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Benchmarking Parallel Natural Algorithms for Telecommunications Devices Design

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Abstract: This work presents the benchmark of three different adapted parallel natural inspired algorithms (Genetic Algorithm, Evolutionary Strategy and Artificial Immune System) integrated to some numerical techniques to optimize a microstrip antenna and crystal based photonic filter. The evaluations were focused on parallel computing impact, considering convergence and runtime simulation analyses. This benchmark contributes to point out their efficiency of these algorithms to optimize telecommunication devices integrated with some numerical solution, and it also provide runtime equation estimative for these optimizations.

Keywords: parallel computing; natural computing; microwave; photonics; optimizations.

I. INTRODUCTION

The computational electromagnetism is an area from Electrical Engineering and Physics which concentrates efforts to develop methods and analytical solutions to calculate phenomena or to model devices in computers [1].

There are two important interrelated directions in this area. At first, the researches towards to develop new numerical solution for recent and complex problems, which in three-dimensional descriptions might be computational expensive in processing and memory storage. At second, is to how these methods would be applied to solve some of the recents trends in the electromagnetism, by microwave or photonics applications, such as the optimization of new 3D metamaterial design [2][3]. These two directions are interrelated by the computational requirements and expertise necessary to provide accurate and efficient approaches to design new devices. The parallel computing are mandatory to attempt some large problems [4][5].

For these reasons, this work provides a suitable benchmark to design microwave and photonic devices with three different parallel natural computing algorithms, evaluating the impact of this parallelism in the convergence of these algorithms and their efficiency in some telecommunications applications.

The Natural Computing is subarea from Artificial Intelligence and it has been explored in computational electromagnetism [6]. It is by the relatively easy way to apply or develop basic versions of these algorithms and by the good convergence results in global optimizations problems, such the telecommunications applications.

In order to describe these work, the second section presents a brief introduction about natural inspired algorithms, focusing on Genetic Algorithm (GA), Evolutionar Strategies (ES) and Artificial Immune System (AIS). The third section presents results from microstrip antennas (MSA) optimizations. The fourth section presents a brief introduction about bi-dimensional Finite Difference Time Domain (2D-FDTD) and some analysis of this numerical method integrated to parallel bio-inspired algorithms to optimize a simple photonic filter based on Photonic Crystal (PhC) structure.

II. MAIN CONCEPTS OF THE NATURAL INSPIRED ALGORITHMS

The natural inspired algorithms are designed in according to nature inspirations or principles and they are aimed to solve problems or to model real world representations [7]. They are usually applied in search or optimization problems to describe real world evolution [8].

For computational electromagnetic point of view, these natural based algorithms are easily described by their data structure, operators (mutation and crossover) to insert new random candidate solutions (individual) in a predefined set of solutions (population) to optimize something according to the objective function, also called fitness [9],[10]. In addition, Computational Electromagnetism the objectives functions are commonly related to devices modeling or phenomena analysis, such as described in the next section.

The next subsections presents some concepts of the natural inspired algorithms evaluated in this work, being Genetic Algorithm (subsection A), Evolutionary Strategy (subsection B) and Artificial Immune Systems (subsection C). Herein are presented the concepts of these stochastic algorithms emphasizing their resources to maximize their convergence optimizations and minimize runtime machine.

A. Parallel Genetic Algorithm:

The GA has a set of candidate solutions (population) in order to satisfy one or more objective functions (fitness) [11],[12] There are operators to maintain the population variability, performing searchs in the computational domain. The main operators are mutation and crossover (recombination). The mutation applies random changes in the individual attributes, such as usually happens in the real world when some new individual is generated by the recombination of two or more individuals, also called crossover. These processes are followed by selections some selection criteria applied in this populations along the generations [12], which follows Darwin Natural Selection Theory [13], chosen best individuals in the se populations.

The GA developed in this work integrates Gaussian and Genical Duplication mutations in a fee of 7.2% and 1.8%, respectively, totalizing 9% of mutation fee. These values were obtained by wide range of analysis applying some of the global functions available in the literature [14]. The chromosomes selection is based on ranking adjustment and followed by an elitist process to guarantee the survival of the best candidate solutions along the generations.

The parallel genetic algorithm version developed in this work was developed using Message Passing Interface (MPI) Standard in the version 2.0, by the MPICH Library. [15].

B. Evolutionary Strategy – (μ/ρ+λ)ES:

The Evolutionary Strategies (ES) are based on the evolution of population along the generations (iterations). ES algorithms are essentially similar than other evolutive algorithms, such as Genetic Algorithm. They have a population iterating to evolute, considering random mutation and recombination to generate new individuals. But, ES algorithms have different data structure representations, two different populations to control the selections criteria [1],[6].

There are represented by μ parents that recombine in a group of ρ individuals to generate λ offsprings. In this case, in each generation the population size changes from μ to $(\mu+\lambda)$ individuals. After the selection, the population into this generation is resized again to μ individuals. It is also different from the Genetic Algorithms.

The selection processes are, basically, defined according to the groups of parents and offspring. In this context, this work implements the $(\mu/\rho+\lambda)$ES, which considers both groups of parents and offspring to sort best candidate solutions for next generations. The non-selected individuals are removed from the population, storing best individuals along the generations.

C. Artificial Immune System – opt-AiNet:

The Artificial Immune System (AIS) can be defined as an adaptive system inspired by theoretical and practice vertebrate immune systems, applied to solve complex computational problems [7]. This technique encapsulates a comprehensive representation of the antigens and antibodies interactions. However, only recently, AIS has been exploited to solve computational electromagnetic problems [5],[8].

In this work a version of the optimization artificial immune network algorithm (opt-AiNet) applying Clonal Selection proposed by (de Castro & Timmis, 2006) was applied in the design based photonic crystal filter.

This AIS version ignores the differences between B-cells and antibody, representing as the same structure, where there are antibody cloning and affinity measurements, promoted by B-cells clonal expansions in order to match with antigens as quickly they can. Here, the matching between antigen and antibody (B-cells) contributes to resize the number of antibodies during the generations and it also improves the algorithm convergence (de Castro, 2006). The only operator adopted by this algorithm is the individual mutation, which is the main responsible to maintain the population diversity. The mutation occurs during the clones generations, here a Gaussian and Genical Duplication mutations are used.

The best individual selection occurs during the suppression process, where a region into the computational domain is specified to measure the affinity between the individuals, selecting only the best individuals to survive, being a type of local search to perform a global search by small regions.

III. BENCHMARKING PARALLEL NATURAL INSPIRED ALGORITHMS TO OPTIMIZE A MICROSTRIP ANTENNA

This convergence benchmark is based on the design of microstrip antennas (MSA) by cavity method [16]. This numerical application was chosen to analyze the parallelism and random number generators (RNG) impact in the convergence of these algorithms. Two wide RNG functions were analyzed, being Uniform and Gaussian distribution, the first is the standard RNG function available in most of the programming languages, such as C/C++, Java and also included in Matlab environment.

The parallel bio-inspired algorithms GA, ES and AIS were similarly parallelized. The total population size of each algorithm is divided and self-generated in each process. For example, a pre-configured population size with 100 individuals to be parallel processed in 5 processes, is going to generate five populations where each one will be composed by 20 individuals. A master node process was defined and by the each generation completion, this master node will receive best individual from all other processes.

The convergence analysis were performed from sequential to ten parallel processed. This numbers are related to the computational resources available in computer cluster configured with ten nodes, each one with AMD Opteron 246 processor, 4 GB of RAM memory, 70 GB SCSI disk and interconnected by 3COM Gigabit switch and cable Kat 5A. The operating system is the Debian Linux distribution, interconnected by SSH (Security Shell) services and RSA cryptography. The parallel applications presented here where developed using the Message Passing Interface 2.0 (MPI 2.0) Standard and available in this work MPICH Library. The compiler is the GCC (Gnu C Compiler) with optimized parameters to improve final runtime performance.

Sequential and parallel versions of GA, $(\mu/\rho+\lambda)$ES and AIS were developed in a similar base, making possible some analysis over the optimization results, evaluating central difference (*cdiff*) presented in (1).

$$c_{diff}=\frac{H_{value}-L_{value}}{H_{value}}\cdot 100 \qquad (1)$$

The *HValue* is the highest values achieved during the optimizations and *LValue* is the lowest value under the same optimization process, considering just the number of processes to perform this optimizations. For these reasons, the evaluations were performed considering the random number generator functions, the number of processes in use and algorithm adopted, being AIS, ES or GA.

In this context, is important to elucidate that each combination is executed ten times to consider their average values. The entire solutions performed by a total of 600 executions, 10 times per algorithm, from 1 to 10 process, 3 algorithms and 2 different random number functions. The total time to execute all tests was 1 hour and 39 minutes, being necessary 9.85 seconds, in average, to perform one evaluation. It is also important to emphasize that these algorithms have population size close to 80 individuals and performed along 1000 iterations(generations).

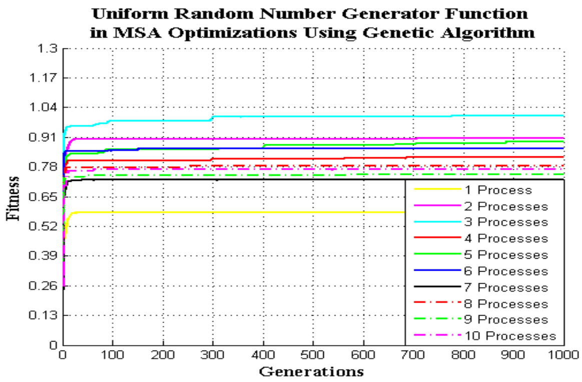

Figure: 1 Parallel Genetic Algorithm with Uniform Random Function Generation to Microstrip Antennas Design.

The first optimization sequence adopted random uniform distribution function for GA (Figure 2), Evolutionary Strategy (Figure 3) and Artificial Immune System (Figure 4). In this case, the AIS presented best convergence results with highest average values in 1.0807095 and the lowest average converged values in 1.0397641. By (1) it achieved a total central difference value of 3.79%.

The parallel GA presented spread variation convergence results, which means a certain convergence instability. The central difference using GA varies from lower average values in 0.5797563081 to 1.0015935, performing a total of variation value around 42.12% between these values.

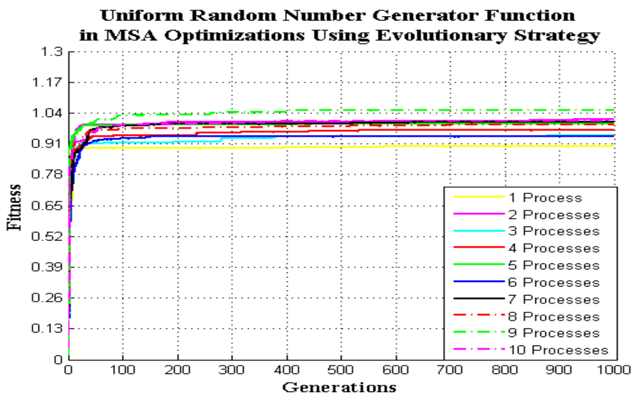

Figure: 2 Parallel Evolutionary Strategy with Uniform Random Function Generation to Microstrip Antennas Design.

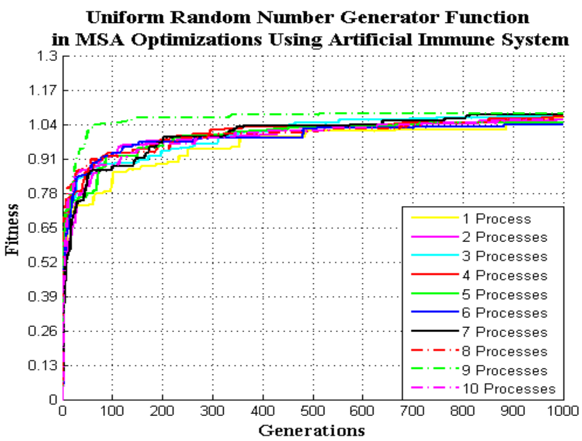

Figure: 3 Parallel Artificial Immune System Algorithm with Uniform Random Function Generation to MSA Design.

The high average values good results in Evolutionary Strategy algorithm, achieving 1.0527163. The *Hvalue* and *Lvalue*, which is 0.8986055, resulted in high variations in convergence being 14%.

The second sequence of MSA design optimization was performed with Gaussian RNG function. The same procedure was adopted for the three algorithms, in number of generations, tests trials and parallel processing. An improvement in final results was general obtained with Gaussian RNG functions in relation to uniform distribution.

The high average level with GA achieved 1.137542, being 5.3% higher than GA with uniform distribution. The lower average is 0.88550579, totalizing a final variation of 0.25203621, which is equivalent to 22.16% (Figure 4).

Other important information to detach is the considerable reduction of the central difference values between higher and lower values, from 42.12% in uniform distribution to 22.16% with Gaussian RNG.

The Gaussian RNG with parallel Evolutionary Strategy has also been decreased and central difference variation was reduced from 14% to 5.14% (Figure 5). The higher and lower average level was 1.151418 and 1.0921845, respectively. This Gaussian distribution has positively impacted the Artificial Immune System also. In Figure 6 is presented the convergence results with higher average values in 1.209313 and lower average value of 1.177635, promoting a variation of 0,031678. It means that the equivalent percentage is 2.62%, which presents lower variation than uniform distribution. In summary, these numerical analyze contributed to determine the parallel processing impact in bio-inspired algorithms developed with these resources. Furthermore, these results show the best performance adaptation of the Gaussian RNG in these algorithms, improving convergence and decreasing parallel variation impacts in the final results. Final optimized microstrip antenna achieved central frequency 2.4 GHz, 6.3 dB of bandwidth, ε_r 96.6% and SWR minimum of 1.72, values close to original reference [9].

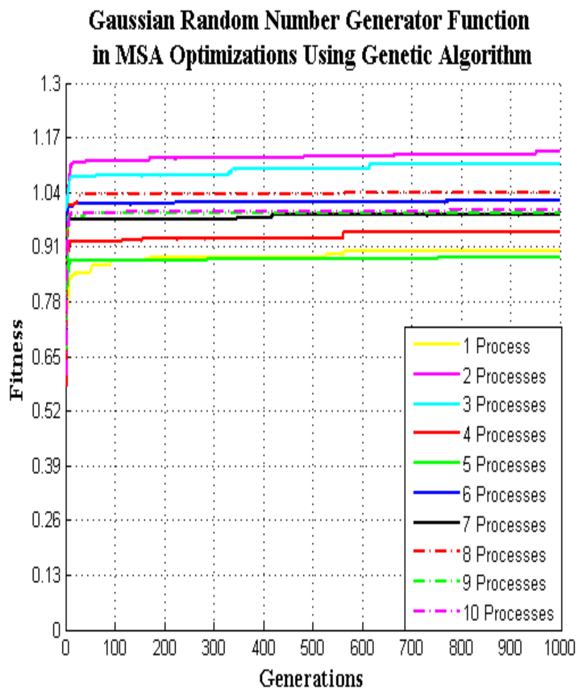

Figure: 4 Parallel Genetic Algorithm with Gaussian Random Function Generation to Microstrip Antennas Design.

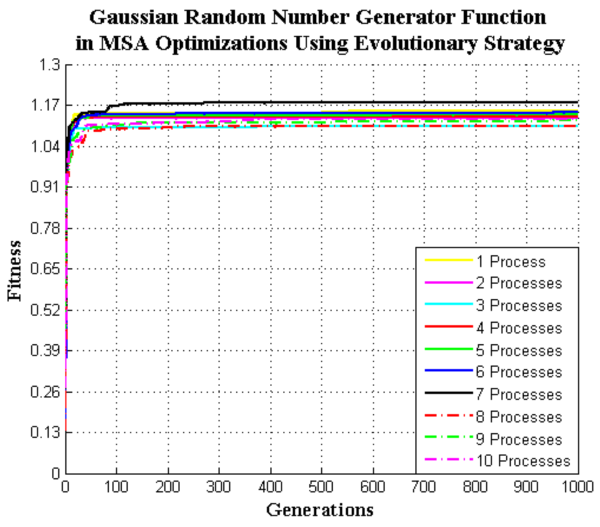

Figure: 5 Parallel Evolutionary Strategy with Gaussian Random Function Generation to Microstrip Antennas Design.

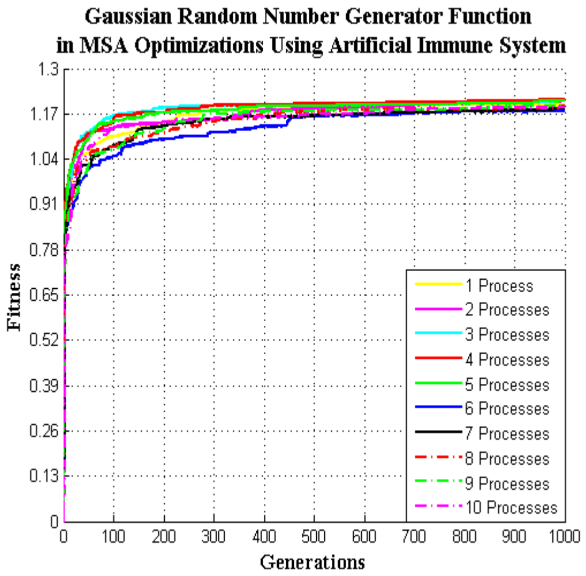

Figure: 6 Parallel Artificial Immune System with Gaussian Random Function Generation to Microstrip Antennas Design.

IV. RUNTIME EVALUATIONS IN A FILTER CRYSTAL PHOTONIC BASED DESIGN

This second analysis was applied to evaluate the algorithms runtime and convergence impact of the sequential and parallel processing integrated with a 2D FDTD method, applied to design Photonic Crystal Filter based device (Figure 7) in $Te_{z.}$ This numerical method was developed with Perfect Electric Boundary conditions and the electric fields were splited according to Bérenger Prefectly Matching Layes (PML) equations [17]. The numerical stability conditions were performed by Courant criteria [18].

This photonic device was composed by 36 columns, arranged in a matrix of 6x6 elements. These layers were made over a substrate with permittivity 2.0, and the columns might assume permittivity equal than the substrate or their values can be 1.0, which is equal than the vacuum permitivitty. The computational domain discretization was made in 441x223 cells, representing 3λ x 1λ, where λ is the wavelength and its value is λ=1.55 µm.

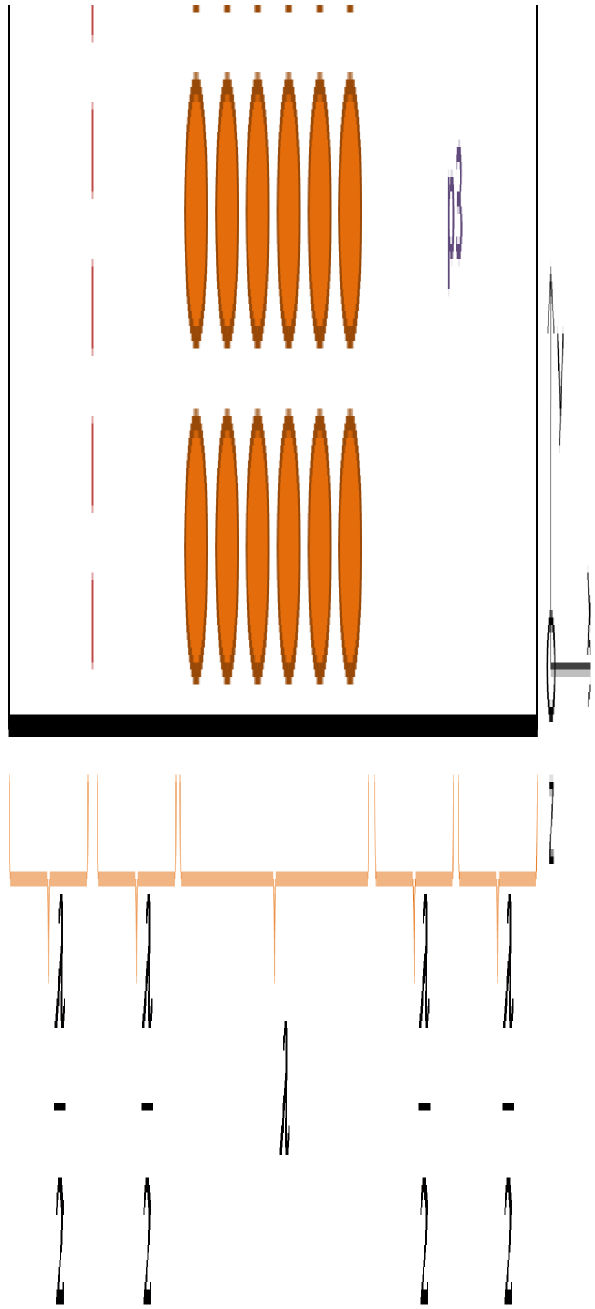

Figure: 6 TEz stop band structure modeled in a 2D FDTD method.

Here, the main optimization objective is the minimization of the electric field propagation calculated in the points points *p1*, *p2* and *p3*. In this numerical optimization an input Gaussian with wavelength in 1.55 µm was modeled.

The sequential and parallel metaheuristic algorithms (GA, ES and AIS) convergence results was analyzed under a sequence of three trials tests for each algorithm and final results is the average of these executions. Every algorithm is using Gaussian RNG function, following previous results.

Each 2D FDTD runtime execution requested in average 95 seconds. It is an important information to estimate the total runtime necessary to optimize this device. These optimizations were performed in a sequential process and with five and ten parallel processes. Table I is presented the machine runtime for sequential optimizations for each algorithm and test performed. The convergence results are presented in Figure. 8.

Table I. Sequential Optimization Runtime

Algorithms	Test 1 (seconds)	Test 2 (seconds)	Test 3 (seconds)	Average (seconds)
AG	96,345	97,104	96,272	96,574.07
ES	57,142	57,481	57,213	57,278.33
AIS	25,438	26,711	25,786	25,978.33

In this sequential optimizations tests the AIS opt-AiNet presented lower runtime simulations than (μ/ρ+λ)ES and GA. The AIS was three time faster close than others. Although, the (μ/ρ+λ)ES presented best convergence results, followed by AIS and GA. These sequential evaluations are necessary to measure their runtime to compare with parallel version, allowing evaluations related to the parallelism impact in these optimizations forwarding the runtime and convergence performance. The second test sequence execute 5 parallel processes and third 10 processes in the previous described cluster. Figure 9 presents the first parallel test results, which five processes, where the (μ/ρ+λ)ES presented again the best convergence results, being followed by GA and AIS.

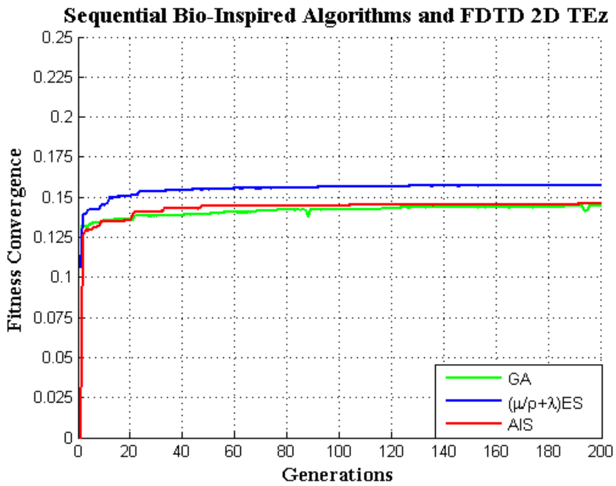

Figure: 6 Sequential bio-inspired algorithms convergence in a 2D stop band device design.

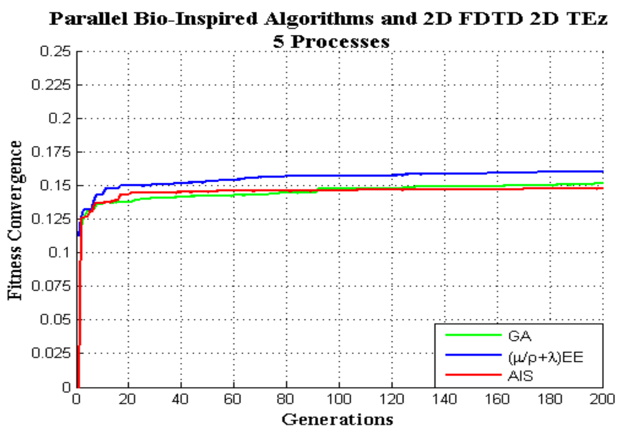

Figure: 7 Parallel bio-inspired algorithms executing 5 processes to 2D stop band device design.

An important result is the runtime simulation, because here parallel the tests with (μ/ρ+λ)ES presented lowest machine runtime, followed by AIS and GA, respectively, as shown in Table II. The GA presented the worst runtime, costing 10.79% than AIS and 60.61% than (μ/ρ+λ)ES. In this case, the parallel AIS runtime was decreased 20.51% when compared to its sequential version.

Table II. Runtime Optimization With Five Parallel Processes

Algorithms	Test 1 (seconds)	Test 2 (seconds)	Test 3 (seconds)	Average (seconds)
AG	22.956	22.938	22.745	22.879,67
ES	14.022	14.245	13.944	14.070,33
AIS	22.538	18.731	20.682	20.650,33

Finally, the third test considers ten processes for the same optimizations and algorithms. The runtime optimization with parallel AIS presented lowest machine runtime, being 51.33% faster than (μ/ρ+λ)ES and 57.17% faster than GA (Table III). The unexpected decrease in the AIS runtime might be explained by the very short number of individuals in each population, which is still under study and evaluations. These final parallel average runtime executions presented parallel AIS 76.75% faster than sequential version. The parallel (μ/ρ+λ)ES with 10 processes was 78.34% faster than its sequential version and parallel GA was 85.40%.

The convergence is still better with (μ/ρ+λ)ES than GA and AIS, such as presented in Figure10. The convergence optimization with AIS in this test has presented some decrease in relation to previous tests, reinforcing the initial considerations that the smaller population sizes in each process may be the cause of these results. This can be justified by the reduction in population variations.

Table III. Runtime Optimizations With Ten Parallel Processes.

Algorithms	Test 1 (seconds)	Test 2 (seconds)	Test 3 (seconds)	Average (seconds)
AG	13.992	14.024	14.289	14.101,67
ES	12.435	12.962	11.827	12.408,00
AIS	6.184	6.321	5.613	6.039,33

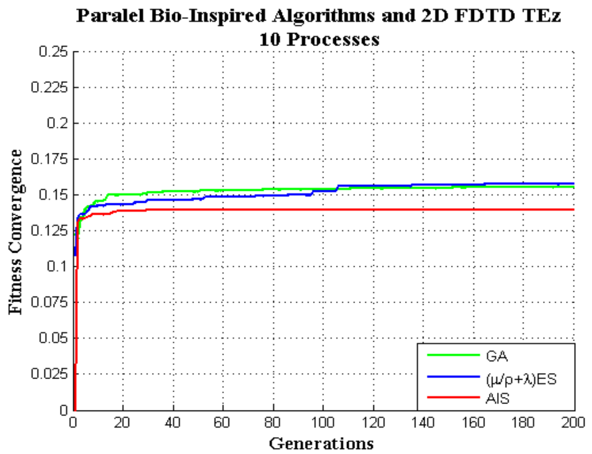

Figure: 8 Parallel bio-inspired algorithms executing 10 processes to 2D stop band device design.

V. CONCLUSIONS

This work presents two main parallel evaluations of parallel bio-inspired algorithms focused on runtime and convergence results.

In the first test sequence some microstrip antennas optimizations were considered to analyze the algorithms convergence. In this case, the AIS algorithms presented best results in maximum values and reduced variations between the different numbers of processes and considering uniform and Gaussian distributions functions in generation of random numbers. This last function contributed to reduce parallelism variation impacts and to improve the convergence results of the AIS, $(\mu/\rho+\lambda)$ES and GA algorithms.

Following the results presented in these previous tests, the second application was performed to to analyze the machine runtime when these optimization algorithms were integrated to 2D FDTD method to model a Photonic Crystal based Filter. The Gaussian RNG function was adopted as standard distribution function in these tests, where the $(\mu/\rho+\lambda)$ES presented best convergence results. By the machine runtime, for sequential and with 5 processes $(\mu/\rho+\lambda)$ES has also presented best results. For 10 parallel processes, the AIS was best solution when the machine runtime execution is considered.

Presenting these convergence and runtime benchmarks for telecommunication applications, this work contributes to point out some interesting efforts to process these complex optimizations in high performance environment configured in computer cluster. This work team group is currently researching about other evolutionary operators, computer architecture approaches and local derivative algorithms, in order to decrease machine runtime and maximize the optimization convergence.

VI. ACKNOWLEDGMENT

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VII. REFERENCES

[1] Silva-Santos, C. H., (2010). Parallel and Bio-inspired Computing to Analyze Metamaterial Microwave and Photonics Structures. Dr. Thesis, University of Campinas, Campinas-SP, Brazil.Bermel,

[2] Peter. "Photonic crystals: Turning data on a dime." Nature Photonics 7.2 (2013): 89-91.

[3] Fan, K., Strikwerda, A. C., Zhang, X., & Averitt, R. D. (2013). Three Dimensional Broadband Tunable Terahertz Metamaterials, arXiv: 1301.3977.

[4] Silva-Santos, C. H., Miranda, M. A. M., Hernández-Figueroa, H. E. (2009). Efficient Parallel Computational Environment to Perform Electromagnetic Simulations. Tangiers. IEEE Mediterranean Microwave Symposium (IEEE-MMS).

[5] da Silva Santos, Carlos Henrique, Marcos Sergio Gonçalves, and Hugo Enrique Hernandez-Figueroa. "Designing Novel Photonic Devices by Bio-Inspired Computing." Photonics Technology Letters, IEEE 22.15 (2010): 1177-1179.

[6] De Castro, L. N. (2006). Fundamentals of Natural Computing Basic Concepts, Algorithms, and Applications. FloridaChapman & Hall/CRC.

[7] De Castro, L. N. Timmis, J. (2002). Artificial Immune Systems: A New Computational Intelligence Approach. England. Springer-Verlag.

[8] De Castro, L. N., Von Zuben, F. J. (2005). Recent Developments in Biologically Inspired Computing. Hershey. Idea Group Publishing, Hersheys.

[9] Donelli, Massimo. "Design of broadband metal nanosphere antenna arrays with a hybrid evolutionary algorithm." Optics Letters 38.4 (2013): 401-403.

[10] Lin, Jun-Lin, Chien-Hao Wu, and Hsin-Yi Chung. "Performance Comparison of Electromagnetism-Like Algorithms for Global Optimization." Applied Mathematics 3.30 (2012): 1265-1275.

[11] Haupt, R. L., Werner, D. H., (2007). Genetic Algorithms In Electromagnetics. New Jersey. John Wiley & Sons.

[12] Mitchell, M. (1998). An Introduction to Genetic Algorithms. Massachusetts. The MIT Press.

[13] Darwin, Charles (1859), On the Origin of Species by Means of Natural Selection, or the Preservation of Favoured Races in the Struggle for Life (1st ed.), London: John Murray, pp. 502, retrieved 2011-03-01.

[14] Brinster, Irina, Philippe De Wagter, and Jason Lohn. "Evaluation of stochastic algorithm performance on antenna optimization benchmarks." Antennas and Propagation Society International Symposium (APSURSI), 2012 IEEE. IEEE, 2012.

[15] MPICH Library, available in http://www.mpich.org, accessed in: February, 12, 2013.

[16] Brianeze, J. R., Silva-Santos, C. H., Hernández-Figueroa, H. E., (2009). Multi-objective Evolutionary Algorithms Applied to Microstrip Antennas Design, Ingeniare. Revista chilena de ingenieria, 17, 3, 288-298.

[17] Bérenger, J. P., (1996). Perfectly Matched Layer for the FDTD Solution of Wave Structure Interaction Problems, IEEE Transactions on Antenna, 44, 1, 110-117.

[18] Taflove, A., Hagness, S. (2005). Computational Electrodynamics: The Finite-Difference Time-Domain Method, Third Edition, Artech House Publishers.