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Teaching Genetic Algorithms and Parameters Setup on Antenna Design

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Abstract—**Evolutionary algorithms are widely being used on any engineering field where optimizations are required over complex problems. Genetic Algorithm (GA) is one of the most popular algorithms over the evolutionary ones. GA are being taught on graduated and post-graduated university courses. Despite this wide spread of the GA usage and variety of applicable field, a correct setup of GA parameters is still not uniquely defined. In this material, the influence of GA parameters setup such as number of populations on each generation, elitism coefficient, mutation function used to generate and push genetic modifications over the population, parent selection functions and reproduction functions choice parameter influence are also analyzed. All parameters are being analyzed on a simple Yagi-Uda constrained antenna problem as a simple test case where linear constraints and genetic coding of variables are of immediate understanding to the reader. At the end, some discussions on the available functions used on GA and different parameter setup and their influence on the GA results are drown. The material concludes with conclusions and bibliographic references designed to help the reader expand his knowledge on optimization algorithms and in particular in the correct use of GA functions on constrained optimization problems.**

Keywords*—*Genetic algorithm, antenna optimization, crossover function, mutation function, GA teaching

I. INTRODUCTION

Engineers are constantly challenged with the search for optimum solutions for complex designing problem. The ever-increasing advances in computational power have fueled this temptation. The well-known brute force design methodologies are systematically being replaced by the state-of the-art optimization techniques.

Different evolutionary algorithms are nowadays being part of graduated and postgraduate university courses [1], [2] as knowledge required by the academic and professional career of students and practitioners. Despite this wide spread of the optimization programming courses, a correct setup of the algorithms is still not taught into details and not uniquely defined parameters setup configurations [2], [3].

Optimization is the task of finding one or more solutions which correspond to maximizing one or more specified objectives and which satisfy all constraints (if any). A single-objective optimization problem involves a single objective function and usually results in a single solution, called an optimal solution [4]

Before any optimization can be done, the engineering problem must first be modeled and later an optimization procedure must be defined and executed over the modeled problem. First, building a suitable model (that is, the formulation of the optimization problem with specifying decision variables, objectives, constraints, and variable bounds) is an important task. Second, an optimization algorithm finds the optima of the model of the optimization problem specified and not of the true optimization problem.

Due to these reasons, the optimal solutions found by an optimization algorithm must always be analyzed (through a post-optimality analysis) for their “appropriateness” in the context of the problem. This aspect makes the optimization task iterative in the sense that if some discrepancies in the optimal solutions obtained are found in the post-optimality analysis, the optimization model may have to be modified and the optimization task must be performed again [4], [5]

One of the advantages of optimization techniques is that they are completely general methods, unrelated to the real system to be designed, and they can hence be applied to any design problem, provided that a fitness function can be defined.

In the following, genetic optimization algorithm will be presented on finding the optimized solution in a simple Yagi-Uda antenna design problem [6]. This optimization technique does not cover all available optimizations algorithms, but is one of the most popular, being at the same time, simple to implement and powerful [7] – [10].

The following material is focused on the Genetic Algorithm and its setup on engineering optimization problem [11]. As the algorithm itself has different settings or/and functions that can be configured by the user, independently by the designing problem, this leads engineers, that are not practical with optimization tools in difficulties or not proper configuration of the optimization tool. Where non proper configuration of the optimization algorithm can extend the convergence time required to obtain the optimal solution or can produce very broad solutions on different optimizations algorithms runs.

In the following material, are analyzed and discussed five GA parameters and their effect on obtained optimal solutions for different optimization procedure executions over Yagi-Uda antenna design [6], [11]. The aim of this discussion is to obtain some guidelines to be used on teaching and using genetic algorithms for optimization problems on graduated university courses and on real engineering constrained problems.

Five GA parameters analyzed in this material are:

1) Population number
2) Elitism number to the next generation
3) Mutation distribution function (Gaussian, uniform, adaptive)
4) Parent selection (uniform stochastic, remainder, roulette, tournament, uniform)
5) Recombination (scattered, single-point, two-points, intermediate, heuristic)

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II. GENETIC ALGORITHM PARAMETERS ON YAGI-UDA ANTENNA DESIGN

Yagi-Uda antenna is one of the simplest antennas that can be designed, its structure consists of one active element, one reflector and one or more directors [6] as presented in figure 1 In this designing procedure, the overall number of parameters to be optimized is 2(N+2) - 1, where N is the total number of directors. The designing parameters are the overall length of each of the elements and relative distances between two consecutive elements.

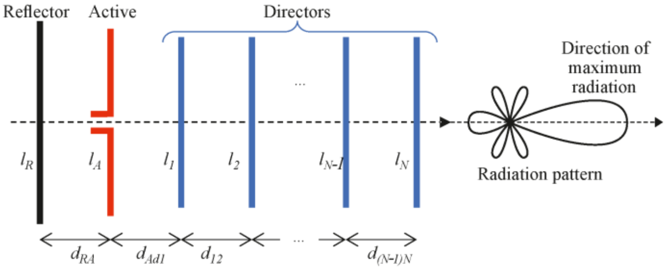

Fig. 1. Yagi-Uda antenna diagram and designing parameters.

Yagi-Uda antenna can be efficiently modeled and analyzed using Method of Moments [6], [12], where all elements position and dimensions are known, the antenna electrical current distribution can be obtained, and radiation pattern calculated. The efficient modeling of Yagi-Uda antenna array using Method of Moments, allows to mathematically model the designing problem, which is the first step on optimization procedure. Those numerical codes can be used as "black-boxes" on optimization algorithms, where only input parameters, such as antenna element position and relative length, can be changed, and the modeling will produce the designed electromagnetic characteristics of the antenna. One or more of electromagnetic characteristics of the antenna can be used as fitness value. The fitness value, obtained by the "black-box" model, can be used on the optimization algorithm as a score to sort all obtained solution and to evolve to a better one. In this work, the maximum antenna gain obtained in the end-fire direction is used as fitness value (greater values means better solution).

Based on these analyses, the maximum directivity obtained is set as fitness function to be optimized (maximized) using GA tool which changes Yagi-Uda antenna element position and length.

So, for 7 elements antenna (1 reflector, 1 active element and 5 directors), the total number of optimizing parameters are 13 = 2 × (5+2) - 1. Those parameters are 7 elements length and 6 relative spaces between them as in figure 1.

Designing parameters in the variable space, are constrained. Element physical length cannot be negative, and the mutual distance cannot be negative value also. So, the designing antenna procedure, is a constrained problem, where all variables can have values in a specific range in a continuous or discrete way. Mathematically, each antenna element length and relative mutual distance can have any value in the specific range (from 0 to a maximum value), but due to the fabrication process and relative fabrication tolerance, only discrete values in the specific range can be selected.

Designing this antenna seems a simple task, and from practical fabrication specifications, common dimensions resolutions are 0.001 λ Where λ is signal wavelength.

Considering theoretical definition of Yagi-Uda antenna [6], each element length can be any value in the 0.2 - 0.7 λ range, and mutual distance in 0.1 - 0.4 λ range with the defined fabrication 0.001 λ resolution.

As an example, designing a Yagi-Uda antenna operating in 300MHz, where λ = 1m, each antenna element length can be any value in the range 20 - 70 cm with 1mm step. Similar constraints are set for mutual distance between elements as better described in table I.

In table I are presented all antennas designing parameters and respective unique values for each parameter.

TABLE I. YAGI-UDA PARAMETER DESIGN POSSIBILITIES

Parameter	Range (λ)	Resolution (λ)	Unique Combinations
l_R	0.2 − 0.7	0.001	501
l_A	0.2 − 0.7	0.001	501
l_1	0.2 − 0.7	0.001	501
l_2	0.2 − 0.7	0.001	501
l_3	0.2 − 0.7	0.001	501
l4	0.2 − 0.7	0.001	501
l5	0.2 − 0.7	0.001	501
d_{RA}	0.1 − 0.4	0.001	301
d_{Ad1}	0.1 − 0.4	0.001	301
d_{12}	0.1 − 0.4	0.001	301
d_{23}	0.1 − 0.4	0.001	301
d_{34}	0.1 − 0.4	0.001	301
d_{45}	0.1 − 0.4	0.001	301
Total combinations	$501^7 + 301^6 \approx 7.9 \times 10^{18}$		

As all the over-mentioned parameters are independent, there are $501^7 + 301^6 \approx 7.9 \times 10^{18}$ combinations which are not practical to be analyzed. Even if we consider just 1 second as simulation time for any antenna analysis, the overall timing is more than 247 × 10^9 years to process all combinations in a brute-force analysis.

For those problems, that cannot be practically solved due to complexity or amount of time required, optimization algorithms are key solution. One of the most popular heuristic algorithms is Genetic Algorithms. The choices of GA to be analyzed riles on its widespread over the research community and undergraduate and graduated university courses [1] – [5].

In figure 2 is presented a schematic of the genetic algorithm flowchart [5]. Each of the presented steps can be further detailed and their implementation has different mathematical models. Is not the purpose of this material to explain in to details each algorithm step or relative functions, which can be found in the scientific literature [3], [5], [13]. The aim of this material is to analyze and discus user choices on GA functions configurations or parameters alternatives, without entering the merit of problem modeling.

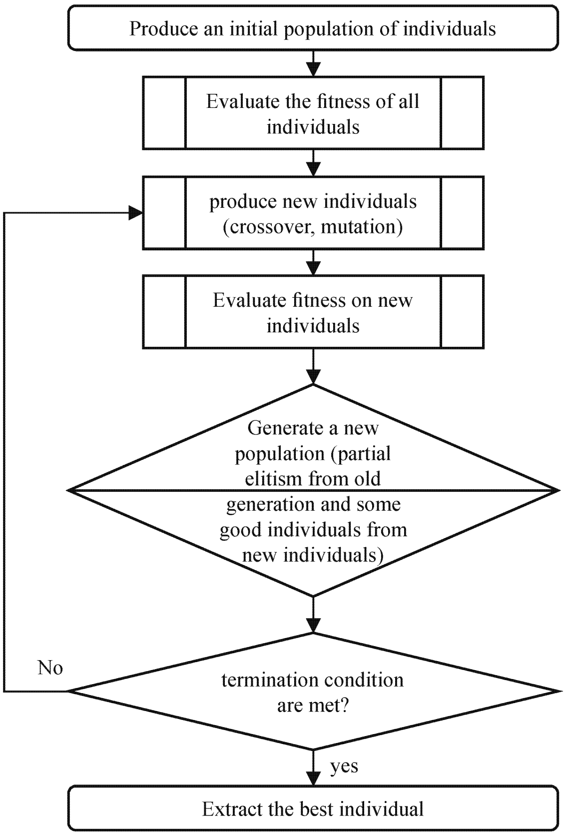

Fig. 2. Basic Genetic Algorithm flow chart.

As an example, there are different mathematical formulations that allows to recombine genetic information (genes in GA terminology) from two parents and generate a new child. Some implementations of GA use a “Single point crossover”' where the chromosome of parents are cut randomly and the two tails of chromosome of each of the parents, are combined to form two new individuals [3], [13], [14]. To obtain the same logical function, a “multiple crossover” function can be used, where in a *n*-point crossover there are *n* crossover points and sub-chromosomes are swapped between the *n* points to generate the new individuals. There are other mathematical functions defining the logical problem of combining the genetic heritage from two parents to create the new generation [11].

The same is true for all logical sub-functions defining the GA workflow. Different functions are defined for choosing which pair of individuals will be selected as parents and combine their genetic heritage to the new generations. For these logical functions, the most spread implementations are called Roulette, Tournament, Remainder, Stochastic Uniform, Uniform distribution etc. [11].

Mutation functions are required to induce some small ($\approx$ 0.01 rate) of genetic modifications to the selected population, as to introduce new and not previously presented genetic information, that can lead the algorithm to spread its search space and avoiding from getting stuck in optimal local solutions. Even the mutation function has a small percentage impact on population generation, its mathematical formulation can be from a Gaussian distribution function, a uniform one or other models [5], [11].

In the following sections, the standard genetic algorithm implemented in Matlab [11] has been used to optimize the constrained antenna design problem defined in figure 1. In this GA implementation, all the previously mentioned parameters are set one at time as to have a better view of their effect on the designed optimal solution, as it will be discussed at the appropriate section at the end.

III. SIMULATION RESULTS

The main GA workflow is presented in figure 2. Where some of important parameters of GA that influences the algorithm convergence to the optimal solution are:

1) Population number
2) Elitism number to the next generation
3) Mutation distribution function (Gaussian, uniform, adaptive)
4) Parent selection (uniform stochastic, remainder, roulette, tournament, uniform)
5) Recombination (scattered, single-point, two-points, intermediate, heuristic)

To have a common and objective evaluation parameter on algorithm convergence and its relative variance, all simulations are set to run as to complete a maximum of 2600 fitness function evaluations ($200 \times N_{var}$). Which means 2600 different antenna designed and analyzed from the total pool of 7.9×10^{18}. With these criteria, is possible to compare different GA setup parameters based on the best obtained solution at the end of the optimization process (after 2600 functions evaluated).

For each parameter combination, three simulations are performed on the Yagi-Uda antenna design. Repeating the same setup multiple times is necessary, as the optimization procedure does not find the best solution but approaches it in an evolutionary way [4], [5]. In any run of any evolutionary algorithms, and not only in GA, the obtained results will be different, but if the algorithm converges, the solutions will have less differences between multiple runs.

In this case, maximum differences between obtained solutions are marked as metric parameter. Grater values (greater differences) means that with the chosen parameter of GA, even one optimal approximate solution is obtained, it can highly differ from one run to another with the same setup. Vice versa, smaller differences between the three identical runs, means that the chosen parameter is a better alternative for this constrained antenna design problem.

A. Population number on GA convergence

In the presented GA implementation, the first setup parameter analyzed is the population number. This parameter can be set on any integer value. Smaller values, means less genetic heritage on each generation and higher probability on different parents to combine their genetic information for generating new populations. Higher values, means greater genetic heritage on each generation, but less probability to combine them between parents on new generations and to evolve. So, there is not a unique response on how to choose this parameter. The choice of this parameters cannot be casual and must be related to the number of optimization variables defining the problem (N_{var} = 13 in this implementation). With these formulations, the number of individuals on each generation, here analyzed, are set as equal to 1×, 5×, 10×, 15× and 20× N_{var}. To maintain the same total number of fitness function evaluation to 2600 ($200 \times N_{var}$), the relative number of

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generations for the above population are set respectively to: $N_{pop} = 200$, $N_{pop} = 40$ $N_{pop} = 20$ $N_{pop} = 14$ $N_{pop} = 10$

In table II are presented the obtained simulation data for three runs of the GA on the same identical setup for each of the population number chosen for analysis.

TABLE II. EFFECT OF POPULATION NUMBER TO GA CONVERGENCE.

No. of populations on each generation	Test no.	Antenna directivity (dB)	Average directivity (dB)	Maximal difference
	1	13.016		
13 ($1 \times N_{var}$)	2	13.644	13.318	0.628
	3	13.295		
	1	12.940		
65 ($5 \times N_{var}$)	2	13.491	13.321	0.594
	3	13.534		
	1	13.413		
130 ($10 \times N_{var}$)	2	13.060	13.372	0.583
	3	13.642		
	1	12.927		
195 ($15 \times N_{var}$)	2	13.264	13.249	0.629
	3	13.556		
	1	12.637		
260 ($20 \times N_{var}$)	2	12.820	12.677	0.247
	3	12.573		

In figure 3 is shown graphically the same information of table II. The maximal differences between different runs of the same setup, is stacked over the average value of the same setup. From the results presented in table II and figure 3, a good tradeoff is population number 130 ($10 \times N_{var}$) as presents an average values higher than the solution with 260 individuals and also not to high spread of solutions on different runs.

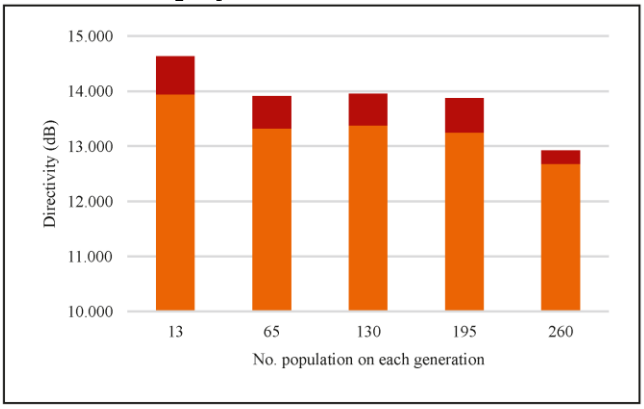

Fig. 3. Population number vs fitness value and variance on three identical algorithm setup runs.

B. *Elitism to the next generation*

From the previous section where the algorithm behavior over population size variation was analyzed, in this section, the case of population number equal to the best performing solutions ($N_{pop} = 130$) will be used here. In this case, all parameters will be fixed and only the elitism counting (N_{elite}), related to the population number as 0%, 5%, 10%, 15% and 20% of N_{pop} will be changed and analyzed.

In table III are presented the obtained simulation data for three runs of the GA on the same identical setup for each of the elite number chosen for analysis. In figure 4 is shown graphically the same information of table III, where to the average directivity obtained from the best solution of the three runs, is stacked the maximal difference of different runs on the same setup.

TABLE III. EFFECT OF ELITISM NUMBER TO GA CONVERGENCE.

No. of elite members	Test no.	Antenna directivity (dB)	Average directivity (dB)	Maximal difference
	1	13.653		
0 (0%)	2	14.203	13.549	1.410
	3	12.792		
	1	13.697		
7 (5%)	2	13.352	13.326	0.766
	3	12.931		
	1	13.233		
13 (10%)	2	13.347	13.387	0.347
	3	13.580		
	1	12.899		
20 (15%)	2	13.130	13.342	1.097
	3	13.996		
	1	13.442		
26 (20%)	2	13.610	13.359	0.586
	3	13.024		

From this result, and this constrained antenna design problem, the best tradeoff between elitism is the solution with 10% (13 individuals in this case).

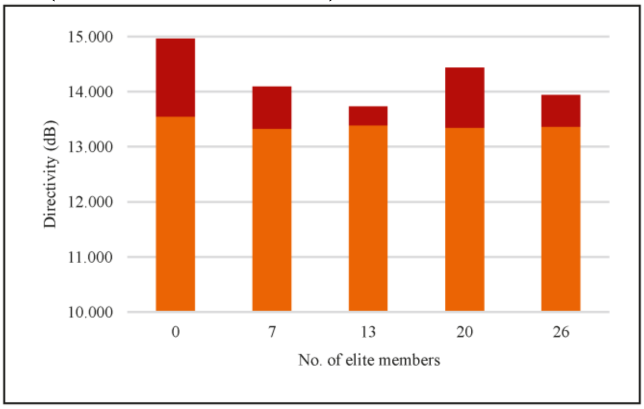

Fig. 4. Population number vs fitness value and variance on three identical algorithm setup runs.

C. *Mutation distribution function*

On the evolutionary algorithm performance, population size and elitism number are key parameters defining the convergence of the optimization process but are not the only parameters. Mutation options specify how the genetic algorithm makes small and random changes in the individuals in the population to create mutated children. Mutation provides genetic diversity and enables the genetic algorithm to search a broader space. Mathematical definition for mutation function are extensively described in the scientific literature, and also can be found in the Matlab manual [5], [11].

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Mutation functions analyzed in this section are mentioned in the first column of table IV [11]. The genetic algorithm setup, for population number and elitism factor are set as the best tradeoff of the previous sections, and respectively N_{pop} = 130 (10 × N_{var}) and N_{elite} = 13 (10% of N_{pop}).

TABLE IV. EFFECT OF MUTATION FUNCTION TO GA CONVERGENCE.

Mutation function	**Test no.**	**Antenna directivity (dB)**	**Average directivity (dB)**	**Maximal difference**
Uniform	1	13.542	13.324	0.830
	2	13.630		
	3	12.800		
Gaussian	1	13.651	13.451	0.782
	2	13.742		
	3	12.960		
Adaptive Feasible	1	13.541	13.331	0.371
	2	13.170		
	3	13.282		

Simulation results are written in table IV and graphically are shown in figure 5.

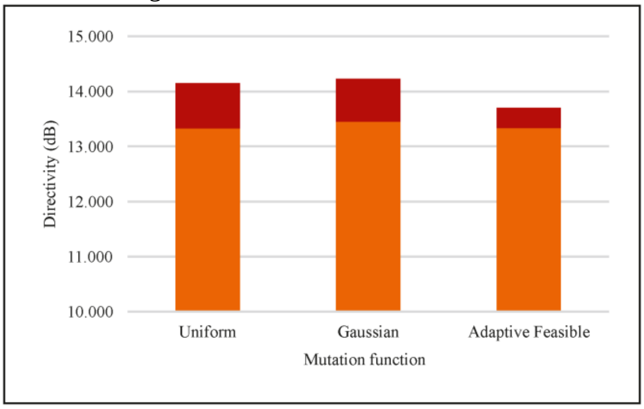

Fig. 5. Mutation function vs fitness value and variance on three identical algorithm setup runs.

From results shown in figure 5, in constrained designing problems, as the antenna here presented, the Adaptive Feasible function produces better results and smaller spread over different runs.

D. Parent selection function

In the genetic algorithm implementations are defined different functions used to select two individuals from current population as to be parents for procreating new child's and generate new generations. Each function has its own mathematical formulations that can be found in the Mathworks [11] website or Matlab manual or on different books treating evolutionary algorithms [4], [5].

Parent selection function is crucial to the convergence rate of GA, as "good" parents (with good fitness score) drive individuals to a better solution. However, the process of parent selection, is critical, as selecting parents with similar genetic information, can lead the optimization procedure in few generations to lose diversity, and solutions (new generations) being close to one other. Having a broad diversity in the populations, is crucial for exploring all the search space. The GA formulations, as to avoid losing diversity, uses mutation functions which with very low probability (≈ 0.01 rate), introduces genetic alterations as described in the previous section.

In this section five different functions, mentioned in the first column of table V, are being analyzed on the same N_{pop} = 130 (10 × N_{var}) and N_{elite} = 13 (10% of N_{pop}) and Adaptive Feasible function for mutation induction.

TABLE V. EFFECT OF SELECTION FUNCTION TO GA CONVERGENCE.

Selection function	**Test no.**	**Antenna directivity (dB)**	**Average directivity (dB)**	**Maximal difference**
Roulette	1	13.170	13.081	0.393
	2	12.840		
	3	13.233		
Tournament	1	13.545	13.584	0.413
	2	13.810		
	3	13.397		
Remainder	1	13.541	13.331	0.371
	2	13.170		
	3	13.282		
Stochastic Uniform	1	13.347	13.164	0.461
	2	13.260		
	3	12.886		
Uniform	1	12.075	12.077	0.645
	2	12.401		
	3	11.756		

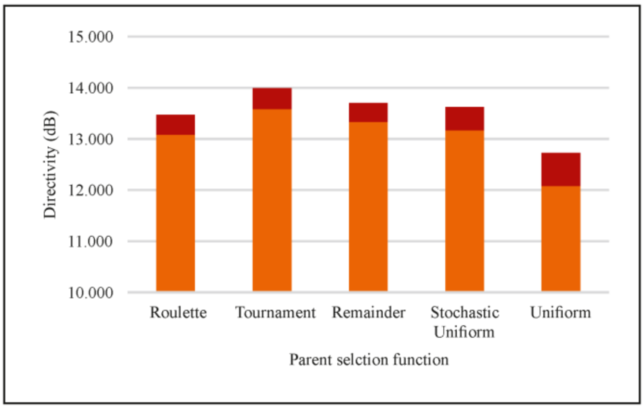

Fig. 6. Parent selection function vs fitness value and variance on GA runs

From the results presented in table V and graphically stacked in figure 6, the best selection function is Tournament. The worst selection function the Uniform function which present the worst obtained optimal solution after 2600 individuals evaluation on all the three runs. Also, the spread of solutions is the highest for Uniform function used to select parents. This results means, that GA need to run on other new generations as to have the same convergence as the Tournament function.

E. Recombination (Crossover) function

Recombination is one of the basic and more important process in any evolutionary algorithms. The recombination functions define how two parents combine their respective genetic heritage to create two child's, members of the next generation mimicking the natural reproduction process.

TABLE VI. EFFECT OF CROSSOVER FUNCTION TO GA CONVERGENCE.

Crossover function	Test no.	Antenna directivity (dB)	Average directivity (dB)	Maximal difference
Scattered	1	13.3476	13.164	0.461
	2	13.260		
	3	12.886		
Single-point	1	12.187	12.737	0.899
	2	12.938		
	3	13.086		
Two-point	1	12.951	12.968	0.405
	2	13.179		
	3	12.774		
Intermediate	1	13.744	13.701	0.105
	2	13.638		
	3	13.722		
Heuristic	1	12.088	12.524	0.935
	2	12.461		
	3	13.023		

In this section, four different functions are being analysed as named in table VI. Their respective definitions can be found in [11].

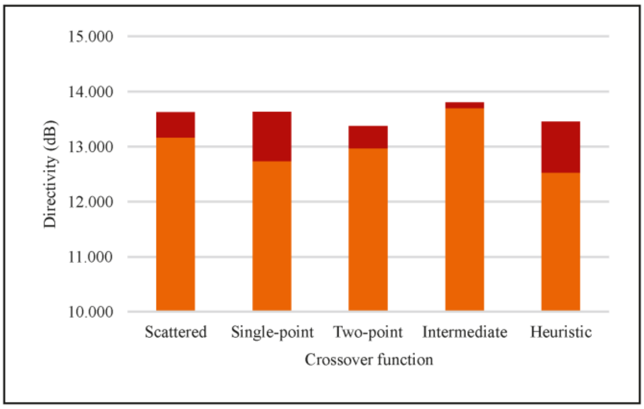

Fig. 7. Crossover function vs fitness value and variance on three identical algorithm setup runs.

From the presented results in table VI and figure 7, the Intermediate function used on recombination process, provides better individuals at the end of the optimization procedure on all three runs and with less spread. The next best function that can be a good candidate, is the Scattered one.

IV. OPTIMIZATION PROCEDURE

Optimization process involving genetic algorithm follows the flowchart shown in figure 2. With the knowledge of the previous sections, a last setup is performed with the best parameters combinations shown in the previous sections.

In figure 8 is shown the evolution of the optimization procedure on each generation. In this configuration, the mean value of the antenna gain (fitness parameter) is shown for the best value in each generation and the mean value over the entire population of the same generation.

Results displayed in figure 8 are for N_{pop} = 130 (10 × N_{var}) and N_{elite} = 13 (10% of N_{pop}), Adaptive Feasible function for mutation induction, Tournament function for parent selection and Intermediate function used for parent reproduction. Total generations number have been increased to 100 as to further evaluate the stopping criteria on optimized solution.

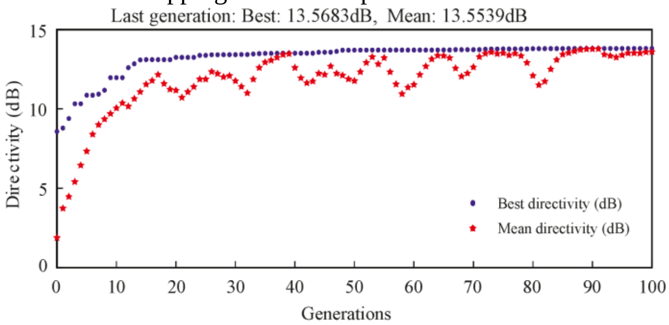

Fig. 8. GA evolution on the optimization process.

The evolution graphic presented in figure 8, shows faster convergence rate on the first 20 generations and later a slower improvement on the optimization process. The mean fitness value (directivity) obtained in each generation shows a good population diversity on each generation. Variations in the mean fitness value on each generation is a good indicator of wide solution search space from the chosen algorithm.

The best solution obtained at the end of the optimization process is shown as antenna profile in figure 9 and relative designing data are in table VII.

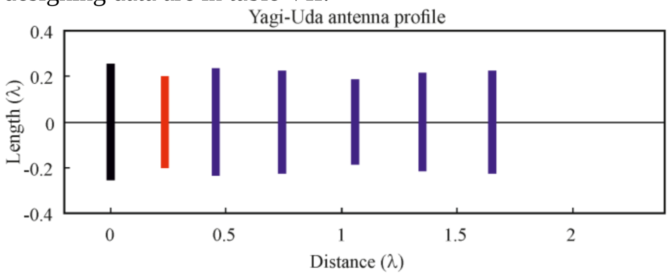

Fig. 9. Optimized Yagi-Uda antenna profile on the procedure described in figure 8.

From data presented in table VII, is evident that all the parameters in this designing process differs from one other and cannot be obtained without an automated optimization procedure as here described.

Results presented in table VII are provided by the genetic algorithm as the best input data, that analyzed by the "black-box" model (Method of Moments used to analyze antenna characteristics), have provided the best results in term of fitness value (maximum directivity).

The numerical optimization has no information about the physical meaning of the optimized problem, which is described by the "black-box" model.

TABLE VII. BEST ANTENNA PARAMETERS DESIGNED AT THE END OF OPTIMIZATION PROCEDURE

Antenna element	Length (λ)	Element position	Distance (λ)
l_R	0.510	d_{RA}	0.235
l_A	0.405	d_{Ad1}	0.219
l_1	0.470	d_{12}	0.289
l_2	0.449	d_{23}	0.317
l_3	0.372	d_{34}	0.293
l_4	0.432	d_{45}	0.298
l_5	0.449	–	–

The result obtained from the optimization, must be analyzed for relevance with the physical problem. For this reason, using the method of moments, as described in [6], we analyze the antenna whose dimensions of each element and relative distance are those presented in the table VII.

The current distribution obtained for this antenna is shown in the figure 10 where a physical meaning of the GA designed antenna takes place.

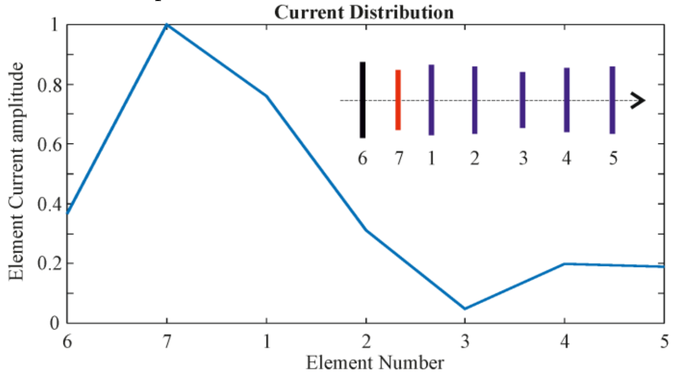

Fig. 10. Optimized antenna current distribution ove r the antenna elements, normalized to the active element amplitude

From electromagnetic antenna theory, known the current distribution on any antenna, radiated field can be calculated. The results of normalized radiated field on E-plane and H-plane are presented in figure 11 and figure 12. Where, H-plane of the antenna is that which is perpendicular to the axis of the elements and includes the direction of maximum radiation. Similarly, the E-plane is the one parallel to the axis of the individual elements including the direction of maximum radiation.

On both graphics, other antenna metrics are drowned such as Half Power Bean Width (HPBW), First Null Bean Width (FNBW), Front to Back ratio (F/B), Side Lob Level (SLL). Information derived by the mathematical model used for antenna analysis (the black-box) and not the optimization algorithm.

If required as metric parameters to be optimized, the mathematical model of antenna analysis must provide as output to the optimization algorithm, the required data information.

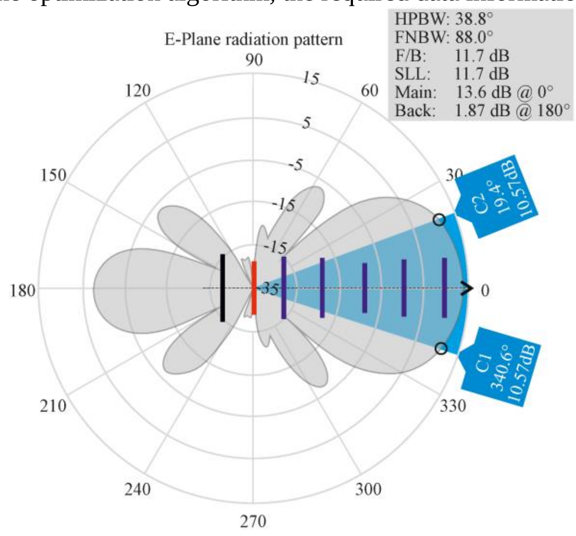

Fig. 11. Polar radiation pattern and antenna metrics on E-Plane.

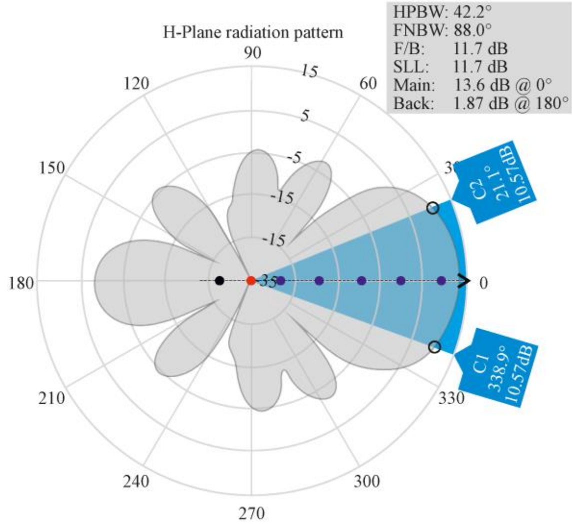

Fig. 12. Polar radiation pattern and antenna metrics on H-Plane.

V. DISCUSSIONS

Genetic algorithms are a very powerful optimization tool. Their ability to find global optima while being able to cope with very wide search space has motivated an increasing number of applications in engineering and related fields.

Teaching optimization methods, at graduated and under-graduated university courses, must logically be divided into two independent but related fields as follows:

1) Designing a numerical model of the physical problem.
2) Definition of an optimization method.

To have a successful optimization process, an appropriate modelling tool of the problem need to be firstly developed, and then, used as a "black-box" to the optimization tool (antenna design model in this example). Optimization algorithm is independent from the physical problem that need to be optimized.

The problem modelling tool, need to be designed with input and output interface to the optimization algorithm. Input interface must accept all the relevant information that can be changed in the problem design (antenna dimensions as in this example), and the output interface must provide all required metrics such as to evaluate and weight the goodness of the solution obtained (the directivity in this examples).

The correct setup of any optimization method, and GA in this case, are related to maintain a wide searching space of the optimal solution while speeding up the convergence to the optimal solution. So, population diversity needs to be monitored on each generation as maintaining population diversity allows a wider exploration of the solution space and avoids getting stuck on local minima. Monitoring the evolution of the optimization process as in figure 8, having mean values that differs from the best solution as shown in figure 8, is an indicator of population diversity. In this example where population is composed by 130 individuals.

Functions used to generate new individuals (crossover), functions that allows selection of new parents and functions that distribute mutations over the current generations can be selected based on the optimizing engineering problem and cannot be a unique good setup for all kind of problems.

VI. CONCLUSION

Genetic Algorithms are well understood and widely used on any engineering field on optimization process, products, and solutions. The optimization process is being more and more taught on graduated university courses as required contemporary competences on any engineering field. Even the GA is one of the most popular algorithms, in many courses, only the algorithm basics are explained, leaving the students on how to setup all algorithm parameters. Even the simplicity of the algorithm, still there are no unique and well-defined setup for all parameters or related to the designing problem.

In this material, an analysis of the influence of the setup parameters on constrained antenna design are presented (variables are limited in a selected range).

In GA setup for constrained problem, population number can be chosen as a starting point considering $10\times$ the number of problem variables ($N_{pop} = 10 \times N_{var}$). Elitism function can be set approximately to 10\% of population (N_{elite} = 10% of N_{pop}) or less, as to avoid losing population diversity from one generation to the next. The Adaptive Feasible function can be selected for the inducing genetic mutations, as required to create new genetic variation and to prevent the algorithm from getting stuck in optimal local solutions. Individuals' selection to become new parents, from the actual generation can be selected using Tournament function and their genetic heritage can be combined based on the intermediate function.

The presented configurations can be used as default setup of GA on constrained problem on teaching not only single-objective optimization problem, but more in general on optimization algorithms which core is based on GA workflow.

The presented setup configuration can be used as starting configuration of genetic algorithms on engineering problems where all input variables are constrained to a limited search space.

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