5th International Conference on Experiments/Process/System Modeling/Simulation/Optimization
5th IC-EpsMsO
Athens, 3-6 July, 2013

DETERMINATION OF ACOUSTIC ARRAY CONFIGURATION FOR OPTIMAL BEAMFORMING USING GENETIC ALGORITHMS: PART I – MODEL/ALGORITHM DEVELOPMENT AND VERIFICATION

Tsahalis D. [1], Moussas V.C.[1,2], and Tsahalis H.-T.[1]

[1] Paragon S.A.
Protopapadaki 19, Galatsi, GR-11147, Athens, Greece
e-mail: htsahalis@paragon.gr, web page: http://www.paragon.gr

[2] School of Technological Applications, Tech. Educ. Inst. (TEI) of Athens,
Ag. Spyridonos Str., Egaleo 12210, Athens, Greece
e-mail: vmouss@teiath.gr, web page: http://users.teiath.gr/vmouss

Keywords: Acoustic arrays; beamforming; farfield noise; antenna response patterns; array geometry; DOA estimation; optimization; genetic algorithms;

Abstract. *This paper deals with the problem of improving the directional response pattern of a beamforming array using genetic algorithms to select the optimal geometry and microphone positions. The methodology adopted is based on the simultaneous optimization of two metrics from the response pattern, i.e., dynamic range & angular resolution. Array optimization also depends on the array beam pattern and the steering direction. A genetic algorithm is used to build a multi-objective array optimization tool and the fitness evaluation is based on the performance metrics of each candidate array configuration. The optimal solutions achieved by the developed tool, lead to new geometries that outperform the original array characteristics in both sensor number and performance metrics*

1 INTRODUCTION

Acoustic arrays are widely applied for sound/noise source detection and localization, using far field Beamforming (BF) and Direction of Arrival (DOA) techniques. The performance of these BF or DOA techniques depends highly on the array response pattern, its directivity, the level of its side-lobes, its main-lobe width, and other performance characteristic. These characteristics are based on the antenna array design parameters such as the number of elements, their spacing, the size of the array, the shape/geometry, etc. To achieve better performance, the acoustic array designer has to solve an optimization problem that involves multiple objectives and many design parameters, in order to select the most efficient array configuration among many candidates.

In antenna array design, while there has been a lot of research on the signal processing aspects of the problem, the physical geometry of the arrays (shape and element location) has received relatively less attention due to the mathematical complexity of dealing with the optimization of the element positions. The recent advances in numerical computing and the large increase in computational capability put array geometry optimization again under investigation [1], using advanced optimization schemes such as genetic algorithms [2], particle swarm [3], ant colony [4], etc.

In this paper the application of genetic algorithms (GAs) to optimal acoustic array geometry selection & configuration is demonstrated. These biologically inspired optimization schemes are robust to problems involving multiple objectives and many design parameters and capable of efficiently searching the parameter space to find a near-global optimal solutions. Example cases are also presented to demonstrate the optimization tool performance.

2 EVOLUTIONARY OPTIMIZATION WITH GAs

Genetic Algorithm is a class of Evolutionary Algorithms that works on the principle of survival of the fittest via natural selection [5]. The basic Genetic Algorithm performs the following steps:

1. Generates an initial population.
2. Computes the fitness for each individual.
3. Selects the parent couples

4. Creates the offsprings from the parents.
5. Selects the final individuals of the next generation
6. Returns to step 2 until a satisfactory solution is obtained.

A Genetic Algorithm optimizer can use various forms of selection, cross-over/ mutation (steps 3 to 5) to evolve the initial population. The important parameters of a GA are the:

- Population size.
- Number of generations.
- Crossover types and Mutation rates.
- Selection procedures.

where,

Crossover, is an exchange of substrings denoting chromosomes, for an optimization problem,
Mutation, is the modification of bit strings in a single individual, and
Selection, is the evaluation of the fitness criterion to decide which individuals from a population will go on to reproduce.

As shown in Figure 1, the GA cycle (steps 2 to 6) is repeated until a termination condition has been reached, such as: a solution that meets the criteria, the maximum number of generations, the maximum time allowed, etc. The members of the last generation with the highest score(s) is the best solution or set of solutions ppredicted by the algorithm.

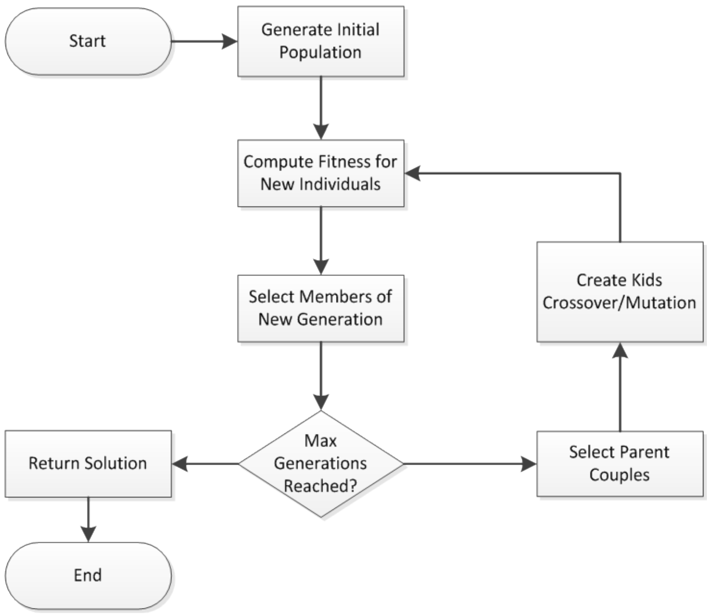


Figure 1. The Genetic Algorithm optimizer flowchart

GA optimizers have been found to perform much better than local optimization methods at dealing with solution spaces having discontinuities, constrained parameters, a large no. of dimensions with many potential local maxima. Evolutionary genetic algorithm (GA) optimizers are particularly effective when the goal is to find near-global maxima in a multi objective optimization problem. These properties make them one of the best candidates to tackle the acoustic array design optimization problem.

3 ACOUSTIC ARRAY DESIGN OPTIMIZATION TOOL

When designing an acoustic array antenna, the designer is faced with a large number of candidate solutions controlled by a larger number of parameters, that must be ordered by some criteria and objectives.
In order to compare and select the best solution, the optimization tool will use a number of criteria for the array performance that depend on the designers needs and restrictions. Such performance indicators/metrics are:

- **Spatial resolution,** the ability to separate two sound sources. It is expressed usually in centimeters. It represents the closest distance between two sources, where they still appear separately and do not merge into a single source. The lower the spatial resolution, the better the source localization. In this work the **Angular Resolution** is used instead, in order to remove the dependency from the unknown source distance.
- **Dynamic range,** expresses sound level differences in dB between real sound sources and surrounding

mathematical artifacts inherent to the sound source localization techniques. The higher the dynamic range, the better the source localization. (In beamforming techniques, the dynamic range is also linked to frequency – the lower the frequency, the higher the dynamic range). In this work it is measured as the difference between the mainlobe and the highest sidelobe.

- **Number of Microphones**, that require acquisition channels & infrastructure that is not always available, so the lower their number the better, as long as the data acquisition requirements are met.
- **Working frequencies,** the f_{min} & f_{max} limits of the array should meet the expected signals from the sound sources.
- etc.

There are many design parameters too that affect the performance of an acoustic array such as:

- The number of array elements,
- their characteristics (MIC pattern, orientation, freq.-range),
- the array Geometry (shape, size, distance, diameter),
- the MIC positions,
- any Restrictions,
- the source signal characteristics (freq.-range, direction, distance, if .), and,
- the focus direction and scan grid.
- etc.

A function to connect the above parameters to the performance metrics is therefore required in order to evaluate each design proposed. As there is no analytical form, the need of a simulation tool to play the role of the fitness function is obvious.

The acoustic array optimization tool structure is therefore composed of two main parts. A Genetic Algorithm optimization part and an Array Analysis/simulation part. At the heart of the optimization tool is the classic GA optimizer which can use various forms of selection, cross-over, and mutation to evolve the design population. The acoustic array analysis part plays the role of a Fitness Function. It calculates the score (metrics) of each individual (array design) and it returns it to the GA for the selection process. Its functioning is based on the Acoustic Array Beamforming Analysis tool presented in [6]. Based on the above, a detailed structure of the module is shown in Figure 2.

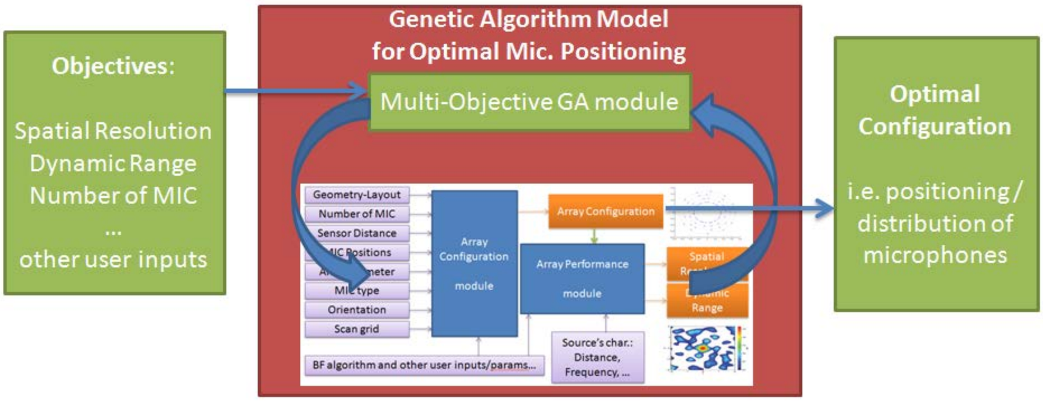


Figure 2. Detailed structure of the Acoustic array design optimization tool
with the GA module and the AABA module cooperation

The optimization starts with a set of initial solutions the first generation. Each individual in a GA generation is a possible array implementation, and it is characterized by a chromosome containing all element positions (in Cartesian coordinates). When the runs are completed, the finally survived/fittest individual(s) is the near-global optimal solution predicted by the optimization tool.

3.1 GA Parameters Setup

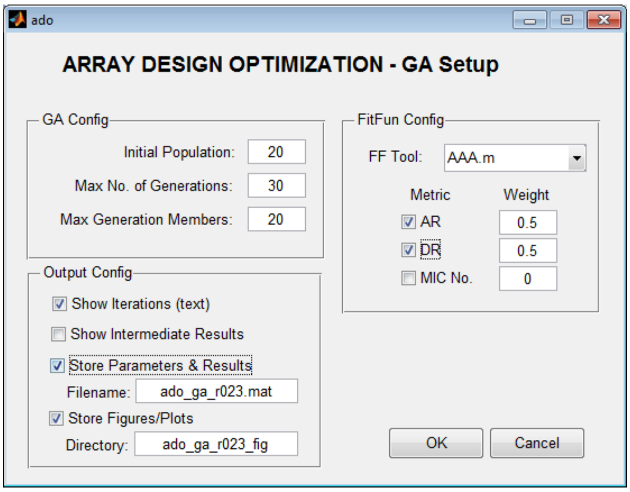


Figure 3. GA Parameters Setup GUI

The GA parameters are passed to the tool by the user either via a GUI or by a common variable ‘options’, Figure 3. The specific Fitness Function (FF) tool AABA offers performance metrics that can be used separately or combined with appropriate weights. The results can be also stored in .mat files for later use and the intermediate results may be suppressed for faster execution.

3.2 Optimization Goals

Depending on the specific array design case under consideration, the goals of the designer may be different. For example:

- When there are multiple sources in the area that need to be separated, the designer must improve the spatial resolution of the array, i.e., the designed array should have as small as possible Angular Resolution (AR) in its main lobe.
- When the array is in a noisy environment with reflections and interference, the designer must increase the difference between the main-lobe and the highest of all side-lobes i.e. increase the Dynamic Range (DR) of the array.
- When in a shortage of acquisition channels or time, the designer must reduce the number of connected/sampled microphones to the minimum acceptable without reducing performance.

It would be simple to solve each of these cases but they are rarely posed alone. The problem with the above goals is that they are contradictory (when AR is improved, DR is decreased, when using less microphones SNR is reduced, etc.) and that they are always posed in combination. This constitutes a Multi Optimization Problem and an advance optimization tool like the one proposed here is required.

4 ARRAY DESIGN OPTIMIZATION

To demonstrate the Array Design optimization tool we selected two representative Test Cases where the proposed optimizer was used to provide optimal solutions, such as:

1. For a specific array configuration, and for a reduced number of microphones, find the subset that will perform equally (or better) to the original setup at a specific direction.
2. Change the array geometry (at random) and find a better one with improved characteristics using the same number of microphones and the same array size.

In our examples the original array geometry is a Uniform Circular Array with 6 concentric circles and with 13 MICs equally place on each circle, i.e. a total of 78 MICs.

4.1 Case 1 – Define an Optimally Reduced Array

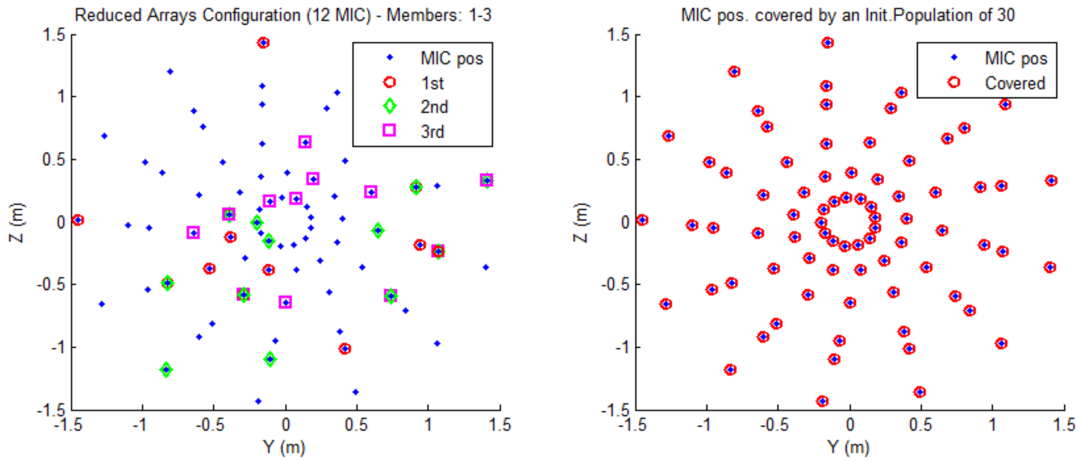
The original array configuration has 78 MICs arranged in four concentric circles uniformly. The objective of the designer is to find a reduced version with fewer MICs without altering the array geometry and by simply deactivating the redundant MICs.

The aim is to define the best subset of these 78 elements that could be used equivalently for the monitoring of the experiments. This would reduce significantly the total amount of recorded data while freeing up a significant number of acquisition channels. The requirements for the new reduced acoustic array are contradictory, and include:

- To keep the same or better Angular Resolution (AR)
- To have the same of lower side lobe level i.e. better Dynamic Range (DR), and,
- To use a subset of the original microphones (i.e., 50 or 40 instead of 78).

These requirements pose to the designer a multi-objective optimization problem where one of the leading methods is the Genetic Algorithm optimization implemented by the developed tool.

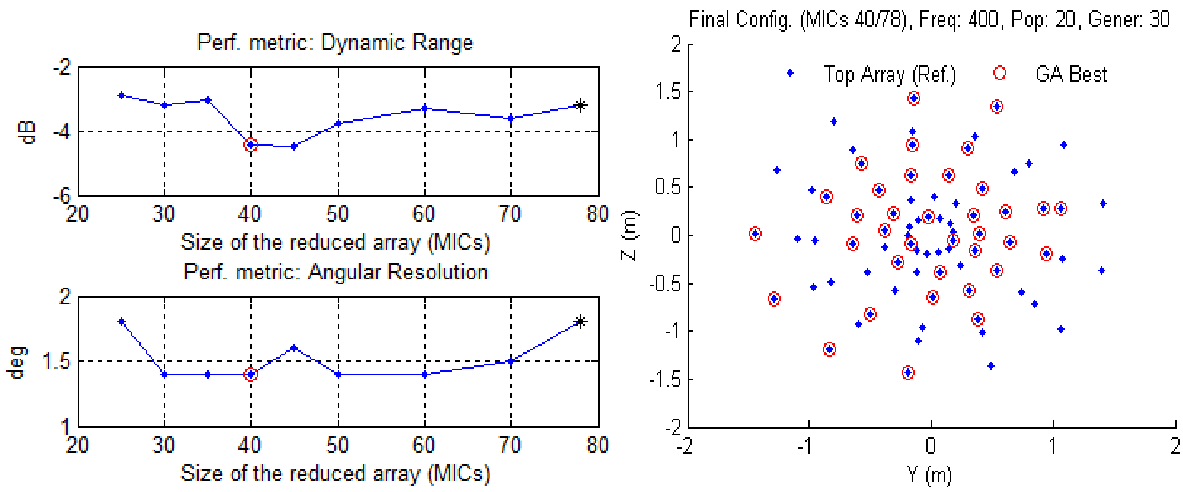
For the 'Top' acoustic array design case, the initial population members have their microphones randomly selected among the originally available 78 positions (Figure 4a). The initial population should be large enough to cover all available positions so they can all participate in the optimization process (Figure 4b).



(a) (b)

Figure 4. a) MIC positions of the first three members of the initial population, and, b) of all 30 members superimposed to show coverage.

After considering a series of reductions (from 70 to 20 microphones) it was found that a reduction of almost 50% (½) of the original channels could be achieved, without reducing the performance of the array. More precisely, starting with an initial population of 20-30 members and after 20-30 generations, the averaged results over a frequency range of 2 – 8 kHz showed that an array with 40 elements (Figure 5a) could perform better than the original one, and also save 38 acquisition channels for additional measurements. The proposed reduced array geometry layout with only 40 elements (microphones) is shown in Figure 5b.



(a) (b)

Figure 5. a) Performance metrics of: the original array (*) & the GA optimally reduced (red O is the overall best), and, b) The original array (blue dots) and the reduced array (red circles)

4.2 Case 2 – Define an optimal geometry configuration for a given number of MICs

The original array configuration has the same 78 MICs as before. The designer now wants to rearrange randomly all microphones inside the outer circle of the array in order to achieve better performance (while keeping the same size). The optimal result is shown in Figure 6.

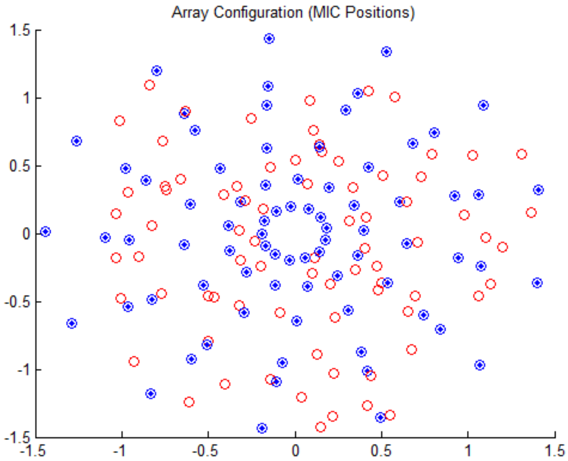
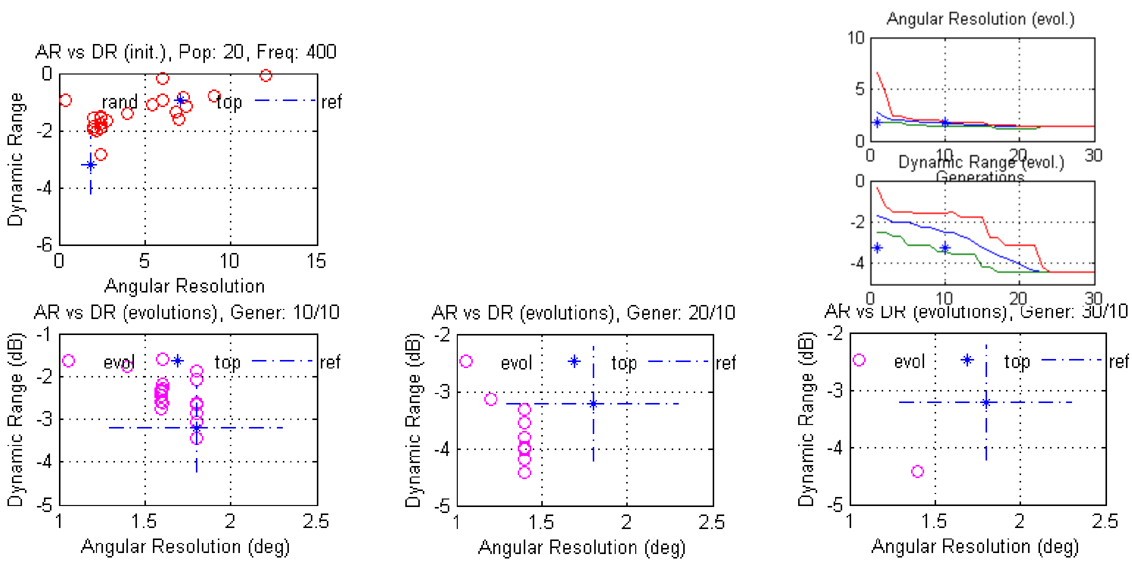


Figure 6. The final optimal random array configuration (red) and the original array (blue).

In order to demonstrate the GA convergence, Figure 7 contains a sequence of snapshots of the optimizer convergence containing the performance scores for the 1st, 10th, 20th, & 30th generation members. It is clearly shown how the newer generations outperform the older ones and finally the original setup too.



(a) (b) (c)

Figure 7. Convergence to the optimal solution: initial population (up-left in red), and the population members after a) 10, b) 20 & c) 30 generations.

5 VERIFICATION USING EXPERIMENTAL RESULTS

Having concluded the design phase of finding an optimally reduced array, a verification step followed during the experimental phase. The experimental data collected for the original (full) array are also used for the optimally reduced array microphone positions.

Using a speaker source of white noise placed at the center of the Pininfarina Wind Tunnel [7], a sequence of experimental data where recorded using the acoustic arrays installed (Figure 8).

Figure 8. A speaker in the wind tunnel producing white noise sound.

By comparing the two responses (2-D & 3-D plots) from the 78mic full array (Figure 9b) and the 40mic GA-optimized array (Figure 9b), it is clear that the response of the optimized array has a narrower main lobe, a lower side-lobes, and detects correctly the source of the signal.

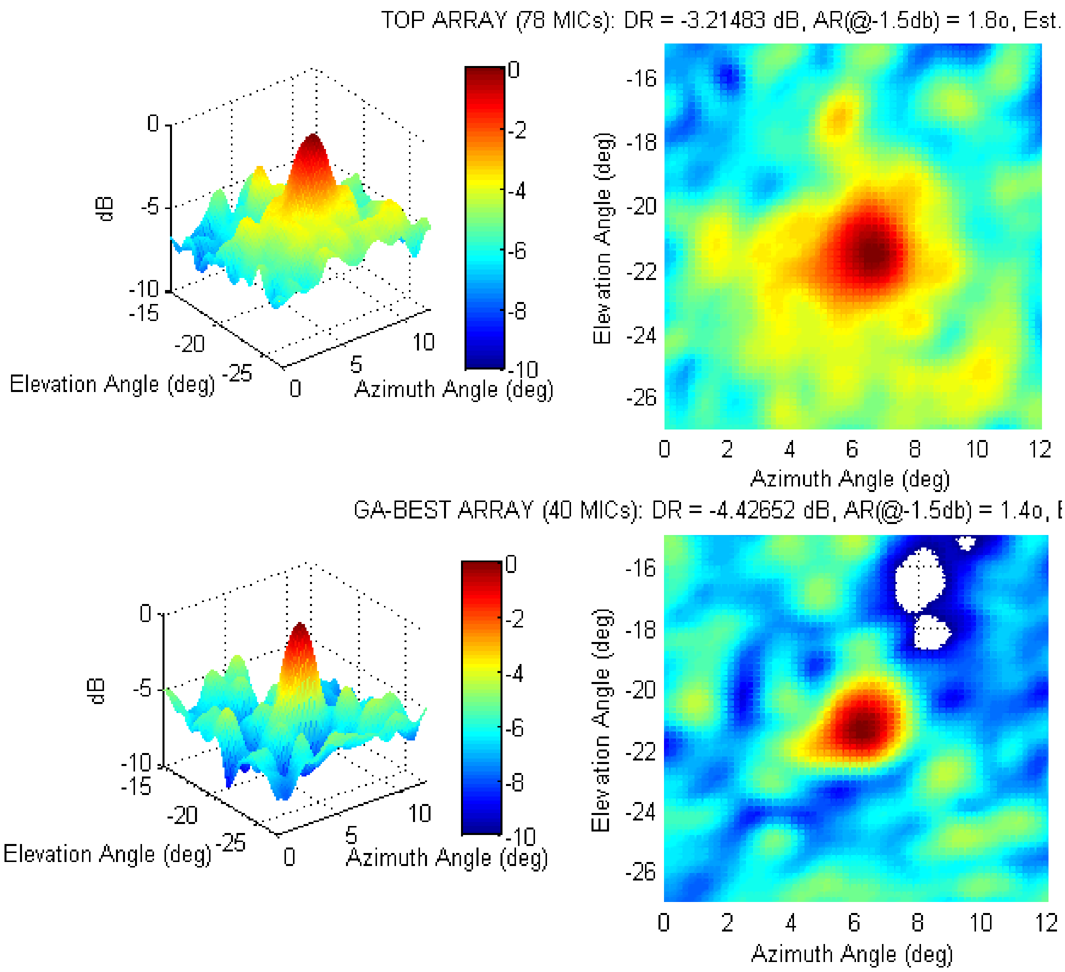


Figure 9. Responses from a speaker noise ssource: a) the original (78mic) array (top) and b) the 40mic optimal (GA best fit) array.

6 CONCLUSIONS

In this paper, an optimization tool, based on Genetic Algorithms, was presented that addrresses the problem of improving the directional response pattern of a beamforming array, and selects the optimal geometry and microphone positions. The method is based on the simultaneous optimization of performance metrics from the response pattern, i.e., dynamic range & angular resolution while keeping the minimum number of microphones/channels and focusing towards the source direction. The optimal solution results of the optimization tool developed, lead to new array design geometries that outperformed the original array characteristics in the scenarios considered. The presented optimization tool offers to the designer the capability to select a priori a better or optimal array configuration and perform the experiments with higher efficiency and accuracy.

7 ACKNOWLEDGMENTS

The work presented in this paper has been partially funded by the European Commission and was performed under the framework of the FP7 CleanSky Joint Technology Initiative project called “Wind Tunnel Tests for the Evaluation of the Installation Effects of Noise Emissions of an Open Rotor Advanced Regional Aircraft” (WENEMOR), Grant agreement no: 278419.

REFERENCES

[1] A. Hoorfar, “Evolutionary programming in electromagnetic optimization: a review,” IEEE Trans. Antennas Propag., vol. 55, pp. 523-537, Mar. 2007.

[2] R. L. Haupt, “Antenna Design with a mixed integer genetic algorithm,” IEEE Trans. Antennas Propag., vol. 55, pp. 577-582, Mar. 2007.

[3] T. B. Chen, Y. B. Chen, Y. C. Jiao and F. S. Zhang, “Synthesis of antenna array using particle swarm optimization,” *Asia-Pacific Microwave Conference Proceedings, vol. 3, 2005*.

[4] O. Quevedo-Teruel and E. Rajo-Iglesias, “Ant colony optimization in thinned array synthesis with minimum sidelobe level”, IEEE Trans. Antennas Propag. Letters, vol. 5, pp. 349-352, 2006.

[5] Whitley L. Darrell (Ed) (1993), *“Foundations of Genetic Algorithms”*, MorganKaufmann 1993.

[6] Moussas V.C., Tsahalis D., and Tsahalis, H.-T., (2013), “Acoustic Array Beamforming Analysis through Modeling, Simulation & Response Estimation”, *Proceedings of the 5th International Conference on Experiments/ Process/ System Modeling/ Simulation/ Optimization, 5th IC-EpsMsO, Athens, 3-6 July, 2013*

[7] G.J. Bennett, J. Kennedy, Petr Eret, F. Cappadona, A. Bianco, R. Letizia, D. Danise, L. Lamotte, C. Picard, A. Finez, P. Castellini, P. Chiariotti, F. Sopranzetti, D. Tsahalis, H. Tsahalis, V. Moussas, A. Paonessa, F. Amoroso, M. Di Giulio, (2013) “WENEMOR: Wind Tunnel Tests for the Evaluation of the Installation Effects of Noise Emissions of an Open Rotor Advanced Regional Aircraft”, *The American Institute of Aeronautics and Astronautics, Proceedings of the 19th AIAA/CEAS Aeroacoustics Conference, 27 - 29 May 2013, Berlin, Germany*.