosome or the entire population. Therefore, we aimed to investigate an operator that could be confidently classified as acting on the population scope. The Migration Topology is such an operator. First, it only changes the composition of the subpopulations and can be categorically classified to act on the population level. Secondly, its relative evidence can hardly be quantified: the positive or negative impact of the MT can not be measured directly as it depends on the whole migration process and needs time to affect the population. These observations make the MT operator in Island Models perfect for our investigation of SAOS on a population scope.

2 Objectives

This paper investigates whether Self-Adaptive Operator Selection (SAOS) is capable of working on a population scope, using only indirect relative evidence of the evolution circle. In particular, we consider the use of Island Models to analyze the impact of migration topologies on the performance of a continuous optimization problem like Schaffers F7 function. We also cover the potential improvement that a self-adaptive algorithm based on an symbolic parameter, such as Migration topology, could lead to.

3 Experimental Setup

3.1 Base Algorithms

As a baseline for our survey we used the three variations of Island Model EA specified in table 1. Symbolic parameters besides the MT were set using good performing operators found in literature. Numeric parameters were tuned using a single-stage, non-iterative parameter sweep on the random topology. First, we will investigate the three EAs, which differ only in MT, separately. Then, we will combine them, using SAOS as described in 3.2.

symbolic parameters			
Representation	float-values		
Phenotype/Genotype	One-to-One Mapping		
Crossover	Blend Crossover		
Mutation	Uncorrelated Mutation using σ_i		
Parent Selection	Tournament		
Survivor Selection	Tournament elitist replacement on $(\mu + \lambda)$		
Island Parameters	Initialized Identical		
Migration	Synchronous		
Emigration	Random		
Migration Topology	Random	One-way Ring	Distance
Immigration	Accept		
Termination	10,000 fitness evaluations		

numeric parameters	
Population Size	100
Number of Islands	4
Island Size	25
Crossover Rate	0.65
Blend Crossover α	0.5
Mutation Rate	0.95
Mutation-Step-Size learning rate	0.05
Tournament Size	2
Elite Survivors	1
λ	25
Emigration Size per island	3
Epoch length	20

Table 1: Technical summary of the basic architecture of the base evolutionary algorithm

We consider three different migration topologies: Random, One-way Ring and Distance. In the random MT, all emigrants are randomly assigned an island to which they immigrate. One-way Ring connects the islands in a ring, each island having exactly one way to emigrate to and one way to immigrate from a unique different island. In the Distance MT, the euclidean distances between the emigrant and each island's fittest individual are computed, and the immigration island is selected as the island which contains the furthest away epochal leader.

3.2 SAOS Description

The SAOS algorithm we propose allows each individual to "choose" its migration topology according to a set of probabilities π encoded in its genotype. Each probability π_i represents the bias of an individual towards one of the three topologies described in 3.1. During crossover, the probability genes of the parents, which are equal after initialization, are first mixed according to the rules of the Blend Crossover followed by an additional normalization step. During individual mutation they are propagated without change.

When an individual is selected for migration, a random mutation is first applied to its set of probabilities:

$$\pi_i^* = \frac{\pi_i + \gamma\pi_i}{\sum\limits_j \pi_j^*}, \quad \gamma \sim \mathcal{N}(0, 0.5),\ i, j \in \{Random, Ring, Distance\}$$

Then, a migration topology is chosen according to the new probabilities. The winning topology is decided in a "best out of 7 draws" roulette wheel contest, meaning the first strategy to be drawn three times is selected. Doing this assigns a greater weight to the probabilities, assuring that the option with the highest chance is selected more often by a random draw and thus, giving the set of probabilities a higher importance in the grand scheme of the algorithm. Once the topology is selected, the individual migrates according to its rules. In order to preserve the integrity of the topologies, no hard caps are enforced upon the immigrant number of each island in the cases of Distance and Ring migration. However, in order to try to ensure that each island still receives immigrants, the Random migrants move last, and only emigrate towards islands which still have open slots (i.e. island population size is less than 25).

3.3 Evaluation Methodology

In order to evaluate the EA's performance, we first conducted tests about each migration topology individually, and then using the SAOS algorithm. Each experiment is run over 500 iterations, using random initial seeds and the Schaffers F7 function for evaluation, and the maximum fitness of each iteration is collected. Moreover, we also log the best fitness of each generation in order to inspect the convergence rate of the EA under each topology.

The second experiment's focus is on the behaviour of the SAOS algorithm in each generation. More specifically, we inspect the evolution of the topology probability genes over time. As each generation is solidified after survivor selection, we log the average probability values among all the individuals of the population. We collect these values over 500 runs and then average over them to track the development.

4 Experimental Results

Our first objective was to investigate the effects of different migration topologies. Therefore, we considered the maximum scores for each run of the algorithms. Fig. 1 shows the results of this experiment.

While the differences in performance are not significant, we can observe a clear ranking of the three topologies. Comparing the average fitness, Distance scores best with 9.55, followed by Ring (9.51) and Random (9,41). Moreover, if counting scores in the top 1% of the fitness range (i.e. over 9.9), Distance is dominant with 13% of results scoring in this interval, followed again by Ring with 9% and Random 7%. The SAOS algorithm shows a behaviour that ranks it at the exact mean among the three topologies: 9.50 average maximum fitness and 10% of scores above 9.9 (Figure 2).

The convergence rate under each topology was also measured. However, they all displayed identical behaviours over generations. Our next experiment analyzed the evolution of the topology probability values in the SAOS algorithm over time. The results of this test are presented in Figure 3.

In the left graph of Fig. 3, the selection probabilities of the three considered topologies are contrasted. The evolution in probabilities over time mirrors the findings of our previous experiment: Distance appears to dominate over the other topologies, resulting in the highest probability. Ring and Random score slightly

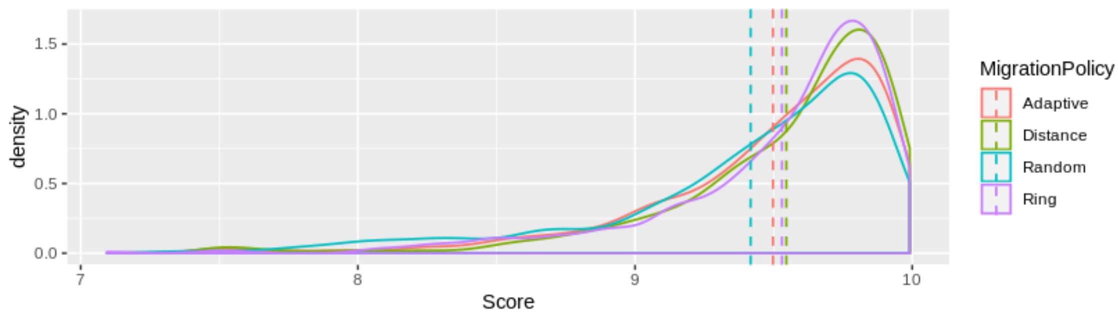

Fig. 1: Score density and mean under each Migration Topology

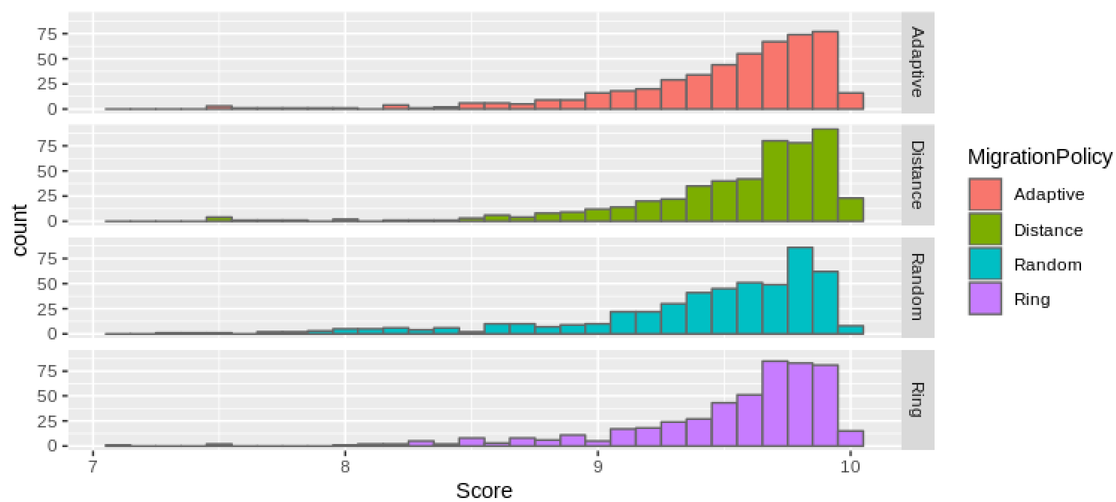

Fig. 2: Score histogram under each Migration Topology

below, resulting in inseparable fluctuations around similar probabilities. In order to verify these findings, we added a fourth option to our SAOS algorithm: no migration. While it may be hard to say which of any given migration topologies is better, it is known that no migration between islands leads to very poor results. Our SAOS EA appears to be able to detect this and clearly reduces its probability, as shown in the right graph of Fig. 3.

5 Analysis and Discussion

The behavior of the SAOS algorithm presents some interesting findings. While the differences between using either Random, Ring or Distance migration topologies individually are rather subtle, our algorithm manages to consistently pick up on these distinctions. Repeated trials all showed that our method seems to introduce a significant bias towards Distance migration, especially in the latter half of the evolution process. Coupled with the significant dominance of the Distance topology when considering results in the 1% area, we argue that directed migration based on Distance is beneficial in the later stages of evolution, introducing an extra amount of exploration in a period where diversity is otherwise usually low.

While the algorithm fails to produce better results by mixing the migration topologies, it certainly manages to shed some light on the effects of MTs on a population scope. By observing the evolution of the topology

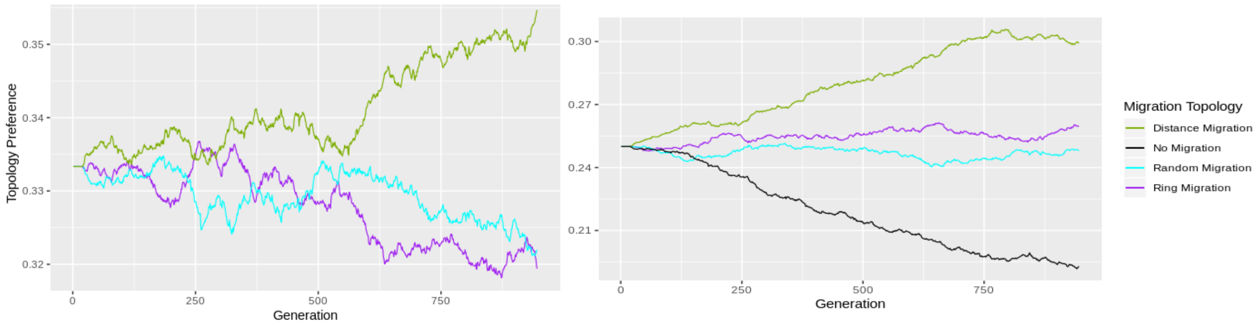

Fig. 3: Topology probability values over generations.

preferences over time, one could more finely tune an algorithm by choosing an appropriate MT for a given problem. Moreover, mixed migration strategies could be implemented by observing the preferred migration method at different points of an EA's lifetime.

6 Conclusions

As expected while formulating the research question, the results we obtained from our experiments clearly show that, with the proper use of migration, we can not only improve the diversity on each island, but also obtain better overall results. In our case, the SAOS algorithm proposed presents an interesting behavior as it is able to somewhat prioritise the better of the three considered migration topologies, and severely discriminate against having No Migration as an option. Moreover, we found that our solution may be able to increase the probability of obtaining promising results by mixing topology strategies and applying the right one at the right moment of the EA's lifetime. Therefore, even if the algorithm proposed does not outperform the best of the individual topologies, we conclude that it is capable of working on a population scope by affecting the outcome of the EA in a positive way. We can also conclude that, in general terms, the implementation of a SAOS based on indirect evidence, e.g. Selection, is a viable approximation to improve or tune different kind of EA's.

As for future work, should time have allowed us, we would have had several ideas to investigate:

- Implementing several well known migration topologies and verifying our results with the help of the Lissovoi Witt [3] paper;
- Creating a feedback loop to allow topology preference probabilities recorded at the end of a run to be fed as initializers for the next runs;
- Extend our SAOS algorithm to not only cover migration topologies, but to self-evolve all the aspects of the migration process (i.e. cover emigration, topology, immigration).

For further research the SAOS algorithm we developed can be found here:
`https://github.com/juliojlgon/EvComp.Group46`

References

1. Eiben, A.E., Smith, J.E.: Introduction to evolutionary computing. Springer (2015)
2. Kramer, O.: Evolutionary self-adaptation: a survey of operators and strategy parameters. Evolutionary Intelligence **3**(2), 51–65 (2010)
3. Lissovoi, A., Witt, C.: The impact of migration topology on the runtime of island models in dynamic optimization. pp. 1155–1162. GECCO '16, ACM (2016)