An Event-based Architecture for Multi-population Optimization Algorithms*

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{abc,lncs}

Abstract. Having the knowledge that both of them are population-based algorithms it can be defined that a migration between 2 or more populations are possible, and this kind hybrid can be helpful to increase the possibility to find the optimal result (the best of the best), there is where fits the concept of Multi-population. For this kind of work we used asynchronous functions, serverless functions, multithread and a distributed architecture taking advantage for functional programming and serverless architecture. Even nature works like that... parallel, asynchronous and distributed.
The distributed architectures are having extensive use in the software industry because of their high performance, many systems are being created and migrating step by step to microservices and... in a nearly future... the new architectures called serverless, which proposes the use of "Function as a Service" (FaaS).

Keywords: Multi-population · Asynchronous · Sub-population · Serverless · Distributed.

1 First Section

1.1 A Subsection Sample

Please note that the first paragraph of a section or subsection is not indented. The first paragraph that follows a table, figure, equation etc. does not need an indent, either.

Subsequent paragraphs, however, are indented.

Sample Heading (Third Level) Only two levels of headings should be numbered. Lower level headings remain unnumbered; they are formatted as run-in headings.

Sample Heading (Fourth Level) The contribution should contain no more than four levels of headings. Table 1 gives a summary of all heading levels.

* Supported by organization x.

Table 1. Table captions should be placed above the tables.

Heading level	Example	Font size and style
Title (centered)	**Lecture Notes**	14 point, bold
1st-level heading	**1 Introduction**	12 point, bold
2nd-level heading	**2.1 Printing Area**	10 point, bold
3rd-level heading	**Run-in Heading in Bold.** Text follows	10 point, bold
4th-level heading	*Lowest Level Heading.* Text follows	10 point, italic

Displayed equations are centered and set on a separate line.

$$x + y = z \tag{1}$$

Please try to avoid rasterized images for line-art diagrams and schemas. Whenever possible, use vector graphics instead (see Fig. 14).

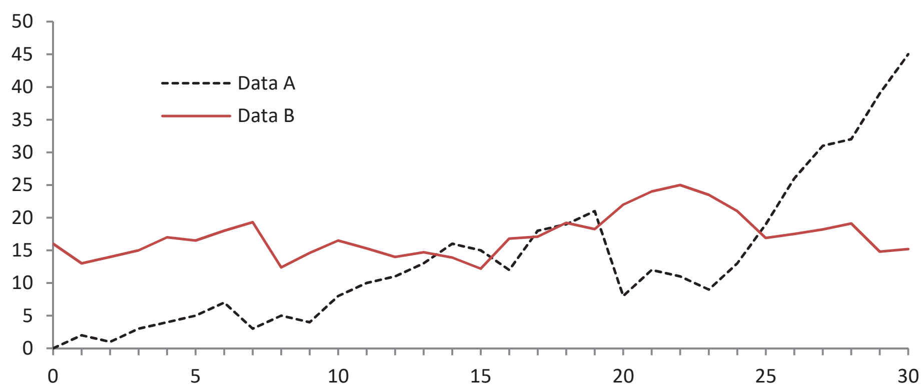

Fig. 1. A figure caption is always placed below the illustration. Please note that short captions are centered, while long ones are justified by the macro package automatically.

Theorem 1. *This is a sample theorem. The run-in heading is set in bold, while the following text appears in italics. Definitions, lemmas, propositions, and corollaries are styled the same way.*

Proof. Proofs, examples, and remarks have the initial word in italics, while the following text appears in normal font.

For citations of references, we prefer the use of square brackets and consecutive numbers. Citations using labels or the author/year convention are also acceptable. The following bibliography provides a sample reference list with entries for journal

2 Experiments and Results

2.1 Experiments

Now that an interaction between sub-populations with different algorithms it is working and hybridation have been a success, using until now the added algorithms (GA and PSO) algorithms, all thanks to the developed architecture, lets procede to the experiments. This section is going to be the execution of several experiments from 2 to 40 dimensions, with a stop criterial of an error below 0.5E-8, without a parameter optimization method, waiting that the architecture by its self would be enough to increase the possibility to find a better optimal result than the traditional methods. All this hoping that the results will probe the needness of this kind of architecture on increasing dimensions. To test if the architecture was useful, several experiments were made to solve benchmark functions, for this case the functions are Sphere, Rastrigin and Rosenbrock. Using 10 sub-population for each experiment and maximum 4 migrations per sub-population with different algorithms and parameters for each sub-population.

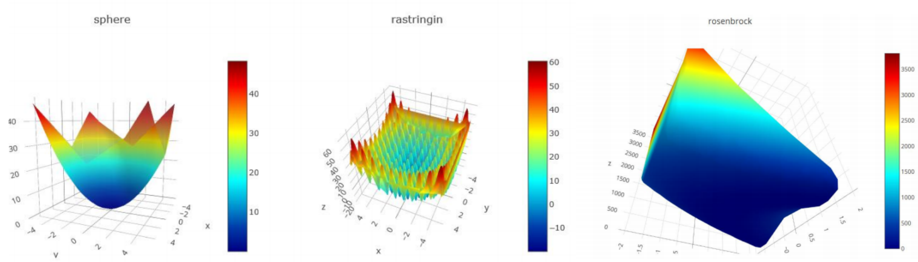

Fig. 2. Benchmark functions for experimentation.

2.2 Parameters Configuration

This architecture modifies the traditional way to work with population based algorithms, then the experiments could not be parameterized as usually are.

Then the experiments are scaled by their number of evaluations and the parameters must be configured to be adjusted to the next criterial, using the next expression:

$$Evaluations = 10^5 Dimensions \tag{2}$$

For example, if the experiment has 2 dimensions, the maximum number of evaluations will be 200,0000, for 10 dimensions will be 1,000,000 of evaluacions and the same with the others dimensions.

Table 2. Parametros experimentos 2 dimensiones

Parameter	Value
Optimización GA	Minimiza
Generaciones GA	50
Dimensiones GA	2
Tamaño de población GA	100
Mutación GA	Aleatorio(Tournament2,Tournament3,Random ,RandomLinearRank,Sequential,Fittest)
Cruce GA	Tournament3
Porcentaje de cruce GA	Aleatorio[10%, 80%]
Porcentaje de mutación GA	Aleatorio[10%,50%]
Función de cruce GA	Uniforme de punto medio
Función de mutación GA	gaussian
Optimización PSO	Minimiza
Iteraciones PSO	50
Dimensiones PSO	2
Tamaño de vector PSO	100
Factor social PSO	Aleatorio[0.5,4.0]
Factor individual PSO	Aleatorio[0.5,4.0]
Peso de inercia PSO	Aleatorio[0.5,4.0]

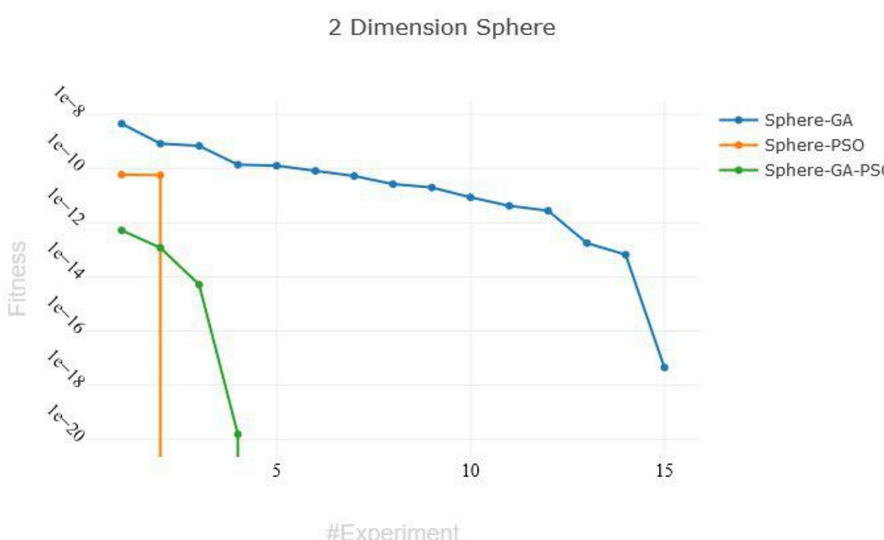

Fig. 3. 2 dimension experiments Sphere.

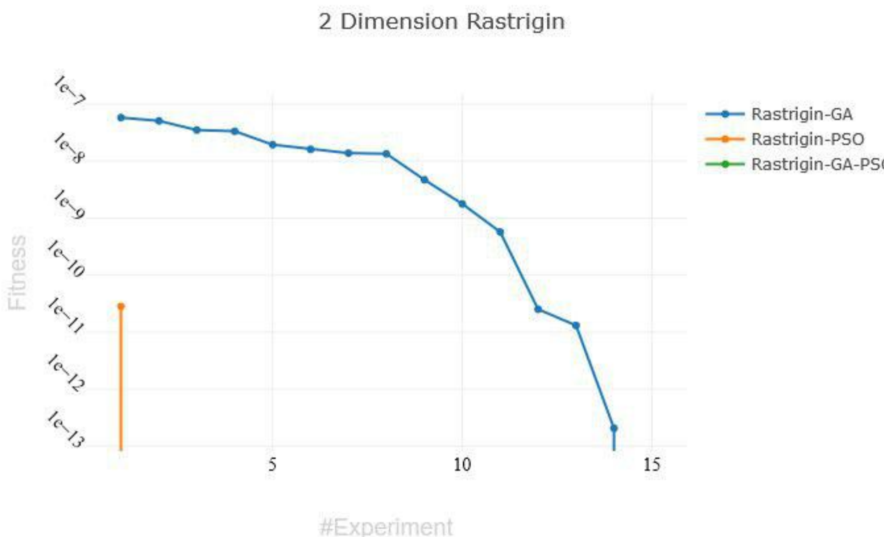

Fig. 4. 2 dimension experiments Rastrigin.

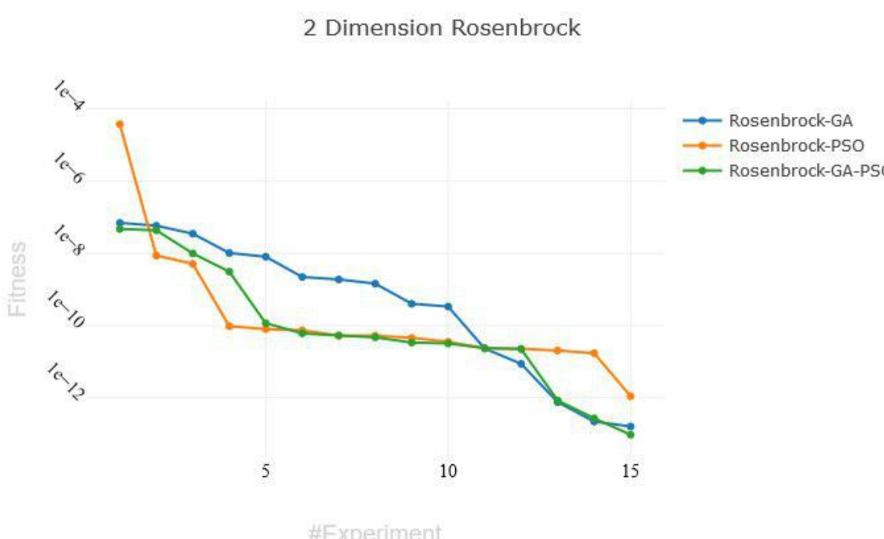

Fig. 5. 2 dimension experiments Rosenbrock.

Table 3. Resultados 2 dimensiones

Fn	Mejor	Promedio	No. Experimento
Rastrigin GA	0	1.65377E-08	15
Rastrigin PSO	0	1.8872E-12	15
Rastrigin GA-PSO	0	0	15
Sphere GA	4.53222E-18	4.36977E-10	15
Sphere PSO	0	7.8012E-12	15
Sphere GA-PSO	0	4.33161E-14	15
Rosenbrock GA	1.62335E-13	1.24176E-08	15
Rosenbrock PSO	1.11674E-12	2.47795E-06	15
Rosenbrock GA-PSO	9.5809E-14	6.90695E-09	15

Table 4. Parametros experimentos 10 dimensiones

Parameter	Value
Optimización GA	Minimiza
Generaciones GA	70
Dimensiones GA	10
Tamaño de población GA	200
Mutación GA	Aleatorio(Tournament2,Tournament3,Random ,RandomLinearRank,Sequential,Fittest)
Cruce GA	Tournament3
Porcentaje de cruce GA	Aleatorio[10%, 80%]
Porcentaje de mutación GA	Aleatorio[10%,50%]
Función de cruce GA	Uniforme de punto medio
Función de mutación GA	gaussian
Optimización PSO	Minimiza
Iteraciones PSO	70
Dimensiones PSO	10
Tamaño de vector PSO	200
Factor social PSO	Aleatorio[0.5,4.0]
Factor individual PSO	Aleatorio[0.5,4.0]
Peso de inercia PSO	Aleatorio[0.5,4.0]

Table 5. Resultados 10 dimensiones

Fn	Mejor	Promedio	No. Experimento
Rastrigin GA	3.21768E-09	2.38015E-06	15
Rastrigin PSO	7.8586E-11	2.715716161	15
Rastrigin GA-PSO	8.01492E-12	5.08668E-09	15
Sphere GA	1.84051E-09	2.5389E-08	15
Sphere PSO	4.50351E-11	4.72855E-09	15
Sphere GA-PSO	3.33851E-11	1.30062E-09	15
Rosenbrock GA	9.58323E-07	1.24176E-08	15
Rosenbrock PSO	4.16711E-07	4.431565444	15
Rosenbrock GA-PSO	3.62472E-07	0.000240251	15

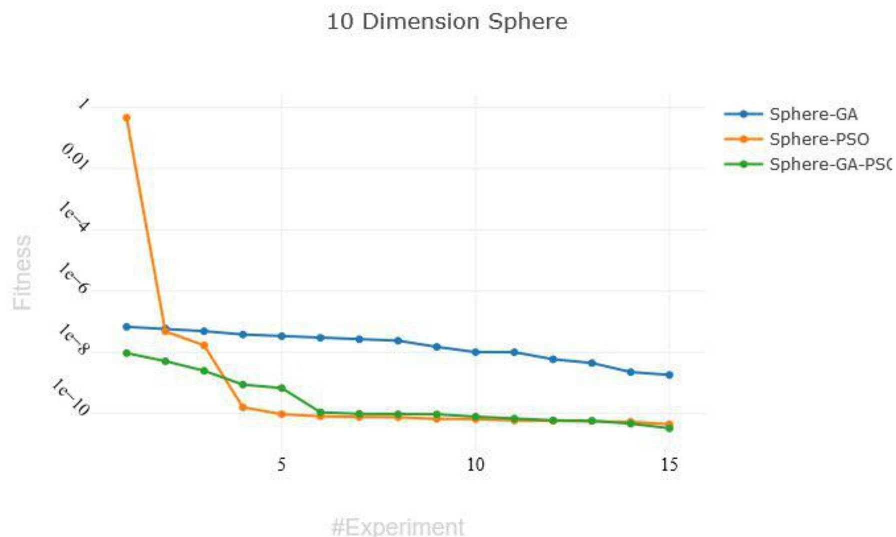

Fig. 6. 10 dimensions experiments Sphere.

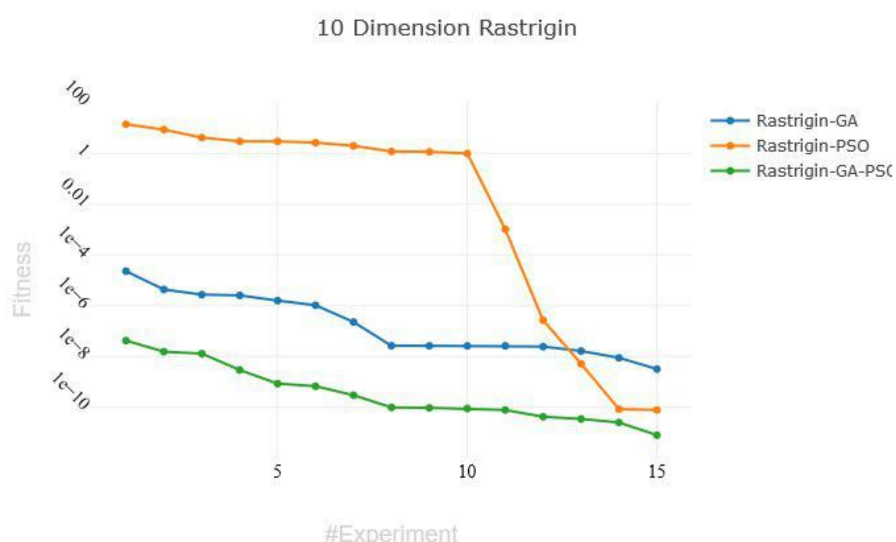

Fig. 7. 10 dimensions experiments Rastrigin.

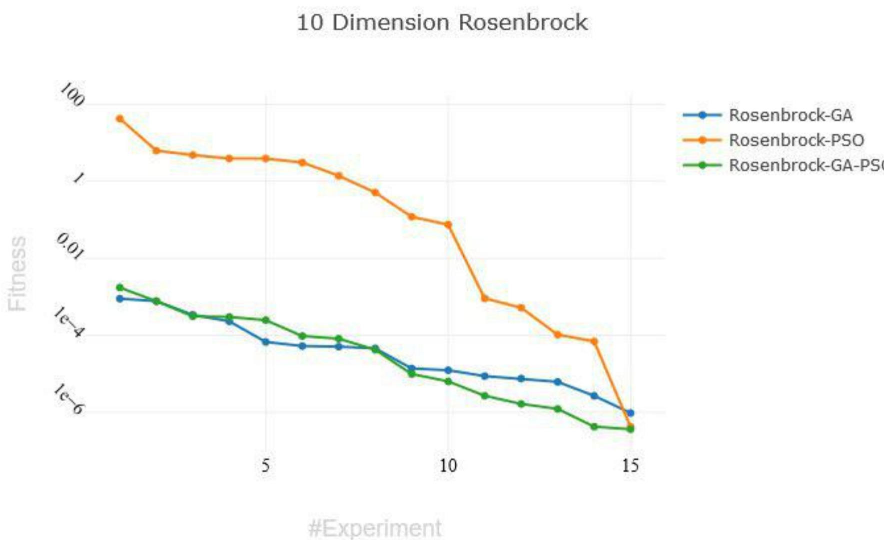

Fig. 8. 10 dimensions experiments Rosenbrock.

Table 6. Parametros experimentos 20 dimensiones

Parameter	Value
Optimización GA	Minimiza
Generaciones GA	70
Dimensiones GA	20
Tamaño de población GA	200
Mutación GA	Aleatorio(Tournament2,Tournament3,Random ,RandomLinearRank,Sequential,Fittest)
Cruce GA	Tournament3
Porcentaje de cruce GA	Aleatorio[10%, 80%]
Porcentaje de mutación GA	Aleatorio[10%,50%]
Función de cruce GA	Uniforme de punto medio
Función de mutación GA	gaussian
Optimización PSO	Minimiza
Iteraciones PSO	70
Dimensiones PSO	20
Tamaño de vector PSO	200
Factor social PSO	Aleatorio[0.5,4.0]
Factor individual PSO	Aleatorio[0.5,4.0]
Peso de inercia PSO	Aleatorio[0.5,4.0]

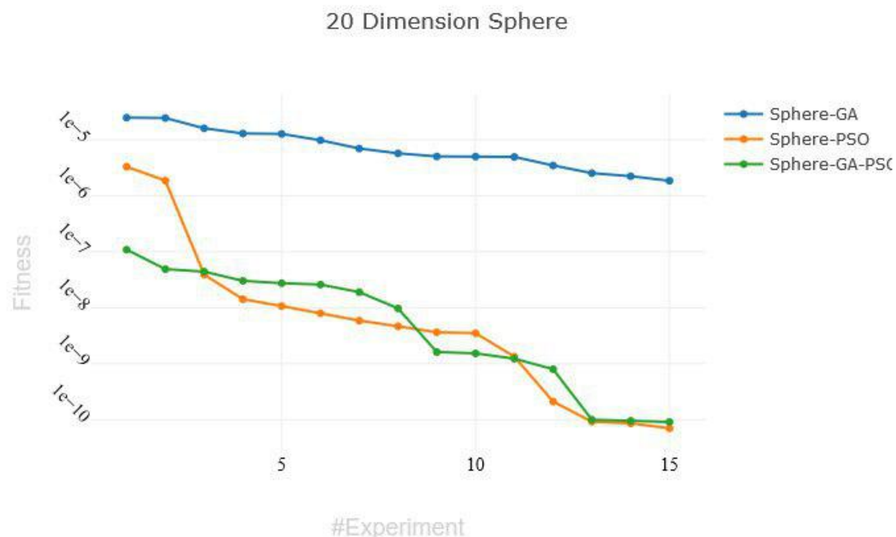

Fig. 9. 20 dimensions experiments Sphere.

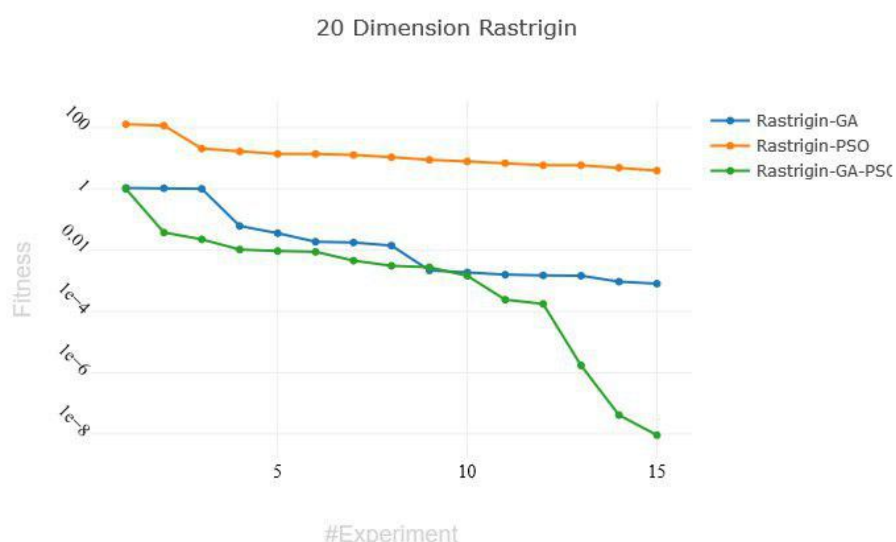

Fig. 10. 20 dimensions experiments Rastrigin.

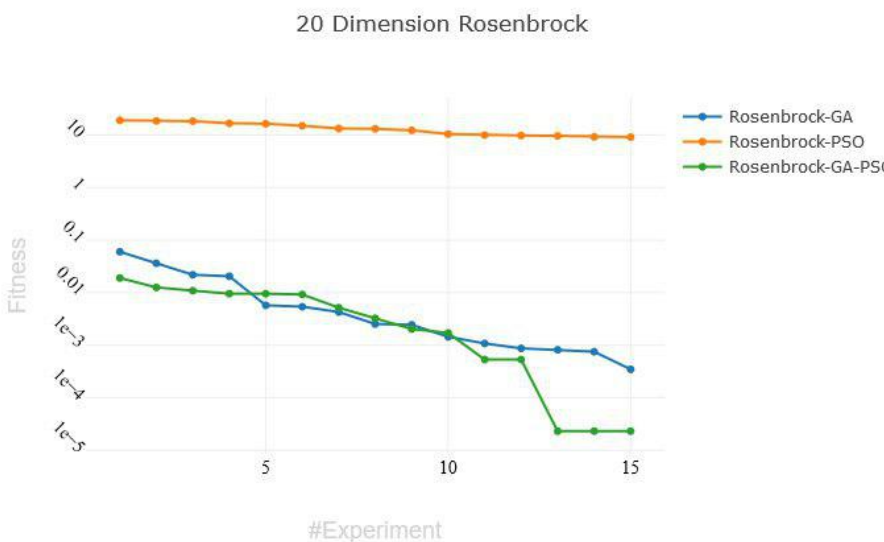

Fig. 11. 20 dimensions experiments Rosenbrock.

Table 7. Resultados 20 dimensiones

Fn	Mejor	Promedio	No. Experimento
Rastrigin GA	0.000808633	0.220596203	15
Rastrigin PSO	3.988070734	25.51777514	15
Rastrigin GA-PSO	9.13E-09	7.38E-02	15
Sphere GA	1.84051E-09	9.22715E-06	15
Sphere PSO	7.04E-11	3.50E-07	15
Sphere GA-PSO	9.11E-11	2.13E-08	15
Rosenbrock GA	0.000348015	0.010958941	15
Rosenbrock PSO	9.119539342	13.37613983	15
Rosenbrock GA-PSO	2.31663E-05	0.005608855	15

Table 8. Parametros experimentos 40 dimensiones

Parameter	Value
Optimización GA	Minimiza
Generaciones GA	70
Dimensiones GA	40
Tamaño de población GA	200
Mutación GA	Aleatorio(Tournament2,Tournament3,Random ,RandomLinearRank,Sequential,Fittest)
Cruce GA	Tournament3
Porcentaje de cruce GA	Aleatorio[10%, 80%]
Porcentaje de mutación GA	Aleatorio[10%,50%]
Función de cruce GA	Uniforme de punto medio
Función de mutación GA	gaussian
Optimización PSO	Minimiza
Iteraciones PSO	70
Dimensiones PSO	40
Tamaño de vector PSO	200
Factor social PSO	Aleatorio[0.5,4.0]
Factor individual PSO	Aleatorio[0.5,4.0]
Peso de inercia PSO	Aleatorio[0.5,4.0]

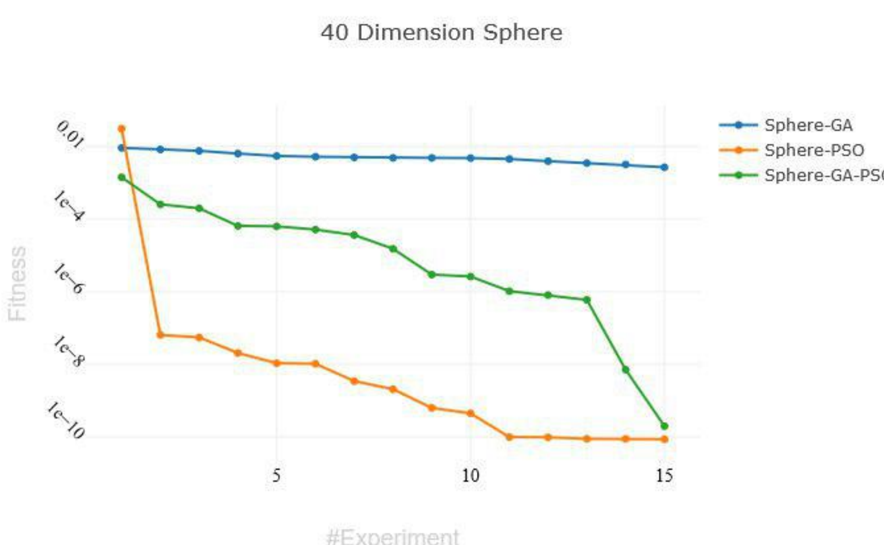

Fig. 12. 40 dimensions experiments Sphere.

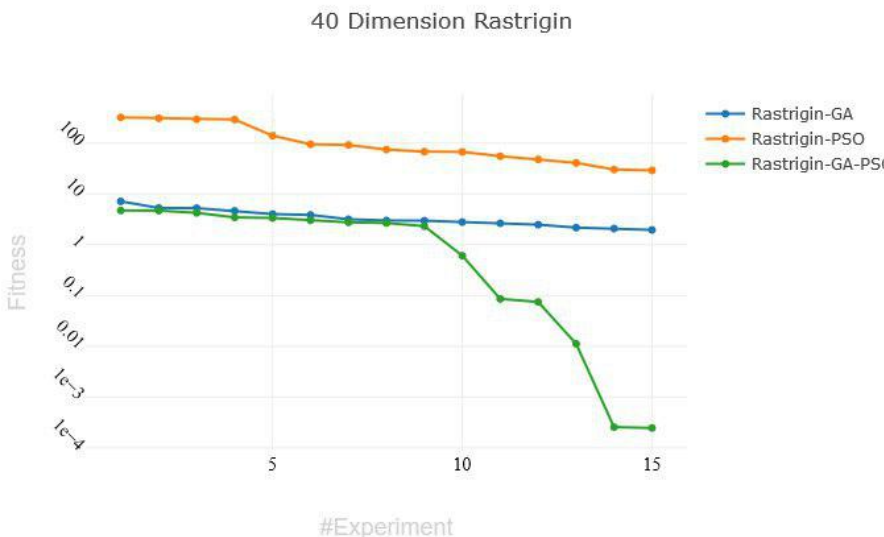

Fig. 13. 40 dimensions experiments Rastrigin.

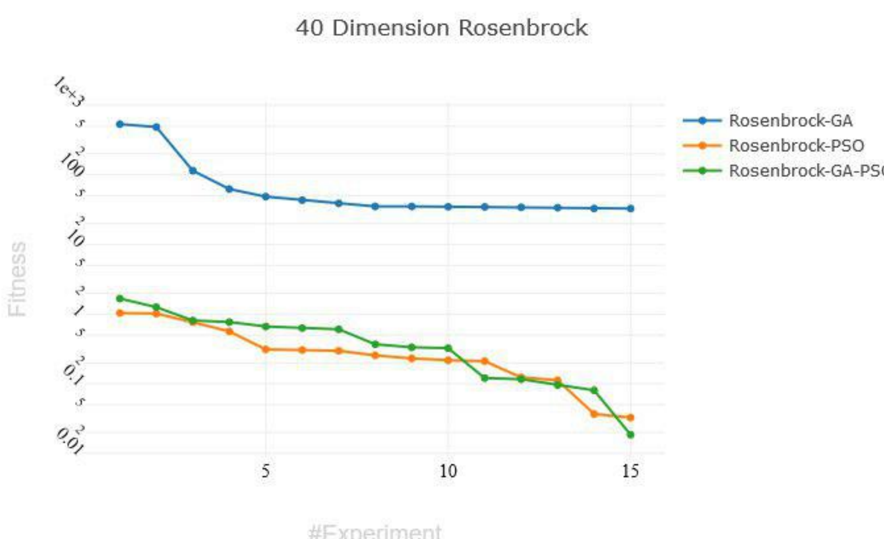

Fig. 14. 40 dimensions experiments Rosenbrock.

Table 9. Resultados 40 dimensiones

Fn	Mejor	Promedio	No. Experimento
Rastrigin GA	1.95478879	3.560837088	15
Rastrigin PSO	29.06596132	130.2865863	15
Rastrigin GA-PSO	2.46E-04	2.13E+00	15
Sphere GA	0.002686956	0.005302951	15
Sphere PSO	8.68E-11	2.07E-03	15
Sphere GA-PSO	2.00E-10	1.41E-04	15
Rosenbrock GA	0.000348015	106.9287542	15
Rosenbrock PSO	0.032708559	0.368395353	15
Rosenbrock GA-PSO	0.018538924	0.525086565	15

References

1. J. M. Hellerstein, J. Faleiro, J. E. Gonzalez, J. Schleier-Smith, V. Sreekanti, A. Tumanov, and C. Wu, "Serverless Computing: One Step Forward, Two Steps Back," vol. 3, 2018.
2. O. Kramer, "Genetic Algorithm Essentials," *Springer International Publishing AG*, vol. 679, pp. 11–20, 2017.
3. C. Guerrero, I. Lera, and C. Juiz, "Genetic Algorithm for Multi-Objective Optimization of Container Allocation in Cloud Architecture," *Journal of Grid Computing*, pp. 1–23, 2017.
4. S. Lalwani, H. Sharma, S. Chandra, S. Kusum, D. Jagdish, and C. Bansal, "REVIEW - COMPUTER ENGINEERING AND COMPUTER SCIENCE A Survey on Parallel Particle Swarm Optimization Algorithms," *Arabian Journal for Science and Engineering*, 2019.
5. S. Blum, R. Puisa, and M. Wintermantel, "Adaptive Mutation Strategies for Evolutionary Algorithms," *2nd Weimar Optimization and Stochastic Days*, pp. 1–13, 2005.
6. S. Everywhere, "The Fn Project,"
7. H. Ma, S. Shen, M. Yu, Z. Yang, M. Fei, and H. Zhou, "Multi-population techniques in nature inspired optimization algorithms : A comprehensive survey," *Swarm and Evolutionary Computation*, vol. 44, no. July 2017, pp. 365–387, 2019.
8. S. Santander-jim and M. A. Vega-rodr, "Comparative Analysis of Intra-Algorithm Parallel Multiobjective Evolutionary Algorithms : Taxonomy Implications on Bioinformatics Scenarios," vol. 9219, no. c, pp. 1–15, 2018.
9. D. Sherry, K. Veeramachaneni, J. McDermott, and U. M. O'Reilly, "Flex-GP: Genetic programming on the cloud," *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 7248 LNCS, pp. 477–486, 2012.
10. R. Goebel, *29th Australasian Joint Conference on Artificial Intelligence, AI 2016*, vol. 9992 LNAI. 2016.
11. J. J. M. Guerv and J. M. Garc, "Introducing an Event-Based Architecture for Concurrent and Distributed Evolutionary Algorithms," vol. 1, pp. 399–410, 2018.
12. L. Moroney, *The Definitive Guide to Firebase: Build Android Apps on Google's Mobile Platform.* 2017.
13. T. Ambler and N. Cloud, *JavaScript frameworks for modern web dev.* 2015.

14. A. D. Barwell, C. Brown, and K. Hammond, "USING PROGRAM SHAPING AND ALGORITHMIC SKELETONS TO PARALLELISE AN EVOLUTIONARY MULTI-AGENT SYSTEM IN ERLANG Wojciech Turek , Aleksander Byrski," vol. 35, pp. 792–818, 2016.
15. C. Paper and E. Alba, "Distributed Genetic Algorithms on Portable Devices for Smart Cities," no. May, 2017.
16. J. L. Technische, "C6.3 Island (migration) models: evolutionary algorithms based on punctuated equilibria," no. January 2000, 2016.
17. J. Kunasaikaran and A. Iqbal, "A Brief Overview of Functional Programming Languages," *electronic Journal of Computer Science and Information Technology (eJCSIT)*, vol. 6, no. 1, pp. 32–36, 2016.
18. D. Hows, P. Membrey, and E. Plugge, "MongoDB Basics," *MongoDB Basics*, 2014.
19. J. Cook, *Docker for Data Science.* 2017.
20. M. Løvbjerg and T. K. Rasmussen, "Hybrid Particle Swarm Optimiser with Breeding and Subpopulations," *Proc. 3rd Genetic Evolutionary Computation Conf.*, pp. 469 –476, 2001.
21. H. M. A. Jimeno, M. J. L. Sánchez, and R. H. Rico, "Multipopulation - based multi - level parallel enhanced Jaya algorithms," *The Journal of Supercomputing*, no. 0123456789, 2019.
22. M. Roberts, "Serverless Architectures," 2016.
23. Y. Kaya, M. Uyar, and R. Tek\D{j}n, "A Novel Crossover Operator for Genetic Algorithms: Ring Crossover," no. May 2014, 2011.