Exploring concurrent and stateless evolutionary algorithms

Improving the algorithmic efficiency and performance of channel-based evolutionary algorithms

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ABSTRACT

Concurrent algorithms use channels for communication, which implies that communication is an integral part of them, so some attention must be devoted to its design. In the design of concurrent evolutionary algorithms, there are several options that can be used for performing this communication. In this paper we will explore how communication overhead can be reduced, and how it influences scaling. The evolutionary algorithm will use a concurrent language, and leverage its capabilities. Eventually, we will try to prove how concurrent version of algorithms offer a good option to leverage the multi-threaded and multi-core capabilities of modern computers.

CCS CONCEPTS

• **Theory of computation → Concurrent algorithms**; • **Computing methodologies → Genetic algorithms**; • **General and reference** → *Performance*;

KEYWORDS

Concurrency, Concurrent evolutionary algorithms, performance evaluation, algorithm design

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1 INTRODUCTION

Despite the emphasis on algorithmic techniques whose foundation is on software techniques that have an ultimate basis on newer hardware features, there are not many papers [16] dealing with creating concurrent evolutionary algorithms that work in a single computing node or that extend seamlessly from single to many computers. Concurrent programming has a physical basis: the existence of multi-core processors that are able to deal with many processes at the same time, and the support for threads, or lightweight processes, within those same processors. This eventually means that many processes (heavy or lightweight) can be leveraged to take full advantage of the processor capabilities.

These capabilities must be matches at an abstract level by languages that build on them so that high-level algorithms can use them without worrying about the low-level mechanisms of creation or destruction of threads, or how data is shared or communicated among them. These languages are called concurrent, and the programming paradigm implemented in them concurrency-oriented programming or simply concurrent programming [2].

These languages are characterized by the presence of programming constructs that manage processes like first class objects; that means that the language includes operators for acting upon them and the possibility of using them like parameters or function's result values. This changes the coding of concurrent algorithms due to the direct mapping between patterns of communications and processes with language expressions; on one hand it becomes simpler since the language provides an abstraction for communication, on the other hand it changes the paradigm for implementing algorithms, since these new communication constructs have to be taken into account.

Moreover, concurrent programming adds a layer of abstraction over the parallel facilities of processors and operating systems, offering a high-level interface that allows the user to program modules of code to be executed in parallel threads [1].

Different languages offer different concurrency strategies depending on how they deal with shared state, that is, data structures that could be accessed from several processes. In this regard, there are two major fields (with some other variations):

- Actor-based concurrency [18] totally eliminates shared state by introducing a series of data structures called *actors* that store state and can mutate it locally.
- Process calculi or process algebra is a framework to describe systems that work with independent processes that interact between them using channels. One of the best known is called the *communicating sequential processes* (CSP) methodology [9], which is effectively stateless, with different processes reacting to a channel input without changing state,

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and writing to these channels. Unlike actor based concurrency, which keeps state local, in this case per-process state is totally eliminated, with all computation state managed as messages in a channel.
- Other, less well known models using, for instance, tuple spaces [7].

Most modern languages, however, follow the CSP abstraction, and it has become popular since it fits well other programming paradigms, like reactive and functional programming, and allows for a more efficient implementation, with less overhead, and with well-defined primitives. This is why we will use it in this paper for creating new evolutionary algorithms that live *natively* in these environments and can thus be implemented easily in this kind of languages. We have chosen Perl 6, although other languages such as Go, are feasible alternatives.

In previous papers [24, 25] we designed an evolutionary algorithm that fits well this architecture and explored its possibilities. That initial exploration showed that a critical factor within this algorithic model is communication between threads; therefore designing efficient messages is high-priority to obtain a good algorithmic performance and scaling. In this paper, we will test several communication strategoes: a lossless one that compresses the population, and a lossy one that sends a representation of population gene-wise statistics.

2 STATE OF THE ART

The problem of communication/synchronization between processes, which nowadays is accomplished by means of threads, has been the subject of long-standing study. One of the best efforts to formalize and simplify that matter is HoareâĂŹs *Communicating Sequential Processes* [9], that proposes an interaction description language which is the theoretical support for many libraries and modern programming languages. In such model, concurrent programs communicate on the basis of *channels*, a sort of pipe buffer used to interchange messages between the different processes or threads, either asynchronously or synchronously. Languages such as Go and Perl 6 implement this concurrency model (the latter including additional mechanisms such as *promises* or low-level access to the creation of threads).

The fact that messages have to be processed without secondary effects and that actors do not share any kind of state makes concurrent programming specially fit for functional languages or languages with functional features; this has made this paradigm specially popular for late cloud computing implementations; however, its presence in the EA world is not so widespread, although some efforts have lately revived the interest for this kind of paradigm [21]. Several years ago it was used in Genetic Programming [4, 10, 28] and recently in neuroevolution [19] but its occurrence in EA, despite being scarce in the previous years [8], has experimented a certain rise lately with papers such as [27] which perform program synthesis using the functional programming features of the ERlang language [3] for building an evolutionary multi-agent system.

Regarding functional languages, Erlang and Scala have embraced the actor model of concurrency and get excellent results in many application domains; Clojure is another one with concurrent features such as promises/futures, Software Transaction Memory and agents; Kotlin [20] has been recently used for implementing a functional evolutionary algorithm framework.

On the other hand, Perl 6 [15, 23] uses different concurrency models, varying from implicit concurrency using a particular function that automatically parallelizes operations on iterable data structures, to explicit concurrency using threads. These both types of concurrency will be considered in this study whilst using the `Algorithm::Evolutionary::Simple`, a Perl 6 library introduced in last year's version of this very same conference [17].

Earlier efforts to study the issues of concurrency in EA are worth mentioning. For instance, the EvAg model [11] resorts to the underlying platform scheduler to manage the different threads of execution of the evolving agents; in this way the model scaled-up seamlessly to take full advantage of CPU cores. In the same avenue of measuring scalability, experiments were conducted in [13] comparing single and a dual-core processor concurrency achieving near linear speed-ups . The latter was later on extended in [14] by scaling up the experiment to up to 188 parallel machines, reporting speed-ups up to 960×, nearly four times the expected linear growth in the number of machines (when local concurrency were not taken into account). Other authors have addressed explicitly multi-core architectures, such as Tagawa [22] which used shared memory and a clever mechanism to avoid deadlock. Similarly, [12] used a message-based architecture developed in Erlang, separating GA populations as different processes, although all communication tooking place with a common central thread.

In previous papers [24, 26], we presented a proof of concept of the implementation of stateless evolutionary algorithms using Perl 6, based on a single channel model communicating threads for population evolving and mixing. In addition, we studied the effect of running parameters such as *generation gap* (similar to the concept of *time to migration* in parallel evolutionary algorithms) and population size, realizing that the choice of parameters may have a strong influence at the algorithmic level, but also at the implementation level, in fact affecting the actual wallclock performance of the EA.

3 EXPERIMENTAL SETUP

The baselinwe we are coming from is similar to the one used in previous experiments [24]. Our intention was to create a system that was not functionally equivalent to a sequential evolutionary algorithms, and that followed the principle of communicating sequential processes. In this kind of methodology, we will have processes (or threads) communicating state through channels. Every process itself will be stateless, reacting to the presence of messages in the channels it is listening to and sending result back to them, without changing state.

As in the previous papers, [25], we will use two groups of threads and two channels. We will see them in turns.

The two groups of threads perform the following functions:

- The *evolutionary* threads will be the ones that will be in principle running the evolutionary algorithm.
- The *mixing* threads will *mix* populations, and create new ones as a mixture of them.

The two channels carry messages that are equivalent to populations, but they do so in a different way:

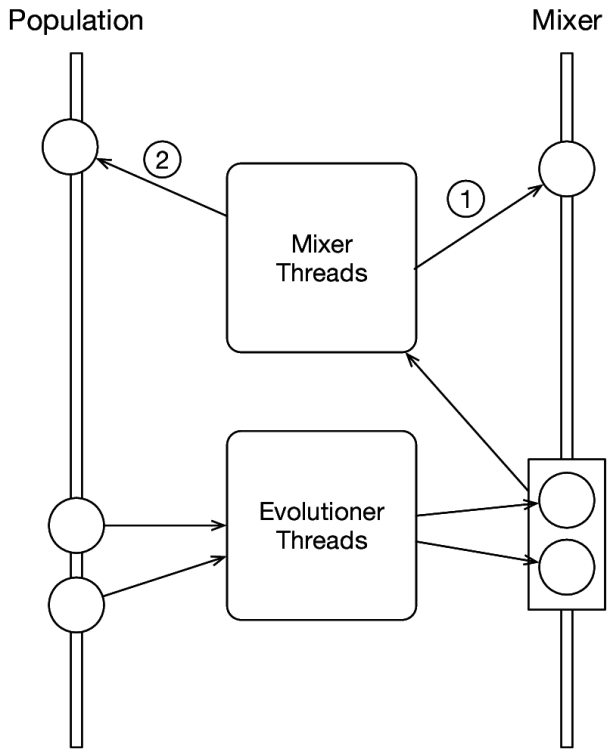

Figure 1: General scheme of operation of channels and thread groups.

- The *evolutionary* channel will be used for carrying non-evolved, or generated, populations.
- The *mixer* channel will carry, *in pairs*, evolved populations.

These will be connected as shown in Figure 1. The evolutionary group of threads will read only from the evolutionary channel, evolve for a number of generations, and place result in the mixer channel; the mixer group of threads will read only from the mixer channel, in pairs. From every pair, a random element is put back into the mixer channel, and a new population is generated and sent back to the evolutionary channel. The main objective of using two channels is to avoid deadlocks; the fact that one population is written always back to the mixer channel avoids starvation in the channel. How this runs in practice is shown in Figure 2, where the timeline of the interchange of messages between the evolver and mixer threads and evolver and mixer channels is clarified.

One of the problems of the baseline configuration was that communication took a great amount of time, adding some overhead to the algorithm. The *message* consisted of the whole population, and the size increased with population size, obviously. This tipped the balance between communication and computation towards communication, so that the more threads, the more communication was taking place. Our first intention in this paper was to slim down messages so that they took less bandwith (or memory) and less time to send and process. In general, this strategy also can be framed in the context of migration strategies, since that is the most similar

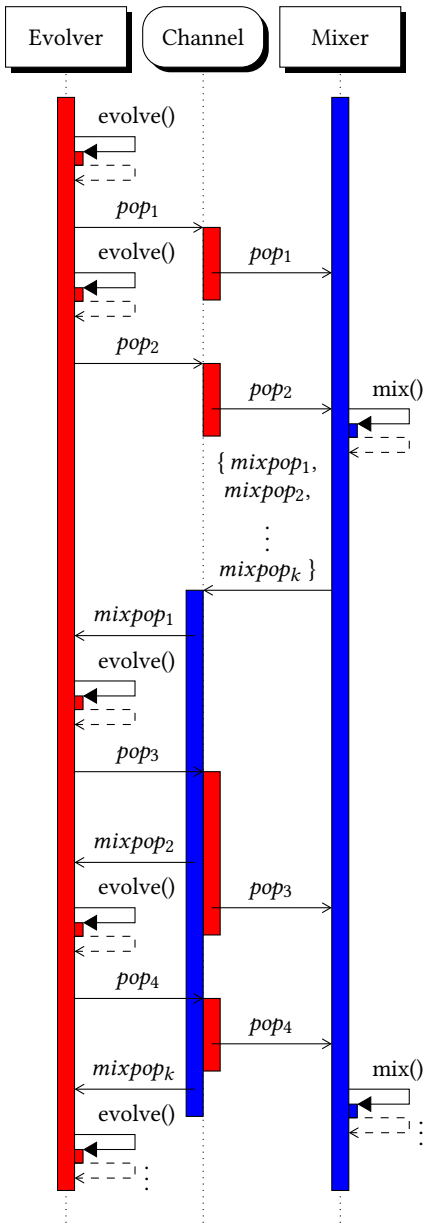

Figure 2: Schematic of communication between threads and channels for concurrent EAs. The two central bars represent the channel, and color corresponds to the *main* function they perform; blue for mixer, red for evolver. As the figure shows, the evolver threads always read from the mixer channel, and always write to the evolver channel.

thing in the context of parallel algorithms. In parallel algorithms, an adequate selection of migration strategies, balancing exploration and exploitation, is the key to achieving high performance, as indicated in [5]. In the context of concurrent evolutionary algorithms we will talk about *population messages*, but their effect is going to

be similar. For this paper, we introduced two different messaging strategies:

- One we have called *EDA*, or estimation of distribution algorithm, whose basic idea is that the population message will contain the probability distribution over each gene. In this sense, this strategy is similar to the one presented by de la Ossa et al. in [6]. Not being an estimation of distribution algorithm *per se*, since the evolutionary thread runs a canonical genetic algorith, when the message is being composed, every (binary) gene of the 25% best individuals in the population is examined, and an array with the probabilities for each gene is sent to the mixer thread. The *mixer* thread, in turn, just takes randomly one probability from each of the two *populations* (actually, distributions), instead of working on individuals. While in the baseline strategy the selection took place in the mixer thread, that eliminated half the population, in this case the selection takes place when composing the message, since just the 25% best individuals are selected to compute the probability distribution of genes. When the evolver thread reads the message, it rebuilds the population based on this distribution.
- The second is called *compress*, and it simply bit-packs the population, without the fitness, into a message which uses 1 bit per individual, and then 64 bits, or simply 8 bytes, to transmit a single individual in the population. This strategy is equivalent to the baseline, except it introduces an additional step of evaluating the population when mixing and receiving it from the evolutionary channel. It is hoped that this additional evaluation overhead does compensates the communication overhead that is eliminated.

In the same way we did in our previous papers, first we will have to evaluate these new strategies compared with baseline; since the overhead will be different depending on the computation time, which in this case is regulated by the number of generations that are going to be performed by every thread, we will first perform an experiment changing that. We will call this parameter the *generation gap*, implying that's the gap between receiving a message and activating the thread and sending it, deactivating it. Besides, what we want to find out in these set of experiments is what is the generation gap that gives the best performance in terms of raw time to find a solution, as well as the best number of evaluations per second.

Additionally, it is impossible to know from first principles if this setup is the only possible. We have to heuristically explore other possibilities; in this case, we will explore another messaging strategy called *no writeback*, or nw, where the mixer thread, instead of sending one of the individuals back again to the mixer thread, sends it to the evolver channel, where it will undergo an additional round of evolution. The main difference between these two strategies is twofold:

- The mixer channel can be empty for some time, since it is not always holding at least one population message (written back every time it is activated). This might lead to *starvation* of the mixer thread, but in fact it will not take long since it is going to be processed immediately by the evolver thread.

Table 1: Parameters used to explore the generation gap

Parameter	Value
Evolver threads	2
Mixer threads	1
Generations	8,16,32
Population size	256
Initial populations	3
Bits	64
Repetitions	>= 15

- Every population is mixed just once, which might lead to improvements in the algorithm.

4 EXPERIMENTAL RESULTS

The experiments have been prepared by using OneMax function with 64 bits. This function was chosen primarily since it was the one used in previous experiments, but also because it is a classical benchmark, it can be easily programmed in Perl 6, and allowed us to focus in what we are interested in, the design of the concurrent evolutionary algorithm itself. We used the open source `Algorithm::Evolutionary::Simple` Perl 6 module for the evolutionary part, and wrote the different scripts in the same language. The latest version, compiled from source, of Perl 6 was used, and experiments were performed in a Intel(R) Core(TM) i7-4770 CPU at 3.40GHz running Ubuntu 14.04 server. All scripts have a free license and have been released in GitHub, where the data generated by every single experiment is also hosted.

In these experiments, the parameters used are shown in Table 1. Two evolver threads are needed, at least, to avoid starvation of the mixer thread. The generation gap was checked for those values in all cases, although in some cases we extended it to 4 and 64 generations. The population was sized in previous papers using the bisection method, and the number of initial populations created and sent to the evolver channel was also designed to avoid starvation; that way, as soon as the first two populations are evaluated simultaneously by the two threads and sent to the mixer channel, this channel will always hold a population that will combine with a fresh one coming from either of the mixer threads.

Since we are exploring the parameter space, we will first try to find out the generation gap and strategy that obtains the smaller number of evaluations, indicating it is the best algorithmic strategy. These are shown in Figure 3, where the two messaging strategies, EDA and compress, with or without writeback, are plotted and compared with the baseline strategy, which uses the full, evaluated population as a message. The first observation is that, in general, the number of evaluations increases with the generation gap. More evolution without interchange with other populations implies more exploitation, and then the possibility of stagnation. For 8 generations the results are very similar, but they diverge with the generation gap. Clearly, the baseline strategy achieves the lowest number of evaluations, for two reasons: it does not need to re-evaluate the population when the message is received, but also, in the case of EDA, the population is rebuilt from its statistical description, so the exact individual (with the possible highest fitness) is not kept.

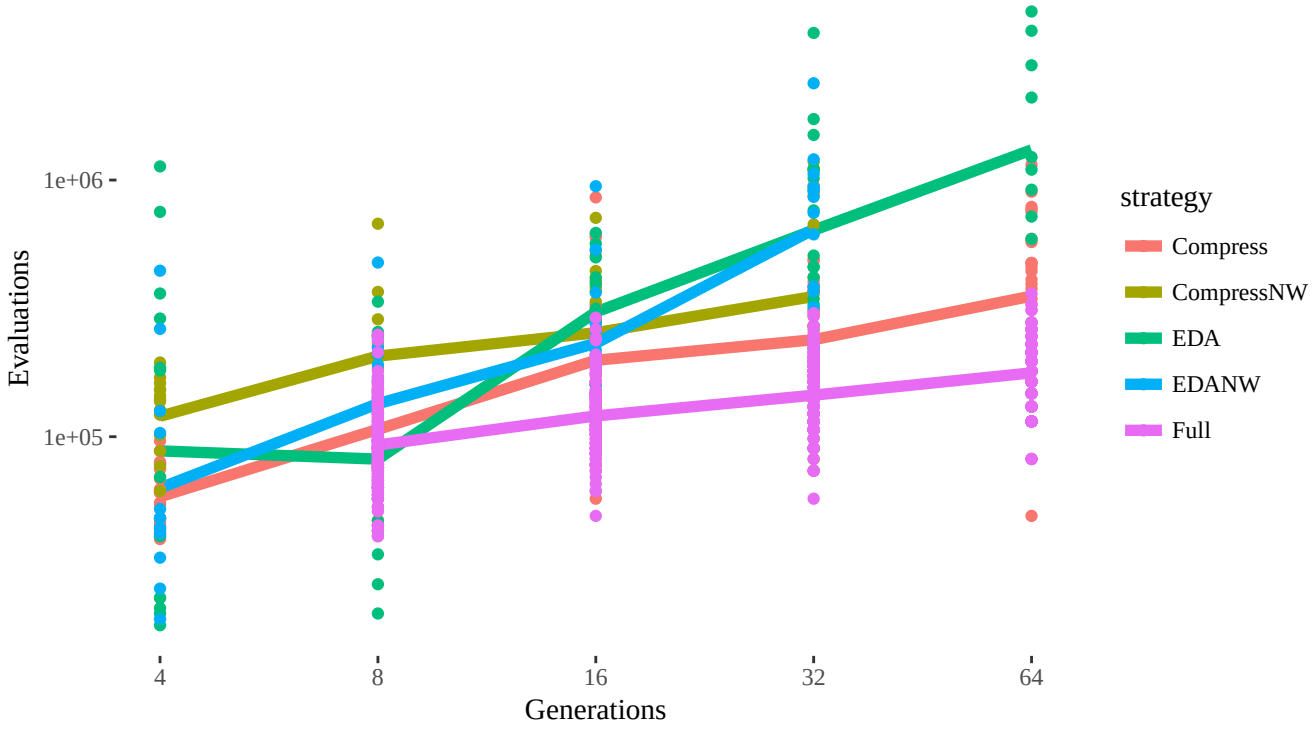

Figure 3: Number of evaluations vs. generation gap for the baseline strategy (in pink) and the EDA and compress messaging strategies, with or without writeback (WB). Lines run over the average value; every point represents the number of evaluations in individual experiments. Smaller, in this case, is better. Please note that both axes are logarithmic.

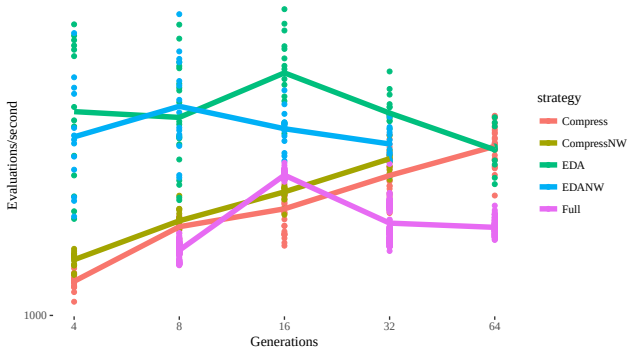

Figure 4: Number of evaluations per second vs. generation gap for the baseline strategy (in pink) and the EDA and compress messaging strategies, with or without writeback (WB). Higher is better. Axes are logarithmic.

The lowest number of evaluations, although not significatively so, is achieved for the EDA strategy with no writeback.

This chart can also be used to check the performance of the *no-writeback* strategies. In principle, since they use more evolved populations, they should be better. As a matter of fact, since they are injecting an additional population that is actually evolved, they use more evaluations. So in principle these strategies will be discarded.

Additionaly, we evaluate the raw performance, in evaluations per second, of all strategies, since at the end of the day, working with concurrent evolutionary algorithms pursue higher speed. This is shown in Figure 4, which shows in the y axis the number of evaluations per second. In this case, the EDA strategy is clearly superior to the rest, beating them significantly for all generation gaps. In this case, generation gap == 8 will be chosen, since it achieves the best combination of algorithmic and wallclock performance.

Our initial intention in this paper was to design a communication strategy that improves the speed of the algorith, and with the EDA strategy we have achieved just that. However, there are two parts in this strategy: using significantly smaller messages, and moving selection strategy from the mixer to the evolver (when computing the probability distribution). In fact, 1/4 of the population is used to compute the distribution, as opposed to the baseline mixer (labeled "Full"), which takes the better half of the pair of populations for mixing. This is undoubtedly a factor that contributes to balance the number of additional evaluations needed for the new, rebuilt, populations. However, the increase of speed must be entirely due to the compactness of the messages used by this strategy.

However, the intention of concurrent evolutionary algorithms is to leverage the power of all threads and processors in a computer, so unlike in previous papers, we must find a version of the algorithm

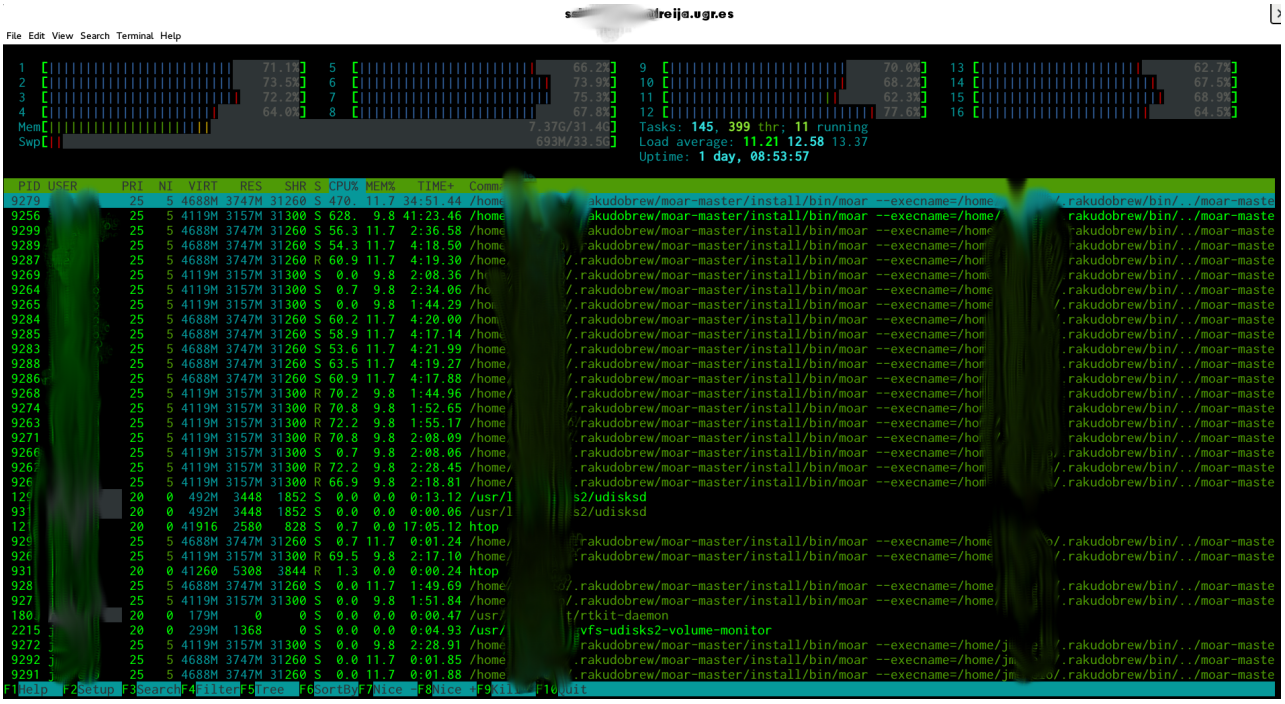

Figure 5: Screenshot using the htop utility of the used machine running two experiments at the same time. As it can be seen, all processors are kept busy, with a very high load average.

that speeds up with the number of threads. We will settle on the communication strategy, EDA, that has been proved to work before, and the population size (256) and generation gap (8) that has been proved to work previously. The number of initial populations was set to the number of threads plus one, as the minimum required to avoid starvation. However, we need to devise a strategy that actually makes scaling possible and profitable. After many tests, eventually the scaling strategy was simply to divide the total population by the number of threads. Initially we had two threads and total population equal to 512, so our strategy, called AP for adaptive population, was to divide the number of total individuals between the threads, so that 4 threads, for instance, get 128 individuals each. We repeated every run 15 times.

In this case, experients were run on a different machine with the Ubuntu 18.04 OS and an AMD Ryzen 7 2700X Eight-Core Processor at 3.7GHz. Figure 5 shows the utility htop with an experiment running; the top of the screen shows the rate at which all cores are working, showing all of them occupied; of course, the program was not running exclusively, but the list of processes below show how the program is replicated in several processor, thus leveraging their full power. Please check also the number of threads that are actually running at the same time, a few of which are being used by our appplication.

We are first interested in the number of evaluations needed to find the solution, which are plotted in Fig. 6. It increases slightly and not significantly from 2 to 4 threads, but it does increase significantly for 6 and 8 threads, indicating that the algorith is performing significantly worse when we increase the number of threads. This is

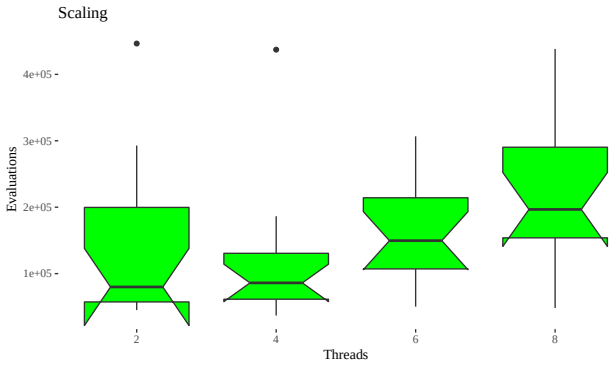

Figure 6: Number of evaluations vs. number of threads. Higher is better.

probably due to the fact that we are simultaneaously decreasing the population size, leading to earlier convergence for the number of generations (8) it is being used. This interplay between the degree of concurrency, the population size and the number of generations will have to be explored further.

But we were also interested in the actual wallclock time, plotted in Fig. 7. The picture shows that it decreases significantly when we go from 2 (the baseline) to 4 threads, since we are using more computing power for (roughly) the same number of evaluations. It then increases slightly we we increase the number of threads; as a matter of fact and as shown in 8, the number of evaluations

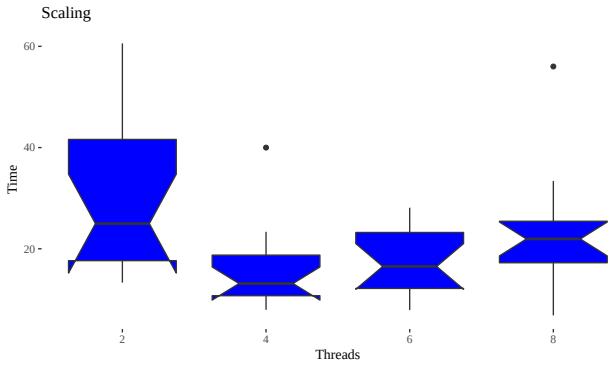

Figure 7: Total time vs. number of threads. Lower is better.

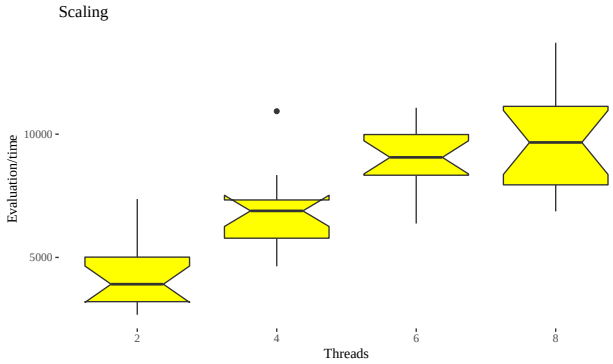

Figure 8: Evaluations per second vs. number of threads. Higher is better.

per second increases steeply up to 6 threads, and slightly when we use 8 threads. However, the amount of evaluations needed overcompensates this speed, resulting in a worse results. It confirms, however, that we are actually using all threads for evaluations, and if only we could find a strategy that didn't need more evaluations we should be able to get a big boost in computation time that scales gracefully to a high number of processors.

5 CONCLUSIONS

Designing a concurrent, stateless evolutionary algorithm brings a new set of configuration decisions that must be taken at the algorithm and at the parameter level. Thus, the main intention in this paper was to explore the parameter space in a concurrent evolutionary algorithm looking for the combination that yields the best performance in terms of time, without sacrificing the algorithmic performance. Since the biggest obstacle to scaling and high performance was the size of messages interchanged with the channel, in this paper we decided to redesign this communication either in an algorithmic specific way, using the distribution of probabilities as a representation of the population, or in a data structure specific way, compressing the bitstring to actual bits in a binary message. We also tested different messaging strategies.

Experiments show that no matter what the communication or messaging strategy is, we need to keep the number of generations the population undergoes to a small number, which resulted to be 8 in this case. This is equivalent to 2048 evaluations, and this is a number which is probably dependent on the problem and the data structure we are evolving. We would need to investigate this number further, and find a methodology to set it in advance, avoiding heuristics. That is left as a future line of work, but meanwhile our conclusion would be the importance of this generation gap in stateless evolutionary algorithms and the need to follow an experimenta strategy to establish its value for particular problems or implementations.

These experiments also yielded the EDA strategy as the fastest, with a relatively low impact in the number of evaluations. The fact that messages are the most compact is probably the main reason, but the fact that it uses a higher selective pressure is probably also a factor that should be taken into account.

Finally, this paper has proved for the first time the good scaling behavior of this kind of concurrent evolutionary algorithms. Simultaneous threads running an evolutionary algorithm do increase the number of simultaneous evaluations, although since this scaling is achieved via population splitting, the actual time achieved reaches its lowest peak with just 4 threads. As a matter of fact, and probably due to hardware limitations, the number of simultaneous evaluations seems to reach a plateau with 8 threads. At any rate, this new concurrent evolutionary algorithm is achieving results that are much better than what the equivalent, single thread, evolutionary algorithm would achieve. It should be noted that the base algorithm used for comparison uses 3 threads already: two evolutionary threads and a mixing thread; thus, the scaled-up version would use a total of 9 threads (8 evolutionary + 1 for mixing).

Although the good performance of this concurrent evolutionary algorithm has been well established in this paper, several lines of research are open. The first one is to continue exploring the algorithm itself trying to find out a scaling strategy that does not have a negative influence in the number of evaluations, so that actual increasing in the number of simultaneous evaluations achieved the equivalent speedup. The second like would be to find out what is the maximum number of simultaneous evaluations that can be achieved, so that an optimum number of threads can be advised, if possible independently of the problem and depending only on the physical number of threads available.

The messaging strategies proposed here can be used only if the problem can be represented via a binary data structure. New strategies will have to be explored for floating-point representation, or more complicated data structures. There are general-purpose strategies for compressing messages, for instance, and they could be used in this case. Estimation of distribution algorithms can also be extended to other types of data, so this is is something that can be also explored.

Finally, we are using the same kind of algorithm in all threads. Nothing prevents us from using a different algorithm per thread, or using different parameters per thread. This opens a vast space of possibilities, but the payoff might be worth it.

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