Rigorous Optimizations of Three-dimensional Antenna Arrays Using Full-wave Simulations

C. Önol[1,2], Ö. Gökçe[1], H. Boyacı[1], and Ö. Ergül[1]

[1]Department of Electrical and Electronics Engineering, Middle East Technical University, Ankara, Turkey
[2]ASELSAN Inc., Ankara, Turkey

Abstract— We present optimizations of three-dimensional antenna arrays using heuristic techniques coupled with the multilevel fast multipole algorithm (MLFMA). Without resorting to any periodicity and infinity assumptions, antenna arrays are modeled with surface integral equations and simulated via MLFMA, which also enables the analysis of arrays with non-identical elements. Genetic algorithms and particle swarm optimization methods are employed on the complex data produced by MLFMA in phasor domain to find optimal sets of antenna excitations. Effectiveness of the developed mechanism is demonstrated on challenging optimization problems for increasing the directive gain of arrays involving patch antennas.

1. INTRODUCTION

Optimizations of antenna arrays for required values of the directive gain, side-lobe level, beamwidth, and in general, for the characterization of the overall radiation pattern, are popular problems in antenna design and engineering [1–3]. Given an array of antennas, the aim is to find the optimal set of excitations of its elements for desired radiation characteristics. For rapid optimizations, simple approaches based on the array factor are very suitable, leading to very efficient designs of excitations. Unfortunately, using these approaches, mutual couplings between antennas are neglected or simplified, leading to significant deviations of the optimization results from real-life measurements when the antennas are strongly coupled [4, 5]. For realistic optimizations, antennas need to be modeled accurately, and if possible, via full-wave solvers; but, using highly accurate solutions for the purpose of optimizations may not be trivial [6, 7].

In this work, we consider rigorous optimizations of antenna arrays using heuristic algorithms, such as the genetic algorithms and particle swarm optimization methods, which are employed on simulation results obtained with the multilevel fast multipole algorithm (MLFMA) [8]. MLFMA allows for accurate simulations of antenna arrays, without any periodicity, infinity, and similarity assumptions, and by taking into account all mutual couplings between antennas. For the optimizations of an M-element array at a single frequency, the number of full-wave simulations is only M, since complex current densities and radiation patterns can be combined via superposition without omitting mutual couplings [2]. For a given array of static elements, these simulations also have common computations, which can be used to accelerate the overall solution phase. The results of M full-wave simulations can be used by the heuristic algorithms in order to perform the optimizations, e.g., for increasing the directive gain at desired directions, minimizing radiations at given locations, and shaping the main beam by controlling the excitations. As an important advantage, the developed optimization environment allows for multi-band optimizations, where radiation characteristics at multiple frequencies are considered and optimized simultaneously for multi-band applications.

2. OPTIMIZATIONS VIA HEURISTIC ALGORITHMS AND MLFMA

We consider three-dimensional finite arrays without any periodicity, similarity, and orientation assumptions on the array elements (antennas). Antenna surfaces are modeled as perfect electric conductors, which are formulated with the electric-field integral equation in phasor domain and discretized with the Rao-Wilton-Glisson functions defined on triangular patches. Matrix equations in the form of

$$\bar{\mathbf{Z}}^{\mathrm{EFIE}} \cdot \mathbf{a} = \mathbf{w}^{\mathrm{EFIE}} \tag{1}$$

are derived and solved, where $\mathbf{a}$ represents coefficients of basis functions to expand the electric current induced on antenna surfaces. Once solved, the electric current can be used to obtain all electrical characteristics of the array and its elements, e.g., radiated fields, directive gains, input impedances, and reflection coefficients. Matrix equations described above are solved iteratively, where the required matrix-vector multiplications are performed by MLFMA. This algorithm works on tree structures that are constructed by recursively dividing given objects (antenna arrays) into subdomains so that far-field electromagnetic interactions can be computed in a group-by-group manner via aggregation-translation-disaggregation stages, while only sparse parts of the matrices (near-field interactions) are stored in memory [10].

The efficient and accurate mechanism constructed for the optimizations of antenna arrays can be further described as follows.

1. In a global setup stage, we compute near-field interactions, translation operators, and preconditioners that are common in all MLFMA simulations required for the optimizations. Near-field interactions can be further accelerated, e.g., by storing only a single set of self interactions for identical antennas with identical discretization, while this is usually not critical in terms of efficiency.
2. Given an array of M elements, M different radiation problems are solved, each corresponding to the excitation of a single antenna. This corresponds to constructing a right-hand-side vector and performing an iterative solution accelerated via MLFMA. Then, complex coefficients of basis functions and/or complex radiated fields derived from these coefficients are stored in memory. We emphasize that all mutual couplings are included in these solutions.
3. Once all solutions are completed, a heuristic algorithm can be used to optimize the desired array characteristics, where each optimization trial corresponds to a set of values for the excitations of antennas. These trial values are used when combining the complex coefficients or complex radiated fields to efficiently obtain the overall characteristics of the array. Given an array geometry, solutions with MLFMA can be used in different optimizations.

As the optimization technique, we use either a genetic algorithm [11] or a particle swarm optimization method [12]. For the results shown in this paper, the developed genetic algorithm seems to work better as it was particularly designed for antenna arrays [9], while we use at least two different methods in all optimizations for verification purposes. This verification is required since the problems considered involve huge optimization spaces that cannot be searched directly. In all optimizers, optimization variables are converted into suitable forms (e.g., to binary chromosomes for the genetic algorithm [9]) to carry out the required optimization rules.

3. NUMERICAL RESULTS

Figure 1 presents genetic-algorithm optimizations of a 10×10 array of patch antennas at 2.45 GHz. The array consists of 3 cm $\times$ 3 cm patch antennas, each excited with a current-injection source model. As also depicted in Figure 1, the antennas are arranged periodically with 6 cm periods on the x-y plane. Each antenna is discretized with 311 unknowns, leading to a total of 31,100 unknowns. The directive gain of the array is optimized at various directions on the z-x cut for different θ values from 0° to 90°. Optimizations of both amplitudes (as 1 or 0, corresponding to

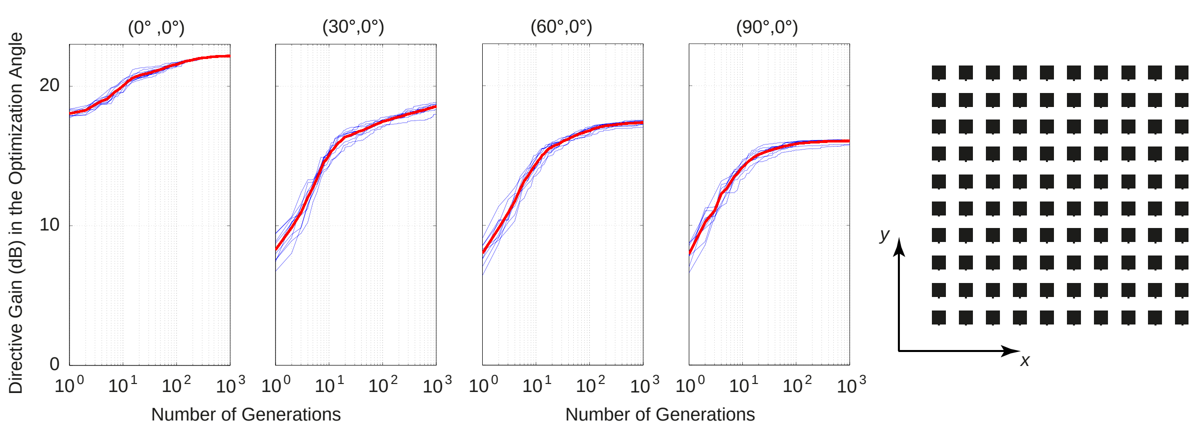

Figure 1: Cost functions with respect to number of generations when the developed genetic algorithm is used to maximize the directive gain of a 10×10 array of 3 cm $\times$ 3 cm patch antennas at 2.45 GHz. Both amplitudes (1 or 0) and phases of antenna excitations are optimized via 80,000 trials. At each optimization angle, 10 repetitions of the genetic algorithm and the average of these repetitions are plotted.

on and off) and phases of antenna excitations are considered. Figure 1 presents the cost functions (directive gain values in the optimization angle) with respect to the number of generations, when the developed genetic algorithm works on a pool of 80 individuals. While a convergence can be observed earlier, the number of generations is fixed to 1000, leading to a total of 80,000 trials per optimization. In addition, for each optimization angle, we present 10 different repetitions, as well as the average behavior shown with bold red. We observe that the genetic algorithm successfully increases the directive gain at all optimization angles.

Figure 2 depicts the radiation patterns of the 10×10 array at 2.45 GHz, when the directive gain of the array is maximized at different θ values from 0° to 90° on the z-x cut. In these results, only the phases of antenna excitations (while amplitudes are fixed to unity) are optimized by using the developed genetic algorithm. For each optimization, 1000 generations are carried out on a pool of 80 individuals. It can be observed that, by maximizing the directive gain, the highest radiation can be obtained at the desired direction.

For comparing the performances of various optimization schemes, Figure 3 presents the results of different optimizations for the 10×10 array at 2.45 GHz. For fair comparisons, all optimization schemes use a total of 80,000 trials to maximize the directive gain at various θ values from 0° to

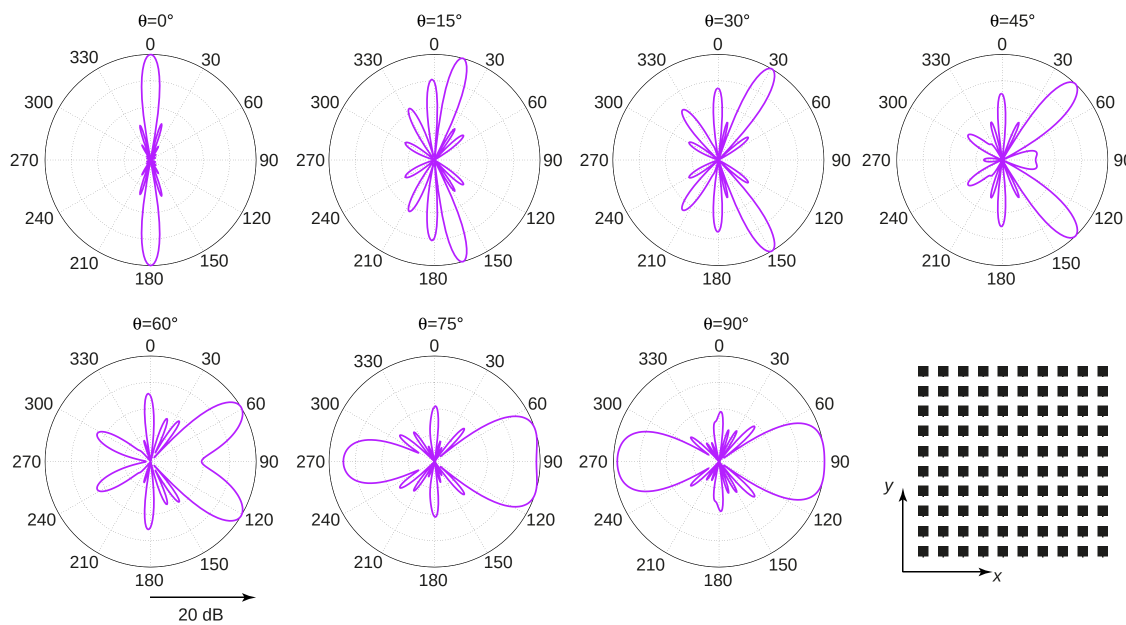

Figure 2: Radiation patterns (normalized electric field intensity values) for a 10×10 array of 3 cm $\times$ 3 cm patch antennas at 2.45 GHz, when the phases of the antenna excitations are optimized via 80,000 trials for increasing the directive gain at various directions on the z-x plane.

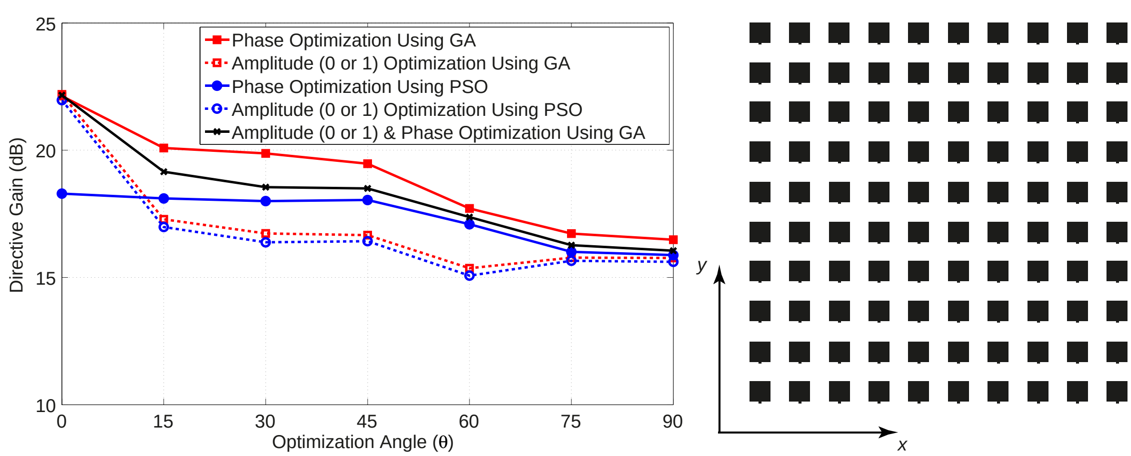

Figure 3: A comparison of optimizations with the developed genetic algorithm (GA) and particle swarm optimization (PSO) methods for a 10×10 array of $3\,\text{cm} \times 3\,\text{cm}$ patch antennas at 2.45 GHz. Each optimization is based on 80,000 trials and repeated for 10 times to obtain average performances.

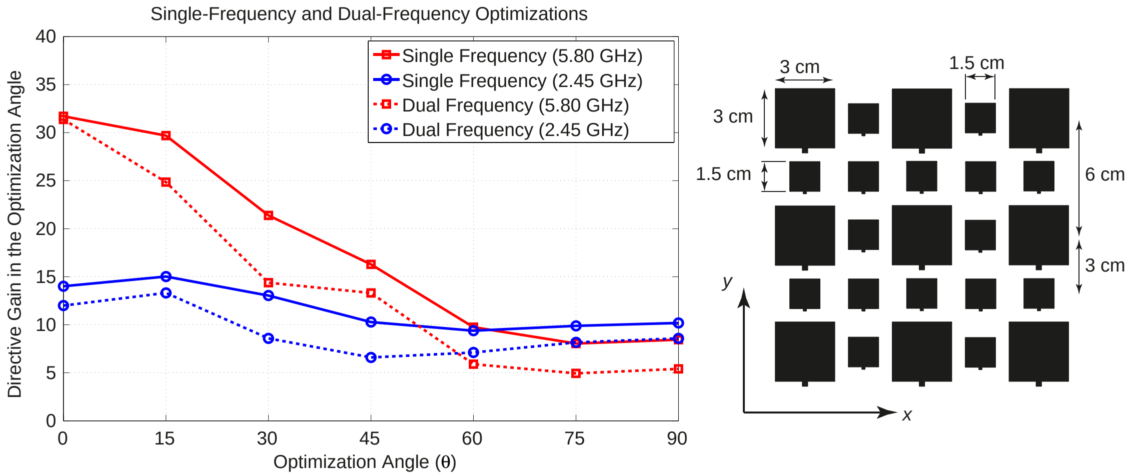

Figure 4: Directive gain values (dimensionless) for a dual-band array of patch antennas when the excitation phases are optimized to obtain the maximum gain values at various directions and at two different frequencies.

$90°$, again on the z-x cut. In addition, to avoid random effects, each optimization is repeated for 10 times and the average performances are depicted. Therefore, the summarized results in Figure 3 are obtained via 350 optimizations (5 optimization schemes, 7 directions, and 10 repetitions), hence a total of 28,000,000 excitation trials (electromagnetic problem solutions). The genetic algorithm use improved optimization operations described in [9]. For the particle swarm optimizations, we improve the original algorithm in [12] by using adaptive speed factors and reducing the value of the inertia parameter as the iterations continue. The following observations can be made:

1. Considering the genetic algorithm, phase optimizations lead to significantly better results than amplitude (0 or 1) optimizations, as the former involves more excitation options to increase the directive gain. An exception is the optimization at $\theta = 0°$, where phase differences between excitations of antennas are not essential for large directivity. Interestingly, optimizing only phases also provides better results than optimizing both phases and amplitudes (0 or 1), while the latter involves a larger optimization space that already contains the space of the former. It appears that 80,000 trials become insufficient to search for optimal phases and amplitudes at the same time, deteriorating the quality of final results in comparison to optimizations in a smaller space for phases.
2. The results obtained with the particle swarm optimizations are almost the same as those obtained via the genetic algorithm when the amplitudes of antenna excitations are optimized. When the phases are optimized, however, we cannot obtain high-quality results, especially when the directive gain is optimized at smaller θ angles. We note that the space for phase optimizations involves excitation sets that lead to identical results in radiation patterns. Consequently, in the particle swarm optimizations, we often observe scattered particles despite all parametric efforts to avoid poor optimizations.

Finally, Figure 4 presents the optimizations of excitation phases for a dual-band array of patch antennas. The antenna dimensions and their arrangement are also depicted in the same figure. The array is located on the x-y plane, and its directive gain is optimized on the z-x cut at various directions from $\theta = 0°$ to $\theta = 90°$. The genetic algorithm based on 80,000 trials is used for optimizations, while the average performances based on 10 repetitions are shown in Figure 4. As an important advantage, the developed optimization mechanism is capable of handling multiple frequencies at the same time. Figure 4 presents the directive gain values obtained when the optimizations are performed at single frequencies (2.45 GHz and 5.80 GHz) and simultaneously at both frequencies. In the single frequency optimizations, only the results obtained for the considered frequency is depicted, as the values for the other frequency are very low. Considering both frequencies at the same time, directive gain values naturally drop in comparison to single-frequency optimizations. Nevertheless, the dual-band optimizations are required to maintain high gain values simultaneously at both frequencies.

4. CONCLUSION

An efficient and accurate mechanism based on heuristic algorithms and full-wave solutions via MLFMA for the optimizations of antenna excitations in array configurations is presented. The develop mechanism is very flexible, allowing for optimizations of three-dimensional finite arrays with nonidentical elements at arbitrary positions and with irregular arrangements. Effectiveness of the optimization environment is demonstrated on regular arrays of patch antennas, as well as on dual-band arrays involving antennas of different sizes.

ACKNOWLEDGMENT

This work was supported by the Scientific and Technical Research Council of Turkey (TUBITAK) under the Research Grant 113E129 and by a BAGEP Grant from Bilim Akademisi — The Science Academy, Turkey.

REFERENCES

1. Orchard, H. J., R. S. Elliot, and G. J. Stern, "Optimising the synthesis of shaped beam antenna patterns," *IEE Proceedings H*, Vol. 132, No. 1, 63–68, 1985.
2. Ergül, Ö. and L. Gürel, "Modeling and synthesis of circular-sectoral arrays of log-periodic antennas using multilevel fast multipole algorithm and genetic algorithms," *Radio Sci.*, Vol. 42, No. 3018, 2007.
3. Yang, K., Z. Zhao, Z. Nie, J. Ouyang, and Q. H. Liu, "Synthesis of conformal phased arrays with embedded element pattern decomposition," *IEEE Trans. Antennas Propag.*, Vol. 59, No. 8, 2882–2888, 2011.
4. Gupta, I. J. and A. A. Ksienski, "Effect of mutual coupling on the performance of adaptive arrays," *IEEE Trans. Antennas Propag.*, Vol. 31, No. 5, 785–791, 1983.
5. Shavit, R. and E. Rivkin, "An efficient and practical decoupling feeding network for antenna phased arrays," *IEEE Antennas Wireless Propag. Lett.*, Vol. 9, 966–969, 2010.
6. Yan, K.-K. and Y. Lu, "Sidelobe reduction in array-pattern synthesis using genetic algorithm," *IEEE Trans. Antennas Propag.*, Vol. 45, No. 7, 1117–1122, 1997.
7. Allard, R. J., D. H. Werner, and P. L. Werner, "Radiation pattern synthesis for arrays of conformal antennas mounted on arbitrarily-shaped three-dimensional platforms using genetic algorithms," *IEEE Trans. Antennas Propag.*, Vol. 51, No. 5, 1054–1062, 2003.
8. Ergül, Ö. and L. Gürel, *The Multilevel Fast Multipole Algorithm (MLFMA) for Solving Large-scale Computational Electromagnetics Problems*, Wiley-IEEE, 2014.
9. Önol, C. and Ö. Ergül, "Optimizations of patch antenna arrays using genetic algorithms supported by the multilevel fast multipole algorithm," *Radioengineering*, Vol. 23, No. 4, 1005–1014, 2014.
10. Chew, W. C., J.-M. Jin, E. Michielssen, and J. Song, *Fast and Efficient Algorithms in Computational Electromagnetics*, Artech House, 2001.
11. Rahmat-Samii, Y. and E. Michielssen, *Electromagnetic Optimization by Genetic Algorithms*, Wiley, 1999.
12. Venter, G. and J. Sobieszczanski-Sobieski, "Particle swarm optimization," *AIAA J.*, 1583–1589, 2002.
13. Robinson, J. and Y. Rahmat-Samii, "Particle swarm optimization in electromagnetics," *IEEE Trans. Antennas Propag.*, Vol. 52, No. 2, 397–407, 2004.