

Genetic Algorithms and Neural Network Approach in Determining the Directions of Linear Patch Antenna Arrays

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Abstract

Ahead of the Internet of Things and the emergence of big data, the interest of research is today focused on radio access and the process of optimizing it or increasing its capacity and capacity flow per user. During the process of determining the arrival directions and beam conformation at the antennas, different types of algorithms can be used, namely deterministic algorithms and heuristics. Genetic algorithms are part of heuristics called meta-heuristics. Although effective, observing a relatively long execution time when applied to spectral estimation methods and the subspace method. This case makes its integration into systems very difficult. The simulation of the same algorithms on the antenna array confirms the results but brings more in terms of signal integrity and throughput because it offers more channels. Several resolutions have been undertaken in this article to reduce the processing time of the genetic algorithm: the definition of a new policy of selection of the initial population and exploitation of the mutation procedure. By applying the genetic algorithm to MUSIC and a process of genetic mutation, we can reduce the latency of the linear antenna by about 70%. The running time of the algorithm leads us to explore neural networks.

Keywords

Array Antenna, DoA, Beam Steering, Genetic Algorithms, Neural Network

1. Introduction

Usually, the spatial distribution of the energy radiated by a base station antenna is pre-fixed at manufacture and cannot be changed in use. This leads to many disadvantages, such as the limitation of the number of users, the relative quality

of communications due to interference by adjacent channels, and the restriction of the range of stations. To correct these shortcomings, wireless communication systems increasingly rely on antenna arrays and the associated synthesis algorithms. Considering the fact that the synthesis algorithms are able to dynamically change and reconfigure their radiation pattern, the communication signal is transmitted only towards the direction of the intended user, possessing in a remarkable way the interferences and the multipath while reducing the spectral efficiency and power efficiency of the system.

In antenna engineering, several synthesis methods have been constructed. Stochastic methods are more robust than deterministic algorithms. Among the most popular stochastic methods, we can cite the genetic algorithm [1] [2], the swarm of particles...Analytical methods display computation times close to 0.1345 s [3] [4]. RBFN and MLP [4] [5] neural network methods associated with analytical methods sometimes improve the computation time. The execution time remains around 0.13 s. By associating genetic algorithms with analytical methods, the average computation time of the genetic algorithm increases and is around 2.7 s.

However, this method, inspired by the work of Marc Darwin [6]-[8] in the 19th century, therefore arouses little enthusiasm and is less and less integrated into the system of antennas and electronic devices because of its latency time. Situations that make it impossible to use them in real-time systems. We propose to reduce the computation time of genetic algorithms.

In the first section devoted to the literature review, we present what has been done in the field of antennas to reduce the execution time of the various synthesis methods in general and stochastic methods in particular. At the same time, we will present the problems related to genetic algorithms.

Thereafter, the second section will present the tools and methods used to contribute to the problem of latency of the genetic algorithm.

Finally, the last section will be devoted to the presentation of the results, discussion, and perspectives.

2. Method

1) *Design*

We used an antenna array because, in a MIMO environment, the antenna offers more input and output possibilities and creates the conditions for efficient use of the genetic algorithm: Choice of the fitness function, define solution types, fix the criteria for stopping the algorithm (Number of generations or stability of individuals after a certain number of generations) and define a new selection policy for the initial population.

2) *Mathematical Formalization of the Antenna Array* [9]

We consider a MIMO system composed of m_t antennas on transmission and m_r antennas on reception. We note x , the vector of size m_t , containing the symbols sent, and y , the vector of size m_r , containing the symbols received. The relation between x and y is then written:

$$y = Hx + n \tag{1}$$

$$C = \log \left(\det \left(I_{m_r} + \rho H Q H^* \right) \right) \tag{2}$$

$$C = \sum_{i=1}^{m_r} \log_2 \left(1 + \frac{\rho}{m_t} \lambda_i \right) \tag{3}$$

where H is the channel matrix of size $m_t \times m_r$, and n is the noise vector. The capacity of the MIMO channel is then written:

I_{m_r} is the identity matrix, ρ is the signal-to-noise ratio and Q is the correlation matrix of the transmitted symbols. λ_i is the eigenvalues of the matrix $H^* H$

a) *Antennes Array* [10]-[12]

In this work, our study will be limited to uniform linear antenna arrays, as represented in **Figure 1** below.

Consider a uniform linear network of elements regularly spaced by a distance (see **Figure 1**). These sources are supplied with the same amplitude and with a phase gradient. For a point P located in the far radiation zone, the total field is the sum of the field radiated by each of the sources, *i.e.*:

$$E(\vartheta) = E_0(\vartheta) \sum_{k=0}^{K-1} \exp \left[jk \left(2\pi \frac{d}{\lambda} \sin \vartheta + \varphi \right) \right] \tag{4}$$

where $E_0(\vartheta)$ is the radiation of an isolated element. The array factor $AF(\vartheta)$, which depends solely on the excitation law of the antenna elements and their arrangements, is defined by:

$$AF(\vartheta) = \sum_{k=0}^{K-1} \exp \left[jk \left(2\pi \frac{d}{\lambda} \sin \vartheta + \varphi \right) \right] \tag{5}$$

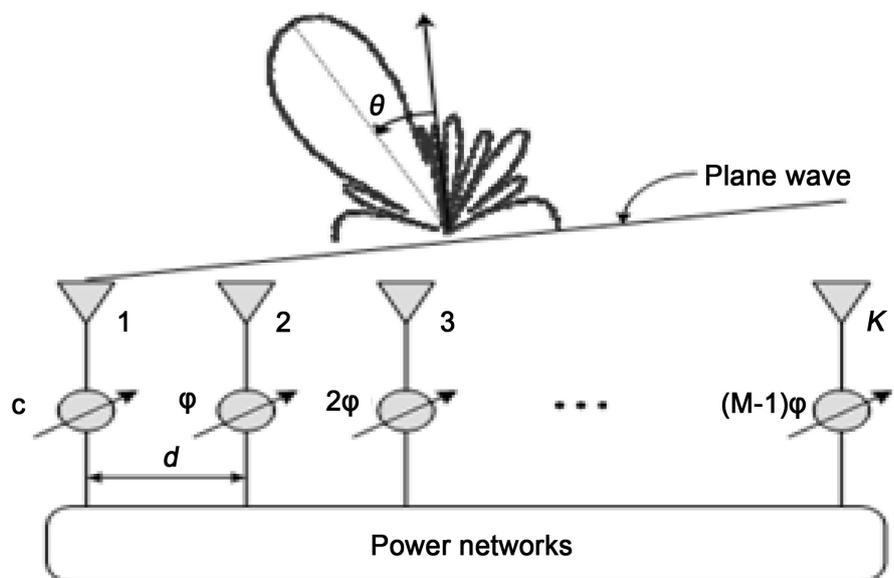


Figure 1. Beam-scanned linear array.

This array factor is further written.

$$AF(\vartheta) = \frac{\sin \left[\frac{K}{2} \left(2\pi \frac{d}{\lambda} \sin \vartheta + \varphi \right) \right]}{\frac{1}{2} \left(2\pi \frac{d}{\lambda} \sin \vartheta + \varphi \right)} \exp \left[j \frac{K-1}{2} \left(2\pi \frac{d}{\lambda} \sin \vartheta + \varphi \right) \right] \quad (6)$$

To obtain a maximum of radiation in a given direction, it is necessary to find the phase gradient that maximizes the modulus of the network factor in this direction, that is:

$$2\pi \frac{d}{\lambda} \sin \vartheta_0 + \varphi = 0 \quad (7)$$

In other words, the pointing direction of the network will be given by the relation:

$$\vartheta_0 = \sin^{-1} \left(\frac{\gamma \lambda}{2\pi d} \right) = 0 \quad (8)$$

Equation

It is possible to adjust the orientation of the radiation of an array antenna by playing on the phase gradient between its antenna elements: this is the principle of sweep antennas [6] [13] [14].

Chromosome Coding:

The directions of arrival that must be found by the GAs are real; each individual of the population representing all the directions of arrival will be coded in real value.

Each chromosome (individual) will, therefore, be a vector of real numbers of size equal to the number of sources to be located.

The value of each of the elements (genes) of the chromosome vector will belong to the set of possible values of the directions of arrival (search space). It is illustrated in **Figure 2**.

ϑ_1
ϑ_2
ϑ_3
ϑ_4
ϑ_5
ϑ_6
ϑ_7
ϑ_8

Figure 2. Chromosome vector.

Search Space:

The search space of the different genes corresponds to the set of values that a

direction of arrival can take. For a linear network, and taking into account the periodicity of the directions, this is any interval of length 180° .

We chose the interval $[-90^\circ, 90^\circ]$.

Any gene found outside this interval after a crossing operation will simply be brought back to the corresponding value by a periodicity of 180° .

Population Initialization:

To try to reduce computation times, the population will be initialized to associate chance and intelligence. The first individual will be generated from a basic DoA estimation method (pre-estimator).

Then, chance will intervene to complete the population by randomly generating other individuals in the vicinity of the first.

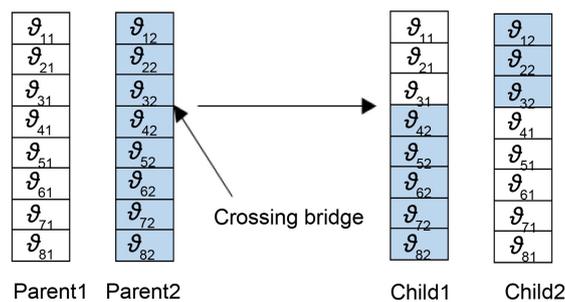
From an individual $[\theta_1, \theta_2, \dots, \theta_L]$, produced by the pre-estimator, we will randomly generate other individuals $[\theta_1 + \alpha_1, \theta_2 + \alpha_2, \dots, \theta_L + \alpha_L]$, where the α_i are random numbers, until the desired population size is reached.

Evaluation:

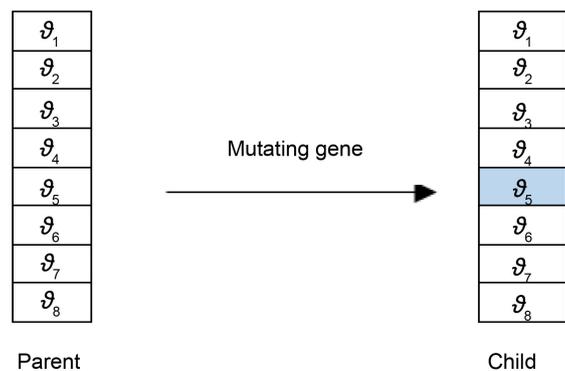
The assessment is based on the fitness of each individual. Given the nature of the cost function, which is a function to be minimized, the fittest individual will be the one whose value of the cost function ($f\{[\theta_1, \theta_2, \dots, \theta_L]\}$ for the individual $[\theta_1, \theta_2, \dots, \theta_L]$) is the lowest.

Crossover:

The crossover method adopted is one-point crossing. The cross point is randomly selected, as illustrated in **Figure 3(a)**.



(a)



(b)

Figure 3. Crossover process.

Mutation:

The mutation comes in very little to reduce the random nature of the search a bit. The mutation rate is set at 2%. The mutant gene is also chosen randomly, as shown in **Figure 3(b)**.

Survival Policy:

Only the best individuals will be part of the next generation, at a rate of 25% for parents and 75% for children.

Stop Criterion:

The DoA estimation process stops if the maximum number of generations is reached or if the best individual has remained the same for the last ten generations.

An example of the parameters of a genetic algorithm applied to the estimation of the directions of arrival:

Chromosome Coding: reel.

Population Size: 50.

Max Generation Number: 50.

Initialization: mixte (Pré-estimation et hazard).

Research Area: $[-90^\circ, 90^\circ]$.

Selection: Emperor-Selective Scheme (EMS).

Reproduction: Crossover (2% mutation).

Stopping Criterion: Maximum number of generations or best stable individual over the last 10 generations.

To reduce the computation time of the directions of arrival, we have tried to take measures aimed at increasing the speed of convergence compared to the classical genetic algorithm. **Figure 4** shows the flowchart of the genetic algorithm. We acted on several levels:

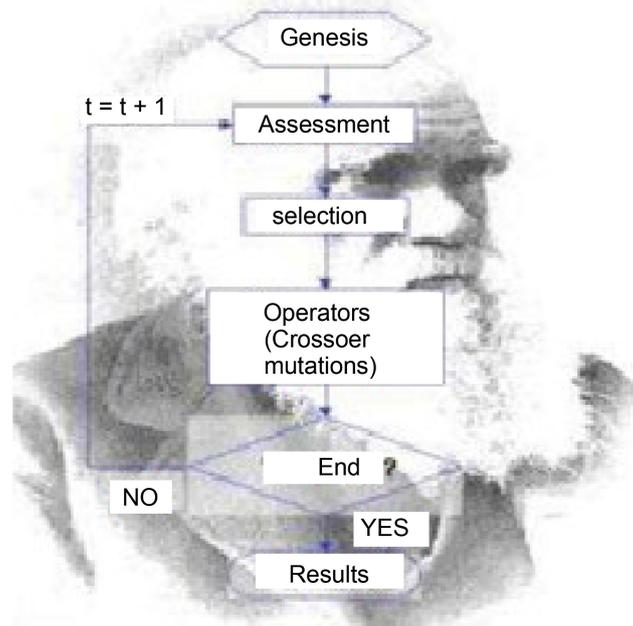


Figure 4. Flowchart of genetic algorithm [7] [8].

- On the choice of coding: real rather than binary.
- At the initial generation, the population is initialized, not randomly as in the classic approach, but a little more intelligently from a supposed good candidate (pre-estimated) provided by a pre-estimator whose choice is based on the compromise resolution/computation time.
- At the mating pool selection, we have opted for the elitist strategy, which consists of taking the best individual as one of the parents of all the children.
- Selection for the future generation: only the best individuals, chosen exclusively between parents and children, are allowed to survive in the next generation.
- On the stopping criterion, the evolution of the population can be stopped when the best individual has remained the same over a certain number of consecutive generations; this allows the algorithm.

3. Results and Discussion

This section presents the results that we obtained by simulation of the various algorithms for the synthesis of the networks of antennas. We compare them to the results obtained by modified genetic algorithms.

1) *Traditional Methods of Determining the Directions of Arrival*

We can observe, for elements too close together, a clear degradation of the quality of the estimation of the angles of arrival. This can be explained by the increase in mutual coupling effects between radiating elements, which are not taken into account in our model.

The noise degrades the quality of the estimate, however, this one has practically no effect on the methods based on the decomposition in subspace like PISARENKO, MUSIC, and Minimum standard, to name a few [15]-[18]. In **Table 1**, we have the processing time of the classic method and AG method calculated by the Matlab code of this method.

Table 1. Comparison of DoA process time.

Method	Average process time (s)
BARLETT	0.17566
CAPON	0.178447
PRONY	0.190271
MEM	0.177403
PISARENKO	0.173082
MUSIC	0.17947
NORM-MIN	0.172794
ML-AG Classique	1.5 (45 gén)
ML-AG Intelligent	0.46 (12 gén)
AG-BARLETT	0.265775

Continued

AG-CAPON	0.274417
AG-MEM	0.269666
AG-PISARZSKO	0.272009
AG-NORM_MIN	0.264251
AG-MUSIC	0.268659

2) Processing Time

The antenna uses 10 elements and four sources. We obtained the following process times:

It is clear that the methods based on genetic algorithms are the slowest. However, with the approach we propose, we manage to reduce the computation time by 70%. We thus go from a computation time ratio of around 10 (classic ML-AG) to a ratio of 3 (intelligent ML-AG) when compared to basic techniques.

Applying a genetic algorithm to MUSIC using an antenna array designed with 10 elements and 3 source samples. Music has the best resolution. **Figure 5(a)** and **Figure 5(b)** plot the distribution of radiated energy to determine the direction of arrival. **Figure 5(c)** shows the convergence of the fitness function. The time of convergence of the classic is too high.

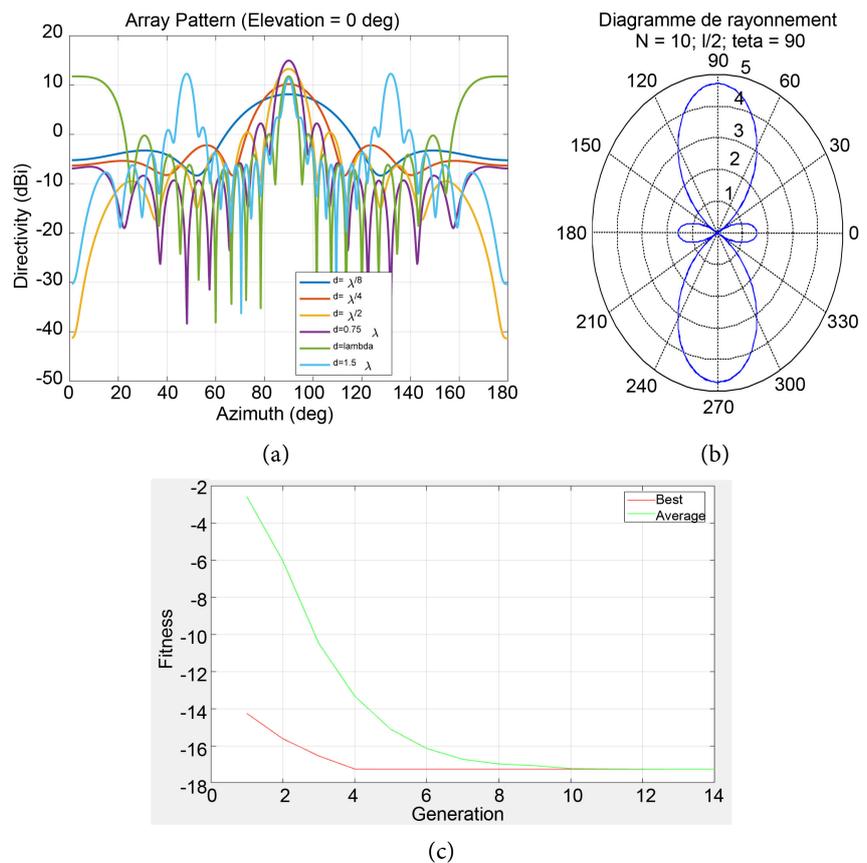


Figure 5. AG_sur_MUSIC on a planar antenna, 10 elements, 3 sources, SNR = 30 dB.

Table 2 shows the error of the estimation process, and **Table 3** shows the process time. The error is null, and the processing time is long for AG, but can be used in real-time applications.

Table 2. The error was committed in the estimation process.

DoA Estimated	DoA Detected	Error Committed
50	50	0
80	80	0
120	120	0

Table 3. Comparison of processing time analysis and AG method.

	Time (s)
Time for Analytical Method	0.603745
Time for AG	1.74493

3) Results (Processing Time) of the AG Approach

To validate our approach, we simulated the classical approaches and the same methods coupled to GA on different types of antenna arrays under the following conditions (**Table 4**): 3 sources (50°, 80°, and 120°), 10 elements with distance factor of 0.5 and 100 samples and 30dB signal to noise ratio. The simulation gives us the following results.

Table 4. Simulation of different algorithms on planer antenna, 10 elements, 3 sources, and rapport signal/noise = 30 dB.

	Analytic Method (s)	AG_Analytics (s)
Prony	0.6927	0.357
MinNorm	0.4149	0.3577
Capon	0.3524	0.2422
Pisarenko	0.2868	0.2438
MEM	0.2999	0.4108
MUSIC	0.1322	0.3821
Barlett	0.03122	0.4219

The results present slowness for genetic algorithms in general. These delays persist when the number of antenna elements is reduced. But it still improves the execution time of the algorithms. We can see this in **Table 5** below.

To improve the efficiency of genetic algorithms, **Figures 4-6** below show the results obtained by GAs. On the first, we have the evolution curve obtained by classic AG, and on the second, the curve obtained by “intelligent” AG. We can see:

- The qualities of the estimates remain comparable in the two cases;
- In the second case, convergence (stability) happens much faster (around the

12th generation) than in the first (around the 40th generation) and practically in a ratio that is between 1/4 and 1/3, which means a DoA estimation time about 3 to 4 times shorter, considering that the time needed for the pre-estimator is negligible compared to the overall time.

Table 5. Simulations of different algorithms on planar antenna, 5 elements, 3 sources, and rapport signal/noise = 30 dB.

	Analytic Method (s)	AG_Analystics (s)
Prony	0.6927	0.357
MinNorm	0.4149	0.3577
Capon	0.3524	0.2422
Pisarenko	0.2868	0.2438
MEM	0.2999	0.4108
MUSIC	0.1322	0.3821
Barlett	0.03122	0.4219

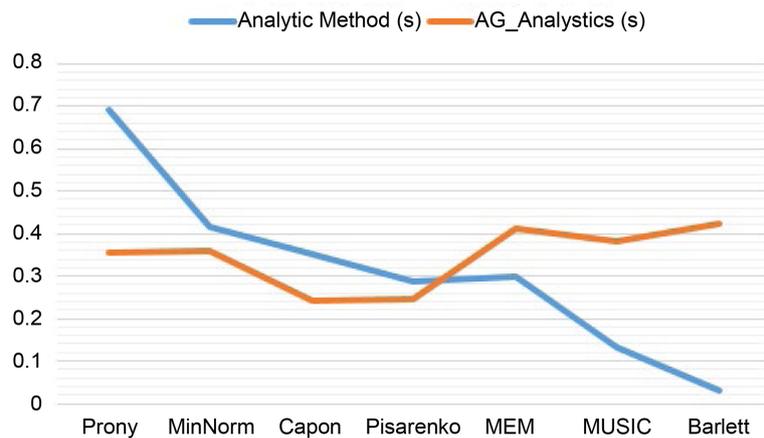


Figure 6. Simulation of different algorithms on planer antenna, 10 elements, 3 sources, and rapport signal/noise = 30 dB.

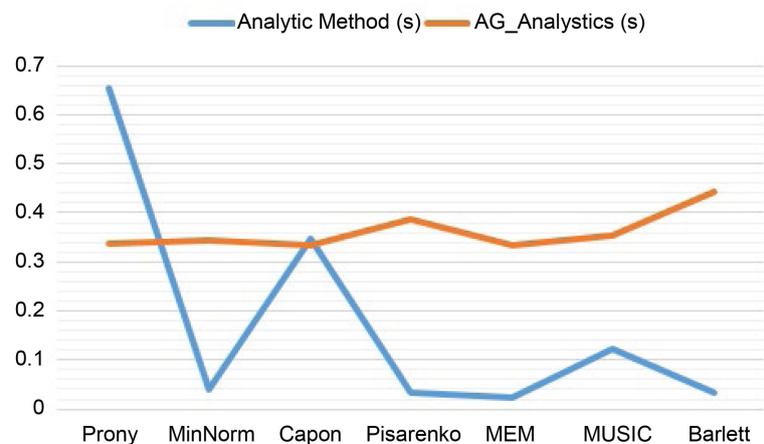


Figure 7. Simulations of different algorithms on planar antenna, 5 elements, 3 sources, and rapport signal/noise = 30 dB.

These results clearly show that the measures taken with the intention of reducing the computation time do indeed have a significant positive effect on the computation time, since they make it possible to save around 70%.

To check the reproducibility of these results, we repeated the simulation with 6 sources and then with 2, and the findings are substantially the same. (Figure 6 and Figure 7)

Figures 8(a)-(c) plot the distribution of radiated energy to determine the direction of arrival. Figure 8(d) shows the convergence of the fitness function. The time of convergence of the classic is too high.

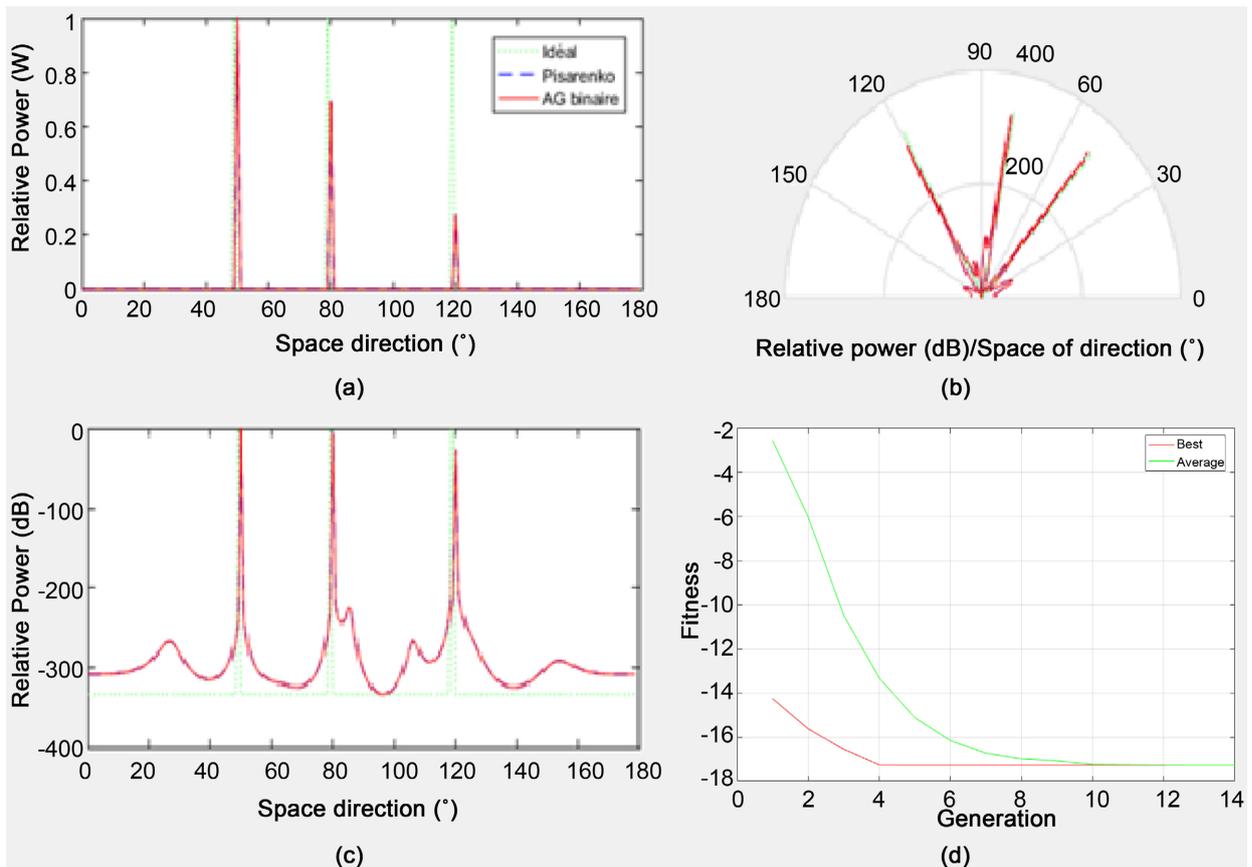


Figure 8. Classic AG with 10 elements and 3 sources.

Figure 6 illustrates the convergence speed of the genetic algorithm using the modified genetic algorithm.

Table 6 shows the error of the estimation process, and Table 7 shows the process time. The error is low and can't disturb our DoA process. The process time is long for AG but can be used in real-time applications.

Figure 8(d) shows the convergence of the fitness function for Smart AG. The time of convergence of this is too low.

The table below shows the result of applying a genetic algorithm to the beam-forming process. The process time is lower than the analytic method. We can read it in Table 5 below.

Table 6. The error was committed in the estimation process.

DoA Estimated	DoA detected	Error Comitted
50	50.5	0.5
80	81.5	1.5
120	86.5	-33.5

Table 7. Comparison of processing time analysis and AG method.

	Time (s)
Time for Analytical Method	0.0770687
Time for AG	0.308275

4) *Classic Methods of Beamforming and Those Combined with Genetic Algorithms*

As explained above, the second part of using smart antennas is beamforming. We have in **Table 8** and **Table 9** below the results of the simulations of the different beamforming algorithms. **Figure 9** and **Figure 10** compare the two algorithms. We highlighted the beamforming time and the efficiency of genetic algorithms to reduce this delay, which, at the beginning, was within acceptable limits. The GA divides the initially high time by 30. The comparison of processing time analysis with the AG method is shown in **Table 10**.

Table 8. Simulation of different beamforming algorithms on antenna planar, AG binaire, 10 elements, 3 sources, and SNR = 30 dB.

	Analytic Method (s)	AG_Analytics (s)
LMS	3.41561	0.142317
CMS	3.59347	0.143728
MVDR	3.24273	0.135114
RLS	4.31776	0.179907
DMI	3.664009	0.152671
Nullsteer	0.118367	0.116543
Conv	0.118367	0.164399

Table 9. Simulation of different beamforming algorithms on AG binary antenna planar, 5 elements, 3 sources, and SNR = 30 dB.

	Analytic Beamforming Method	AG_Analytic Beamforming Method(s)
LMS	0.6927	0.357
CMS	0.4149	0.3577
MVDR	0.3524	0.2422
RLS	0.2868	0.2438
DMI	0.2999	0.4108
Nullsteer	0.1322	0.3821
Conv	0.03122	0.4219

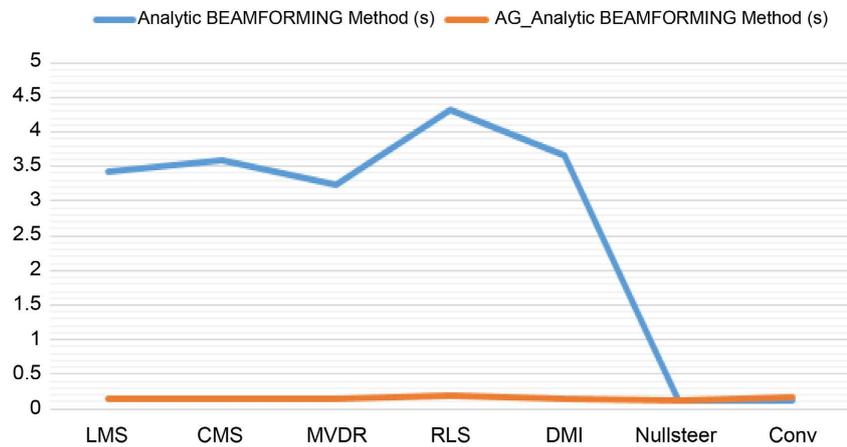


Figure 9. Simulation of different beamforming algorithms on antenna planar, AG binaire, 10 elements, 3 sources, and SNR = 30 dB.

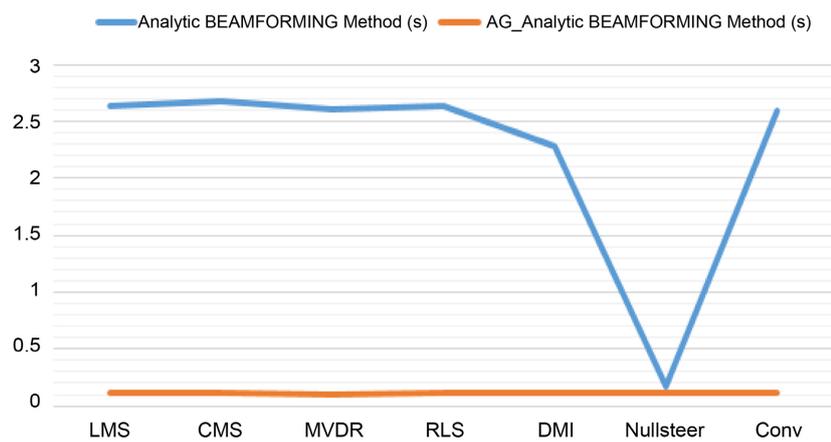


Figure 10. Simulation of different beamforming algorithms on AG binary antenna planar, 5 elements, 3 sources, and SNR = 30 dB.

The determination of signal arrival and beamforming has another virtue, which is the reduction of energy consumption in a 5G architecture [19]. It is illustrated in **Figure 11**.

Figures 11(a)-(c) plot the distribution of radiated energy to determine the direction of arrival using AG_sur_Nulls. The processing time in **Table 9** is satisfactory for real-time applications.

4. Conclusions

The results allowed us to assess the effects of a certain number of parameters on the precision of the algorithms for calculating the angles of arrival and the shaping of the associated beams within the framework of a wireless communication system with networks of antennae. The tests carried out show that:

- Despite the diversity of the quality of the results provided, the computation times remain comparable for the classic DoA estimation methods, the slowest being the PRONY approach (linear prediction).

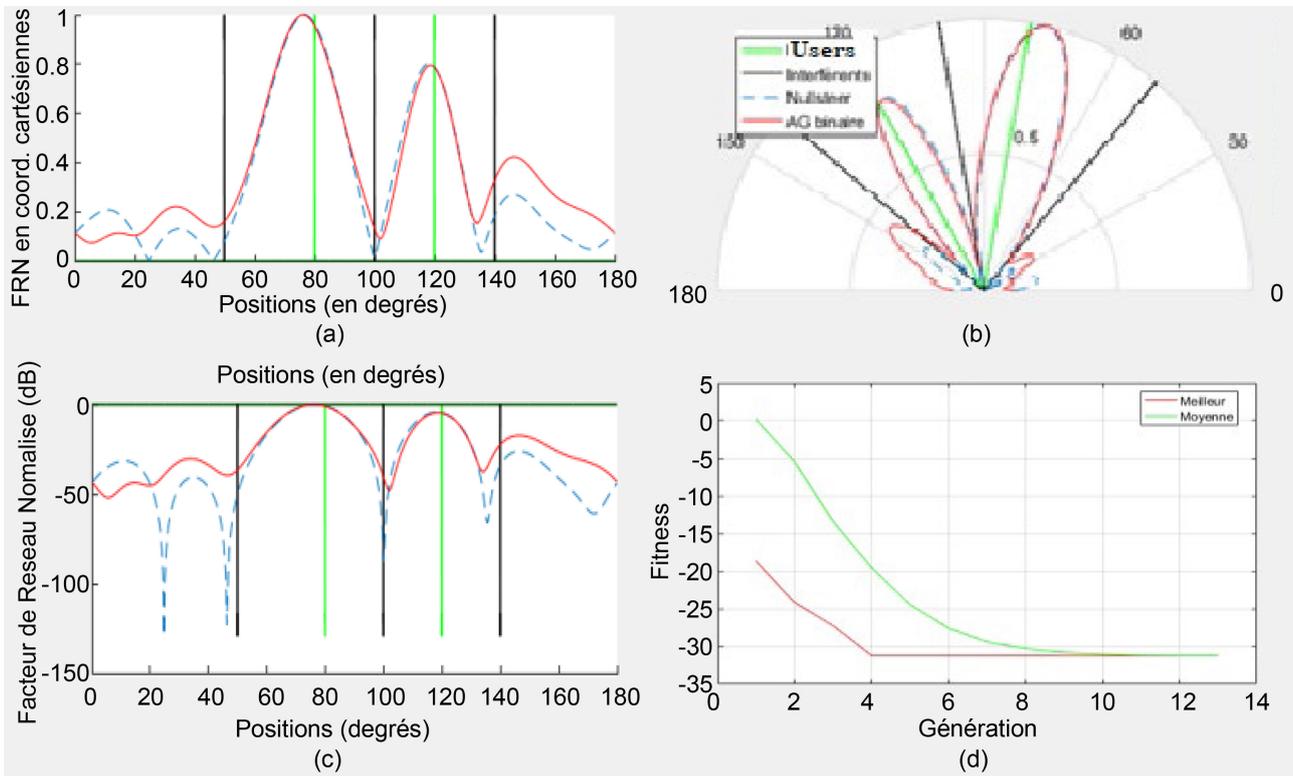


Figure 11. Smart AG with 2 sources.

Table 10. Comparison of processing time analysis and AG method.

	Time (s)
Time for Analytical Method	0.127897
Time for AG	0.11627

- The classic GA approach, which has the advantage of being a global optimum search technique, requires a longer calculation time which is around 10 times the time required for a local optimum approach.
- In addition, AG reduces beam shaping time by 30 times.
- We also note that GAs and spectral methods reduce the influence of noise on communications to zero.

We have proposed a new approach based on GAs, which we have named “smart GA”. It considerably reduces this computation time. The result obtained is around 70% reduction.

The tests carried out show that despite the diversity of the quality of the results provided, the computation times remain comparable for the classic DoA estimation methods, the slowest being the PRONY approach (linear prediction); the classical GA approach requires a longer computation time which is around 10 times the time required for a local optimum approach. In addition, AG reduces beam shaping time by 30 times. We also note that GAs and spectral methods reduce the influence of noise on communications to zero.

Among other processing techniques, neural networks have been used to avoid interference in planar antenna arrays. They also offer computational capabilities and performance [20]-[22]. However, neural networks seem to have a head start because they use a learning and memory module to save the different positions of the useful signals.

Data Availability

The data used to support the findings of this study are included in the article. The code used to plot and process data can be provided in a supplementary section.

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Conflicts of Interest

The authors declare that there are no conflicts of interest.

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