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A study on the effects of varying the population size of distributed Evolutionary Algorithms in heterogeneous and homogeneous machines

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Abstract This paper presents a study on population size tuning in a distributed Evolutionary Algorithm. The proposed adaptation strategy is done taking into account the computational power of each node of an heterogeneous cluster comparing the average number of generations attained in each machine. The same sizes are also tested in an homogeneous scientific cluster. Two problems with different characteristics have been tested: the linearly-solvable OneMax problem and the deceptive and multimodal MMDP function. Results show that setting this parameter according to computational power decreases the time required to obtain the optimum in both problems when using heterogeneous clusters. Also, a study of the influence of the parameters in each section of the algorithm is presented.

Keywords Evolutionary Algorithms · Genetic Algorithms · Service Oriented Architecture · Service Oriented Science · Web Services · Interoperability · Heterogeneous computation · Distributed computing

1 Introduction

New trends in distributed computing such as Cloud Computing [6], GRID [3] or Service Oriented Science [11] are leading to heterogeneous computational devices, for instance laptops, tablets or desktop PCs, working in the same experimental. Thus, many laboratories, which do not count with classic clusters but the usual workstations used by scientists, can leverage this motley set as an heterogeneous cluster. In fact, distributed Evolutionary Algorithms (dEAs) [4] have been tested successfully in these systems.

The heterogeneous dEAs that can be used over these ad-hoc networks can be divided in two categories: dEAs with different parameter setting for each node (heterogeneous parameters), or dEAs running the same algorithm in heterogeneous nodes. It has also been proved [2] that this type of algorithms are even more efficient in heterogeneous hardware configurations than in homogeneous devices. This can be explained by different reasons, such as different memory access times, cache sizes, or even implementation languages or compilers in each machine, leading to a different explotation rate of the search space. The heterogeneous parameters configuration has also been proved as more efficient in time than a fixed set of parameters for different problems [16].

Our motivation in this work is to combine both ideas and adapt the population size of the islands to the heterogeneous hardware. To calculate the computational power, the algorithm is executed in each machine; then, the total size of individuals is distributed according to the number of generations attained in each node in the same time. Two different problems (MMDP [15] and OneMax [23]) have been used as a benchmark.

In this work, a distributed system has been developed to solve the following questions:

- Can a distributed EA be adapted to take the most of the capability of an heterogeneous cluster?
- Does the proposed population size adaptation to the computational power scheme any effect in both systems?
- Is there any difference in using an homogeneous or heterogeneous cluster?

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– How does each section of the algorithm is affected by the different configurations?

The rest of the work is structured as follows: after the state of the art, we present the developed algorithms and experimental setting(Sections 3 and 4). Then, the results of the experiments are shown (Section 5), followed by conclusions and suggestions for future work lines.

2 State of the art

In the field of Evolutionary Computation (EC) there are two different approaches about the algorithm parameter setting: *parameter control* and *parameter tuning* [10]. The first one refers to set a number of parameters of an Evolutionary Algorithm (EA) and to change these parameters in running time. The parameter tuning consist in establish a good set of parameters before the run (and do not change them during runtime).

Computational performance of nodes or network speed can also be inherent parameters of an algorithm. In [2] the authors compared a distributed Genetic Algorithm (dGA) in homogeneous and heterogeneous clusters. Super-linear performance was obtained in the heterogeneous ones, being more efficient that the same algorithm in homogeneous. Some authors have expanded this idea by adapting the algorithm to be executed: in [8] the authors presented a distributed hybrid meta-heuristic that combines GAs and Simulated Annealing (SA). Their system executes the heavy (in computational terms) algorithms (GAs) in faster nodes, and simpler meta-heuristics (SA) in slower nodes, obtaining better results than other configurations. In [17] different configurations of heterogeneous machines for a tree topology were studied. However, the heterogeneity was simulated in an homogeneous cluster with programs to add computational load. Load-balancing was also applied taking into account the computational load of the nodes in [13]: a small benchmark was executed in all nodes at the beginning of the algorithm in order to distribute individuals of an Evolutionary Strategy (ES). However, there was no communication between the nodes.

In the area of heterogeneous parameters, but homogeneous hardware, setting in each node a random set of parameters can also increase the performance of a distributed Genetic Algorithm (dGA), as explained in [16]. That model outperformed a tuned canonical dGA with the same parameter values in all islands. Finally, adapting the migration rate has produced better results than homogeneous periods in homogeneous clusters, as explained in [22].

Our work presents a combination of some of the previous ideas, where an initial parameter tuning given by the computational cost of the machines is performed. To our knowledge, there are not works that modify parameters of the GA depending of the node where the island is being executed.

3 Service Oriented Evolutionary Algorithms

EAs are a general technique for solving optimization and search problems based in the evolution of species and natural selection. These algorithms are formed by a population of possible solutions (called *individuals*) that competes using their *fitness* (quality of adaptation) with the rest of solutions. In each iteration of the algorithm (or *generation*) the individuals are evolved by means of selection and recombination/mutation to create a new set of candidates, until a *stop criterion* (i.e. number of generations) is met. Fitness function is a quality function that gives the grade of adaptation of an individual respect the others. This function is usually the problem to solve.

There are different ways to parallelize the EAs:

– *Farming model (centralized EAs)*: A central node coordinate several slave nodes. The central node executes the EA in a sequential way, but distributes the individuals of the population to the slaves just for being evaluated. An example can be seen in [18], where slave nodes evaluates fitness function for simullation of nuclear devices.
– *Island model (distributed EAs)*: A number of nodes executes simultaneously the EA, working with different sub-populations at the same time. Each certain number of generations is interchanged (migrated) between populations. Figure 1 shows this model with a ring topology.
– *Cellular EAs (fine grain EAs)*: Each node has one individual of the population, and selection and reproduction is limited with the individuals of the neighbourhood of the node [9]. Usually a bi-dimensional grid is used for topology.

The distributed EAs are very popular because the implementation is not complicated and they explotate a coarse grain parallelism with sporadical communications, being appropiated to be executed in distributed architectures such as clusters or GRIDs [21].

As discussed in [14] the evolutionary algorithms research area is a propitious environment to migrate to SOA for several reasons: SOA fits with the genericity advantages in the development of software for EAs [12] and adds new features, like language independence and

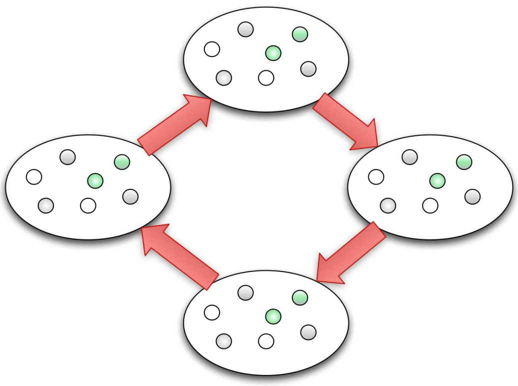

Fig. 1 Island model using a ring topology.

distribution mechanisms. Moreover, there are a large number of frameworks for EAs mostly imcompatible due to different programming languages, operating systems or communication protocols (see [20] for a survey). Also, new research trends, like self-adaptation [5], require many changes and modifications in the algorithms behavior in real-time. And finally, the increase of technologies such as GRID and Cloud Computing [6], where the computation elements are distributed in different machines, with many operating systems and programming languages.

4 Experimental setup

This section presents the parameters and systems to conduce the experiments.

The algorithm to improve is a dGA. Parameters are described in Table 1. The algorithm is steady-state: the offspring is mixed with the parents and the worst individuals are removed. A ring topology is used, and the best individual is sent after a fixed number of generations of each node (64). Two different parameter configurations have been used: 64 individuals per node (homogeneous size) and a different number of individuals proportional to the number of generations attained in this first homogeneous size execution (heterogeneous size).

Figure 2 shows the pseudo-code of the used algorithm.

The problems to evaluate are the Massively Multimodal Deceptive Problem (MMDP) [15] and the OneMax problem [23]. Each one requires different actions/abilities by the GA at the level of population sizing, individual selection and building-blocks mixing. The MMDP is designed to be difficult for an EA, due to its multimodality and deceptiveness. Deceptive problems are functions where low-order building-blocks do not combine to form higher order building-blocks. Instead, low-order building-blocks may mislead the search towards local optima, thus challenging search mechanisms. MMDP it is composed of k subproblems of 6 bits each one (s_i). Depending of the number of ones (unitation) s_i takes the values shown in Table 4.

```
population ← initializePopulation()
while stop criterion not met do
   parents ← selection(population)
   offspring ← recombination(parents)
   offspring ← mutation(offspring)
   population ← population + offspring
   if time to migrate then
      migrants ← selectMigrants(population)
      remoteBuffer.send(migrants)
   end if
   if localBuffer.size ≠ zero then
      population ← population + localBuffer.read()
   end if
   population ← removeWorst(population)
end while
```

Fig. 2 Pseudo-code of the used dEA.

Table 1 Parameters used.

Name	Value
Total individuals	256
Population size in HoSi	64
Population size in HeSi	98, 84, 66, and 8
Crossover type	Uniform crossover
Crossover rate	0.5
Mutation rate	1/genome size
Selection	2-tournament
Replacement	Steady-state
Generations to migrate	64
Genome size for MMDP	150
Genome size for OneMax	5000

Table 2 Basic deceptive bipolar function (s_i) for MMDP.

Unitation	Subfunction value
0	1.000000
1	0.000000
2	0.360384
3	0.640576
4	0.360384
5	0.000000
6	1.000000

The fitness value is defined as the sum of the s_i subproblems with an optimum of k (equation 1). The search space is composed of 2^{6k} combinations from which there are only 2^k global solutions with 22^k deceptive attractors. Hence, a search method will have to find a global solution out of 2^{5k} additionally to deceptiveness. In this work $k = 25$.

$$f_{MMDP}(\mathbf{s}) = \sum_{i=1}^{k} fitness_{s_i} \quad (1)$$

OneMax is a simple linear problem that consists in maximising the number of ones in a binary string. That is, maximize the expression:

$$f_{OneMax}(\mathbf{x}) = \sum_{i=1}^{N} x_i \tag{2}$$

To test the algorithm two different computational systems have been used: an *heterogeneous cluster* and an *homogeneous cluster*. The first one is formed by 4 different computers of our lab with different processors, operating systems and memory size. The latter is a dedicated scientific cluster formed by homogeneous nodes. Table 4 shows the features of each system.

Because the operating system and architecture heterogeneity the OSGiLiath framework [19], based in Java, has been used. This is a service-oriented evolutionary framework that automatically configures services to use and be used in a local network. In this case, each node offers a migration buffer to accept foreign individuals. Also, to avoid bottlenecks in distributed executions, asynchronous communication has been provided to avoid idle time using reception buffers (that is, the algorithm does not wait until new individuals arrive). This kind of communication offers excellent performance when working with different nodes and operating systems, as demonstrated by [2]. The transmission mechanism is based in ECF Generic server (over TCP)[1]. The source code of the algorithms used in this work is available in `http://www.osgiliath.org` under a GPL V3 License.

Each different configuration has been tested 30 times. Acronyms for each configuration are HoSi (homogeneous population size), HeSi (heterogeneous population size), HoHa (homogeneous hardware) and HeHa (heterogeneous hardware).

The number of individuals in each node of the HeSi configuration is proportional to the average number of generations obtained in the nodes of the HoSi/HeHa configuration for the MMDP problem. Thus, the HeSi configuration uses 98, 84, 66, and 8 individuals (from N1 to N4). Note that, having two nodes with the same processors and memory (N1 and N2), they have different computational power.

5 Results

The objetives of the parallel programming are to tackle large computational problems, increase the performance of algorithms in a finite time, or reduce time to solve the problem. In this work we focus in the last objective. As claimed in [1], assessing the performance of a parallel EA by the number of function evaluations required to attain a solution may be misleading. In our case, for example, the evaluation time is different in each node of the heterogeneous cluster, and the real algorithm speed could not be reflected correctly. However, the number of evaluations has been included in this section to better understand the results. The total number of generations, and the maximum number of generations required by the slower node in each configuration are also shown It is difficult to compare the performance of HoHa and HeHa for the same reasons: the evaluation time is different in each system (and also in each node).

5.1 MMDP Problem

Table 4 shows the results for the MMDP problem. These results are also shown in the boxplots of the Figure 4 (evaluations) and Figure 3 (time). Table 6 shows the statistical significance of the results. First, a Kolmogorov-Smirnov test is performed to asset the normality of the distributions. If the results fit a normal distribution, then a Student's T-Test is calculated. Otherwise, the non-parametric test Wilcoxon signed rank is applied (see [7] for a tutorial for comparing EAs).

In the HeHa system, adapting the population to the computational power of each node makes the algorithm to end significantly faster, but with the same number of evaluations (with no statistical significance). This can be explained because the evaluation time is different in all nodes. On the other hand, in the HoHa system, setting the same population sizes makes no difference in time and evaluations, that is, changing this parameter does not influence the performance of the algorithm.

To see the difference of how the evolution is being performed, the average fitness in each node of HeHa is shown in Figures 5 and 6. As can be seen, with the HeSi (Figure 6), the local optima are overtaken in less time than HoSi (Figure 5). This can be explained because in HeSi, the migration from N4 to N1 is performed faster, adding more heterogeneity to the whole system. White gaps in the figures are the time where the nodes are sending the individual to other nodes (not while they are receiving them). In the HoHa systems, the populations are evolved at the same time, being the average fitness similar in all nodes during all run.

5.2 OneMax Problem

Results for this problem are shown in Table 5 and Figures 7 and 8. In this problem, adapting the population sizes decreases significantly the time for solving in

[1] `http://www.eclipse.org/ecf/`

Table 3 Details of the clusters used.

Name	Processor	Memory	Operating System	Network
Homogeneous cluster				
Cluster node	Intel(R) Xeon(R) CPU E5320 @ 1.86GHz	4GB	CentOS 6.7	Gigabit Ethernet
Heterogeneous cluster				
N1	Intel(R) Core(TM)2 Quad CPU Q6600 @ 2.40GHz	4GB	Ubuntu 11.10 (64 bits)	Gigabit Ethernet
N2	Intel(R) Core(TM)2 Quad CPU Q6600 @ 2.40GHz	4GB	Ubuntu 11.04 (64 bits)	Gigabit Ethernet
N3	AMD Phenom(tm) 9950 Quad-Core Processor @ 1.30Ghz	3GB	Ubuntu 10.10 (32 bits)	100MB Ethernet
N4	Intel (R) Pentium 3 @ 800MHz	768 MB	Ubuntu 10.10 (32 bits)	10MB Ethernet

Table 4 Results for the MMDP problem.

Configuration	Max. generations	Total generations	Total evaluations	Time (ms)
HoSi/HeHa	146401,48 ± 65699,69	380967,25 ± 168568,84	24382416,51 ± 10788405,87	136914,03 ± 60028,48
HeSi/HeHa	96051,5 ± 45110,90	289282,3 ± 135038,10	21784528,66 ± 10161989,38	109875,76 ± 49185,51
HoSi/HoHa	107334,46 ± 78167,19	393119,86 ± 241835,27	25273201,06 ± 15386663,12	237759,43 ± 178709,86
HeSi/HoHa	149732,6 ± 81983,74	438171,16 ± 240169,19	24430043,46 ± 13395037,34	245776,93 ± 134715,52

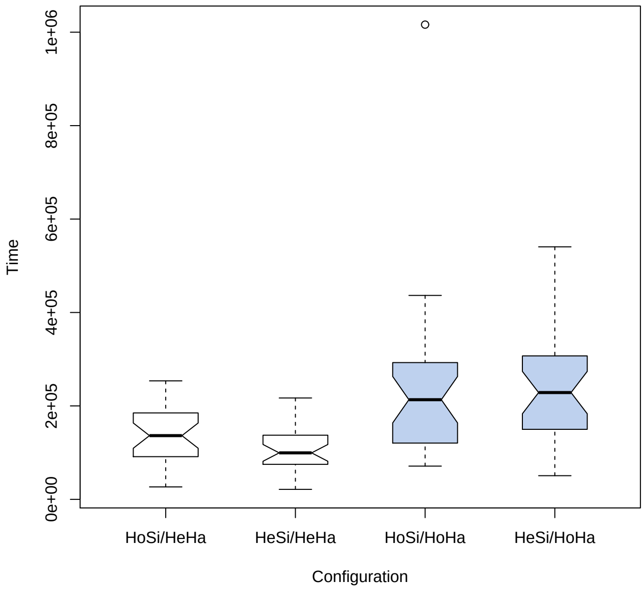

Fig. 3 Time to obtain the optimum in the MMDP problem (milliseconds). White is the heterogeneous cluster and gray the homogeneous one.

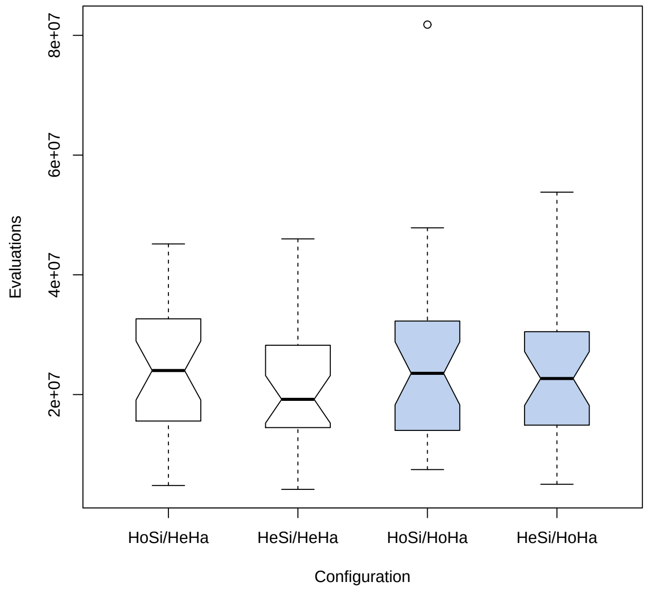

Fig. 4 Number of evaluations for MMDP problem. White is the heterogeneous cluster and gray the homogeneous one.

the heterogeneous cluster, and, as before, the number of evaluations remains the same (see statistical significance in Table 6). In the homogeneous system, the effect of changing the population sizes is more evident, and this time the evaluations (and therefore, the time) are reduced (both significally).

The efficiency on OneMax problems depends more on the ability to mix the building-blocks, and less on the genetic diversity and size of the population (as with MMDP). No genetic diversity is particularly required. When properly tuned, a simple Genetic Algorithm is able to solve OneMax in linear time. Sometimes, problems like OneMax are used as control functions, in order to check if very efficient algorithms on hard functions fail on easier functions. As can be seen in Figure 9, the HoSi/HeHa, the average fitness of all populations are increasing in linear way. However, the lower processor evaluates extremely less times. On the other side, in Figure 10, the adaptation of the population size makes that lower processors increase the number of evaluations, but the average fitness is also maintained in linear way (and in smaller increase rate) between migrations. However, the other processors are still spending more number of evaluations. That is the reason why the number of evaluations is higher in HeHa, and lower in HoHa. Computational time is more efficiently used in faster nodes, having more chance to mix the indi-

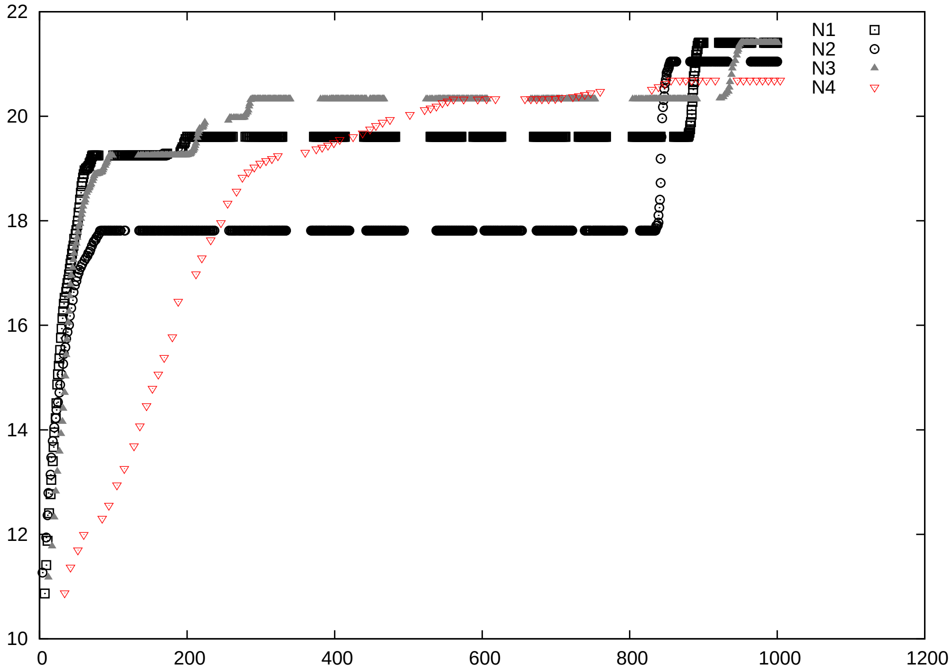

Fig. 5 Average fitness in the first 1000 milliseconds of execution of the four nodes of the heterogeneous cluster with the same population sizes (HoSi/HeHa) for the MMDP problem.

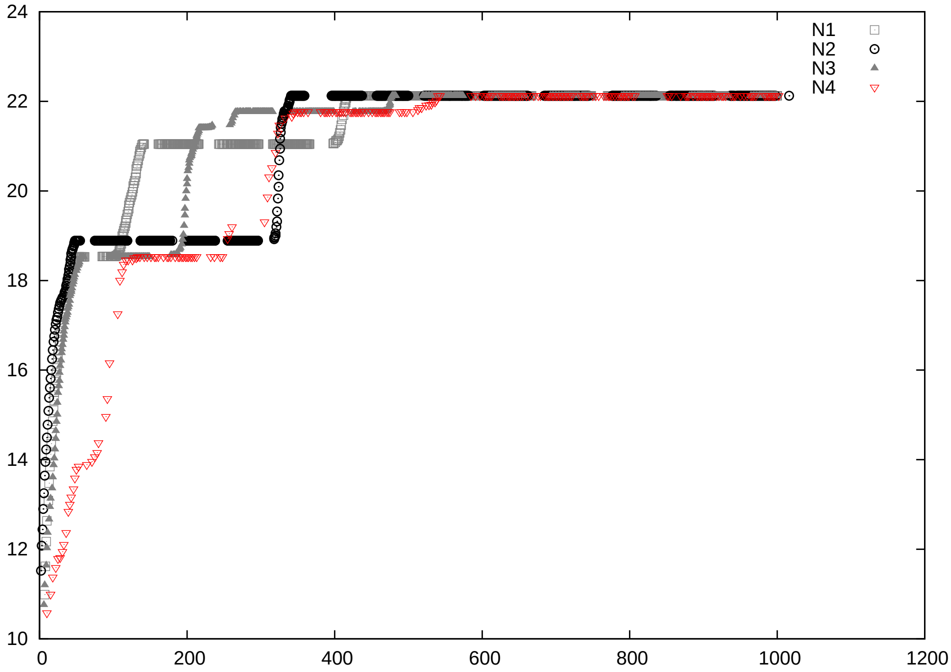

Fig. 6 Average fitness in the first 1000 milliseconds of execution of the four nodes of the heterogeneous cluster with different population sizes (HeSi/HeHa) for the MMDP problem.

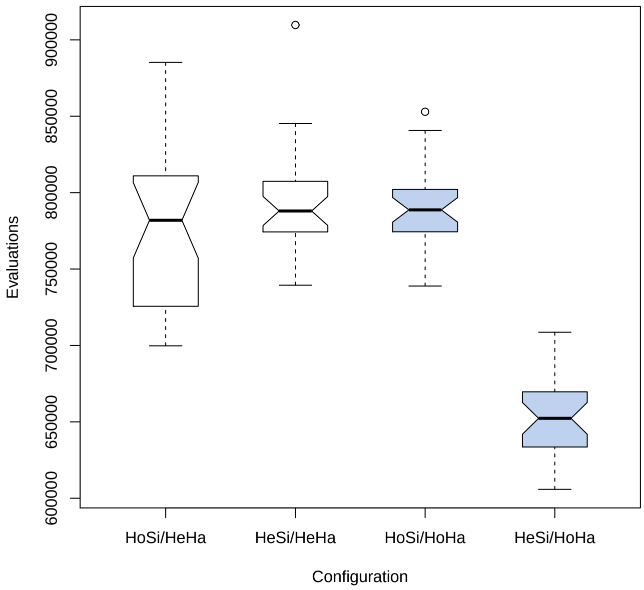

Fig. 7 Number of evaluations for OneMax problem. White is the heterogeneous cluster and gray the homogeneous one.

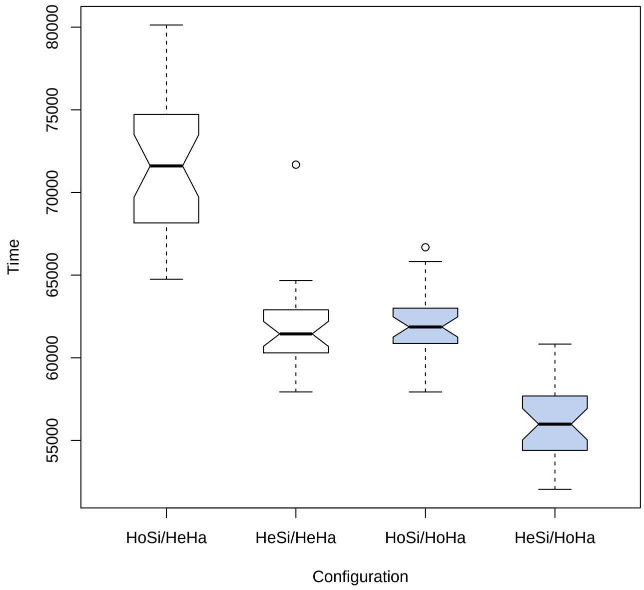

Fig. 8 Time to obtain the optimum in the OneMax problem (milliseconds). White is the heterogeneous cluster and gray the homogeneous one.

viduals. Also, because the larger size of the individuals in the OneMax problem (5000 bits vs. 150), the transmission time is larger, (white gaps in the figures). That also implies for N4 send their best individual to N1 in a extremely large time when using HoSi (each 64 generations).

5.3 Analysis of the time

This sub-section analyses the time of each stage of the EA in each node of the clusters for each configuration. Tables 7 and 8 show the average and standard deviation of the time spent in each section of the algorithm (He=Heterogeneous cluster, Ho=Homogeneous cluster). Figures 11 and 12 compares graphically these results. As can be seen, the migration is the most costly operation in all configurations, being the migration in HeHa more time consuming than HoHa. This is due because we are using the multi-purpose laboratory network, instead of the specific one used in the HoHa system. Note that the std. deviation of the migration is larger in this cluster. In the MMDP problem (Table 7) changing the population size does not affect the migration time, but only the rest of the sections of the algorithm. However, with larger data communications (individuals of 5000 elements of the OneMax problem), the population size affect the migration time of all nodes. This could be due to synchronization of the migration buffers: if the slowest machine is sending/receiving, deadlocks can be propagated (as seen in Figure 9). Results also show how the sections of the algorithms depends of the node of execution (recombination needs more time than mutation in both problems only in the node HeN4). The reason of this could be that the creation of new objects (memory allocation) in Java in limited memory (and SWAP access) requires more time than iteration (mutation) of reserved memory. The adaptation of the time makes the slower node of HeHa behaves in simillar way than the other nodes (same time in each section). Also, the size of the individuals affect some parts of the EA (for example, in the OneMax the mutation requires more time than the replacement). However, it must be taken into account that the duration of each part of the algorithm is not related with the time to attain the optimum, but how the diversity and search guidance is maintained. QUE MAS METO AQUI QUE MOLE?

6 Conclusions

New trends, such as Cloud Computing or Service Oriented Architecture are providing a massively amount of heterogeneous computational devices. This work shows a preliminary study about adapting the population size of an EA to the computational power of different nodes in an heterogeneous cluster. Results show that adapt-

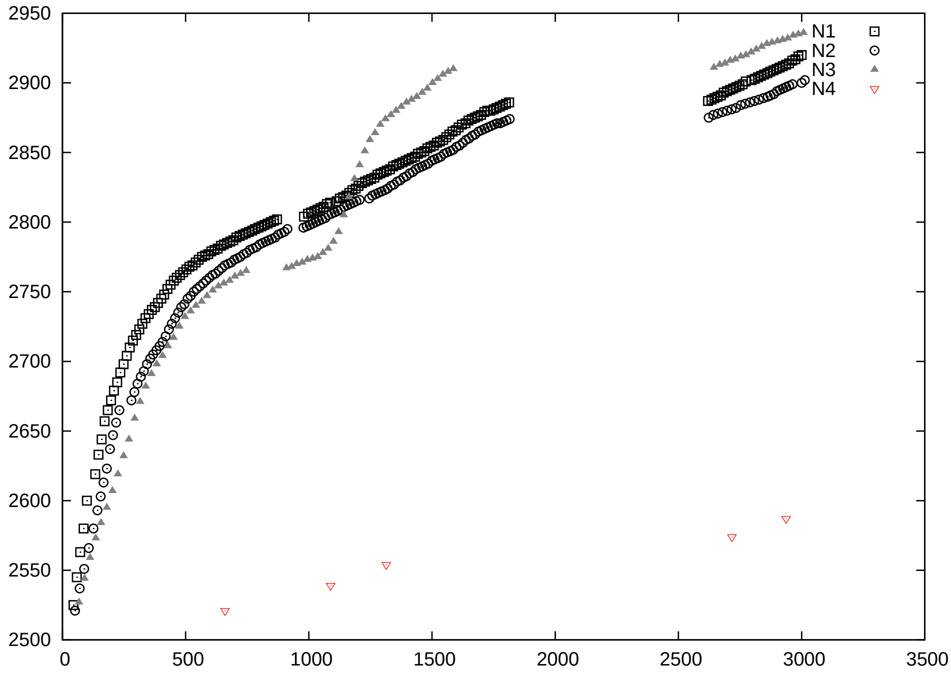

Fig. 9 Average fitness in the first 3000 milliseconds of execution of the four nodes of the heterogeneous cluster with the same population sizes (HoSi/HeHa) for the OneMax problem.

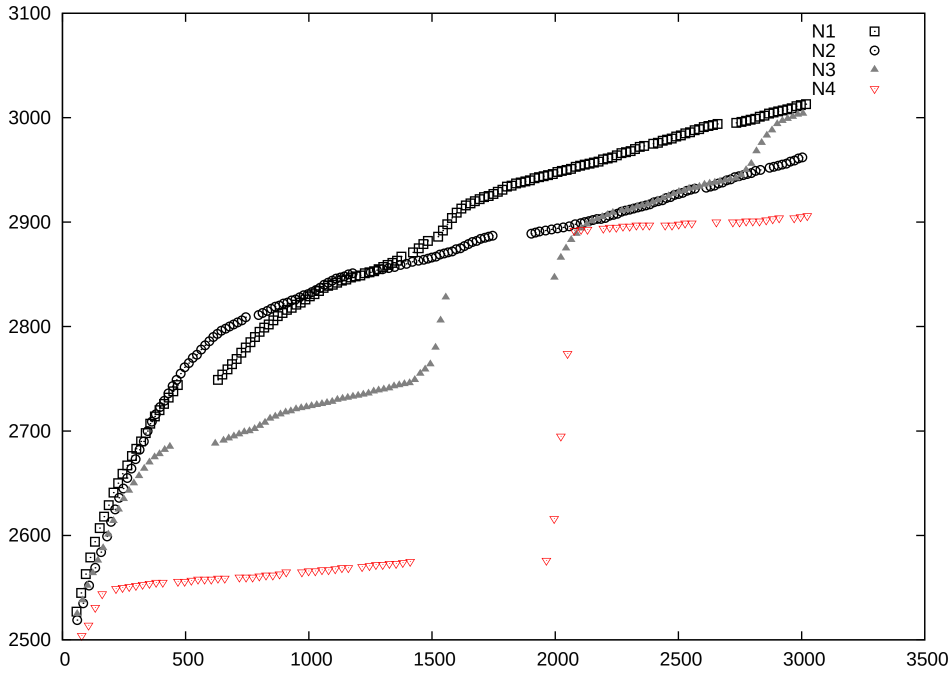

Fig. 10 Average fitness in the first 3000 milliseconds of execution of the four nodes of the heterogeneous cluster with different population sizes (HeSi/HeHa) for the OneMax problem.

Table 5 Results for the OneMax problem.

Configuration	Max. generations	Total generations	Total evaluations	Time (ms)
HoSi/HeHa	4739,41± 305,32	12081,51± 776,35	773729,03± 49686,72	72152,32± 4994,71
HeSi/HeHa	3438,03 ± 149,47	11277,33± 471,77	794157,73± 31843,10	61870,2 ± 2518,74
HoSi/HoHa	3133,36± 101,70	12347,83± 394,99	790773,33± 25279,52	62105,03± 1964,75
HeSi/HoHa	13897,86± 625,27	20725,63± 929,43	651952,8 ± 29114,54	56120,53± 2491,92

Table 6 Statistical significance of the results.

Configuration	Normal	Test applied	P-value	Significant difference?
Time for MMDP				
HoSi/HeHa vs HeSi/HeHa	Yes	T-Test	0.032	Yes
HoSi/HoHa vs HeSi/HoHa	No	Wilcoxon	0.567	No
Evaluations for MMDP				
HoSi/HeHa vs HeSi/HeHa	Yes	T-Test	0.231	No
HoSi/HoHa vs HeSi/HoHa	No	Wilcoxon	0.958	No
Time for OneMax				
HoSi/HeHa vs HeSi/HeHa	Yes	T-Test	9×10^{-15}	Yes
HoSi/HoHa vs HeSi/HoHa	No	Wilcoxon	1×10^{-6}	Yes
Evaluations for OneMax				
HoSi/HeHa vs HeSi/HeHa	No	Wilcoxon	0.14	No
HoSi/HoHa vs HeSi/HoHa	Yes	T-Test	2×10^{-27}	Yes

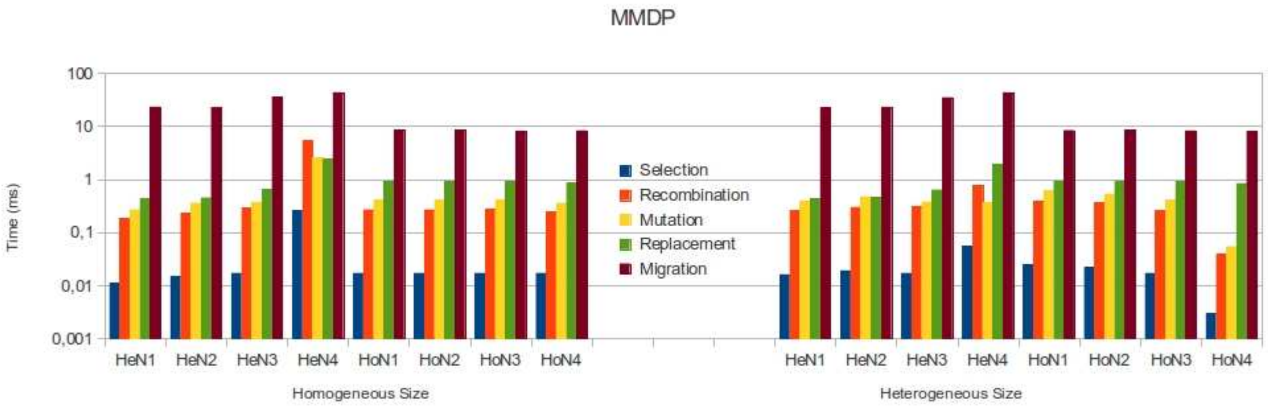

Fig. 11 Average time in each section of the algorithm for the MMDP problem.

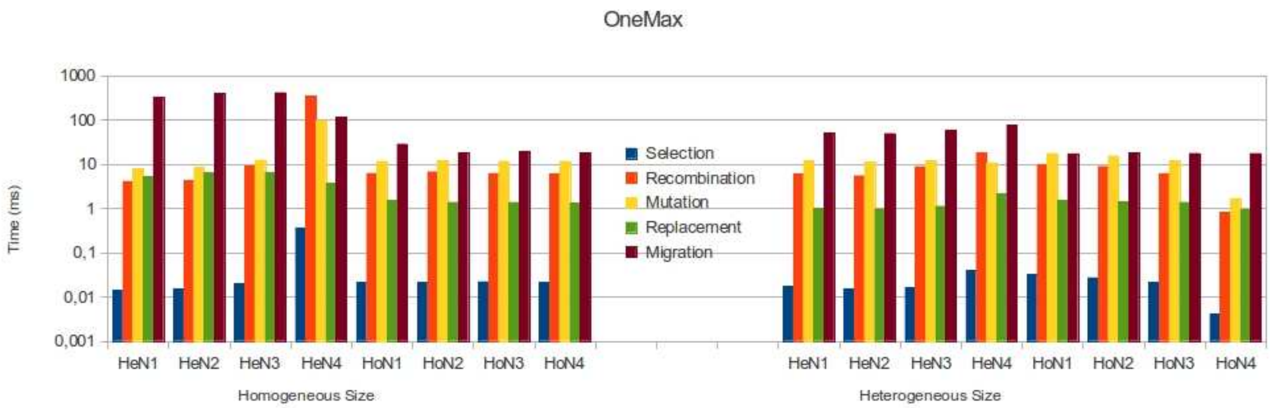

Fig. 12 Average time in each section of the algorithm for the ONEMAX problem.

Table 7 Times of the sections of the algorithm for the MMDP problem.

Homogeneous Size					
Node	Selection	Recombination	Mutation	Replacement	Migration
HeN1	0,011 ± 0,023	0,181 ± 0,149	0,269 ± 0,064	0,429 ± 4,873	23,097 ± 31,917
HeN2	0,015 ± 0,009	0,231 ± 0,116	0,357 ± 0,043	0,449 ± 5,214	22,928 ± 35,187
HeN3	0,017 ± 0,016	0,291 ± 0,132	0,372 ± 0,117	0,655 ± 6,533	36,139 ± 38,434
HeN4	0,257 ± 0,371	5,381 ± 14,941	2,556 ± 1,611	2,400 ± 5,588	43,490 ± 9,475
HoN1	0,017 ± 0,016	0,268 ± 0,555	0,405 ± 0,051	0,913 ± 1,350	8,428 ± 5,276
HoN2	0,017 ± 0,029	0,267 ± 0,409	0,405 ± 0,037	0,911 ± 1,419	8,441 ± 4,869
HoN3	0,017 ± 0,021	0,272 ± 0,589	0,404 ± 0,249	0,914 ± 1,420	8,177 ± 4,072
HoN4	0,017 ± 0,010	0,247 ± 0,479	0,356 ± 0,042	0,857 ± 1,636	8,284 ± 4,770
Heterogeneous Size					
Node	Selection	Recombination	Mutation	Replacement	Migration
HeN1	0,016 ± 0,012	0,259 ± 0,402	0,384 ± 0,086	0,435 ± 4,760	22,389 ± 31,184
HeN2	0,019 ± 0,015	0,297 ± 0,408	0,467 ± 0,256	0,464 ± 4,956	23,044 ± 32,704
HeN3	0,017 ± 0,016	0,303 ± 0,522	0,376 ± 0,118	0,634 ± 6,156	34,804 ± 35,557
HeN4	0,055 ± 0,161	0,769 ± 4,056	0,361 ± 0,653	1,957 ± 8,160	43,300 ± 26,672
HoN1	0,025 ± 0,017	0,389 ± 0,676	0,603 ± 0,060	0,929 ± 1,300	8,396 ± 4,147
HoN2	0,022 ± 0,017	0,362 ± 0,523	0,530 ± 0,228	0,921 ± 1,265	8,498 ± 4,694
HoN3	0,017 ± 0,011	0,259 ± 0,558	0,403 ± 0,050	0,916 ± 1,409	8,250 ± 4,516
HoN4	0,003 ± 0,005	0,039 ± 0,333	0,054 ± 0,029	0,836 ± 1,513	8,089 ± 4,602

Table 8 Times of the sections of the algorithm for the OneMax problem.

Homogeneous Size					
Node	Selection	Recombination	Mutation	Replacement	Migration
HeN1	0,014 ± 0,016	4,063 ± 3,290	7,826 ± 0,513	5,300 ± 62,474	328,262 ± 387,402
HeN2	0,015 ± 0,019	4,221 ± 3,251	8,325 ± 1,348	6,390 ± 71,926	398,119 ± 428,012
HeN3	0,020 ± 0,022	8,896 ± 3,561	12,289 ± 0,393	6,505 ± 77,069	410,141 ± 480,055
HeN4	0,362 ± 0,920	341,888± 381,390	97,075 ± 119,923	3,638 ± 14,627	112,680 ± 43,776
HoN1	0,021 ± 0,013	6,181 ± 2,386	11,545 ± 0,468	1,506 ± 3,642	28,355 ± 8,606
HoN2	0,021 ± 0,013	6,685 ± 1,927	11,779 ± 1,242	1,364 ± 2,437	18,034 ± 7,422
HoN3	0,022 ± 0,016	6,154 ± 2,238	11,585 ± 0,506	1,363 ± 2,437	18,948 ± 6,072
HoN4	0,021 ± 0,007	6,124 ± 2,346	11,560 ± 0,519	1,314 ± 2,308	17,920 ± 4,816
Heterogeneous Size					
Node	Selection	Recombination	Mutation	Replacement	Migration
HeN1	0,017 ± 0,002	5,955 ± 3,569	11,761 ± 0,500	1,000 ± 11,748	50,470 ± 81,518
HeN2	0,015 ± 0,002	5,448 ± 3,102	10,879 ± 1,545	0,972 ± 11,253	48,942 ± 77,468
HeN3	0,016 ± 0,003	8,733 ± 2,180	11,672 ± 0,870	1,113 ± 7,352	59,133 ± 8,825
HeN4	0,040 ± 0,035	17,943 ± 23,543	10,751 ± 1,683	2,144 ± 9,815	76,816 ± 15,500
HoN1	0,032 ± 0,014	9,587 ± 5,671	17,506 ± 1,083	1,482 ± 2,245	17,121 ± 6,302
HoN2	0,027 ± 0,015	8,826 ± 5,850	15,262 ± 1,091	1,422 ± 2,766	17,831 ± 14,158
HoN3	0,021 ± 0,013	6,108 ± 3,461	11,655 ± 0,534	1,365 ± 2,294	17,440 ± 6,578
HoN4	0,004 ± 0,002	0,807 ± 0,749	1,653 ± 0,051	0,922 ± 2,672	17,411 ± 12,177

ing the population size decreases the execution time significantly in heterogeneous clusters, while changing this parameter in homogeneous clusters does not always performs better. This is a promising start for adapting EAs to the computational power of each execution node.

In future work, a scalability study will be performed, using more computational nodes and larger problem instances. Also, other parameters such as migration rate or crossover probability will be adapted to the execution nodes. This studies will lead to automatic adaptation during runtime, with different nodes entering or exiting in the topology or adapting to the current load of the system.

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