

Genetic-Algorithm Optimization of an Array for Near-Field Plane Wave Generation

Neil N. Jackson* and Peter S. Excell

University of Bradford, U.K.

*Now with Motorola P.L.C., Swindon, UK

Abstract

An alternative approach to the design of an array antenna to be used to generate plane waves in the near field is presented. The original array was designed on the basis of a triangular grid of seven elements arranged in a hexagon, to minimize the number needed to achieve approximately uniform illumination of the test zone, under the assumption of isotropic element radiation patterns. In the alternative approach, a genetic algorithm was used to discover more economical distributions of elements which could still generate acceptable approximations to a plane wave zone. It was found that considerable simplifications from the 'common sense' approach were possible.

1. Introduction

The desirable incident field distribution in a radiative susceptibility test is a plane wave, existing at least over a test zone large enough to enclose the equipment under test (EUT). A susceptibility test is intended to seek out the worst-case response of the EUT, equivalent to finding the main lobe amplitude of an antenna, and such a measurement is relatively tolerant of imperfections in the quality of the plane wave zone. Typical accuracy criteria for established electromagnetic compatibility tests of this type would correspond to a spread in the field amplitude of 3dB peak-to-peak (often up to 6dB) and a phase spread of 90° peak-to-peak. This is in contrast to the situation for precision antenna measurements, where deep nulls and low sidelobes have to be measured in close proximity to the main lobe: maximum amplitude uncertainties of 0.1dB and phase variations of 22° are then common criteria. The quality criterion on the plane wave zone for EMC testing is thus lower than that for antennas, but the desired bandwidth is likely to be greater and the pressure to constrain costs greater.

Test facilities for antennas which create a local plane wave region in the near field ('Compact Ranges') almost always use illuminating antennas that are variants on standard reflector antenna designs. The same principle has been extended to EMC testing, with the modified criteria discussed above, but its use of space is rather uneconomical for many purposes [1]. To overcome this deficiency, the use of array antennas for illumination of the range has been investigated, with some success [2]. The array was designed on the basis of a triangular grid of seven elements arranged in a hexagon. This arrangement was chosen intuitively as, in principle, it minimizes the number of elements needed to achieve approximately uniform illumination of the test zone, under the assumption of isotropic element radiation patterns. To achieve a high-quality plane wave zone, it is necessary to feed the elements with differing signals having non-intuitive ratios of relative amplitude and relative phase and this greatly adds to the cost and complexity of the scheme. These signal amplitudes and phases have to be found by optimization procedures based on a least-mean-squares method [2]. It is thus desirable that the number of elements in the array be reduced by a systematic procedure that can still guarantee maintenance of a

plane wave test zone that conforms to chosen criteria representing an acceptable approximation to a local plane-wave zone.

As an experiment in application of genetic algorithm (GA) methods to antenna design, such an approach was investigated as a way of producing a thinned array design for an EMC-quality compact range that would still be capable of generating an acceptable approximation to a local plane wave over a specified test zone. The method requires the running of numerical simulations of the antenna very many times over, and this can become costly in use of computer time. To minimize this requirement, the array elements in this experimental study were chosen to be simple dipoles: the behavior of an array of more directive elements, such as log-periodic antennas will not be significantly different in the direction of the test zone, since their main-lobe amplitude is relatively invariant with angle. Clearly, there will be great differences between the behavior of dipoles and directive antennas in other directions, but these are not of importance for the present application.

2. Genetic Algorithm Implementation

A genetic algorithm has the following general form [3,4]:

1. Create a population of N random individuals (chromosomes).
2. Assess the performance of each individual.
3. Rank individuals with respect to performance and assign a fitness value dependent on ranking.
4. Select M individuals (parents) from the population for breeding, the probability of being chosen being proportional to fitness.
5. Randomly pair parents and crossover parts of each chromosome (genes) to form N offspring.
6. Randomly mutate genes in the offspring chromosomes.
7. Assess the performance of each new individual in the population of offspring.
8. Record best individual.
9. Repeat from step 3 for required number of generations.

For applications in electromagnetics, steps 2 and 7 can represent vastly larger computational tasks than all of the rest put together. In the present work, the industry-standard program NEC-2 [5] was used for these steps.

2.1 Population Representation and Initialization

Genetic algorithms operate on a number of potential solutions called a population. The population is composed of a number of individuals (chromosomes), which contain an encoded description of the parameters (equivalent to 'phenotypes' in biological terminology) to be optimized. The most commonly used method of encoding phenotypes is as binary strings [3], which are concatenated to form a chromosome.

After devising a suitable encoding scheme, an initial population of chromosomes (typically around 100) is randomly generated.

2.2 The Objective and Fitness Functions

The chosen objective function, $O(x)$, is used to provide a measure of how individuals have performed with respect to the problem space. The individual with the best value of $O(x)$ is assigned a rank position of N and the worst $O(x)$ is assigned a rank position of 1. Another function, called a fitness function $F(x)$, is then used to transform $O(x)$ into a measure of relative fitness. The fitness value is assigned according to the rank position, p_x of individual x . The fitness function is then derived from the rank position by application of a bias or selective pressure parameter, B , towards the most fit individuals. In the present case the following simple linear function was adopted:

$$F(x) = \frac{B(p_x - 1)}{N - 1} \quad (1)$$

Hence, best-fit individuals will have a fitness function equal to B and worst fit individuals will have a fitness function of zero.

2.3 Selection

Selection is the process of determining the number of times a particular individual is chosen for reproduction and, thus, the number of offspring that it will produce. The simplest selection method uses the fitness function values to reject a percentage of the population that performs badly [4]. A better selection technique [6] employs a roulette wheel selection (RWS) mechanism to select individuals probabilistically. In roulette wheel selection each individual in the population has a roulette wheel slot, sized in proportion to its fitness. In mathematical terms this may be expressed as shown in Equation (2):

$$\text{Prob}(x \text{ selected}) = \frac{F(x)}{\sum_{i=1}^N F(i)} \quad (2)$$

A real-valued interval is determined as a sum (S) of the fitness values over all the chromosomes in the current population and individuals are then expressed as a proportion of this sum. To select an individual, a random number is generated in the range from zero to S and the individual whose segment spans the random number is the individual to be selected. This process is then repeated until the desired number of individuals has been selected.

2.4 Mating or Crossover

The basic operator for producing new chromosomes in genetic algorithms is that of crossover. Like its counterpart in nature, crossover produces new individuals that have some parts of both parents' genetic material. Several crossover strategies exist, each with their associated merits. The simplest form of crossover, and the one employed here, is that of single point crossover [6]. The chromosomes selected are randomly shuffled and then paired for breeding. A crossover point is randomly selected, dividing each parent chromosome into two gene strings which are then swapped to generate two new chromosomes (offspring).

To maintain the size of the original population, the new individuals, created by crossover of the selected individuals, must be reinserted into the old population. This was achieved by creating sufficient new individuals to replace the least-fit half of the old population. The most-fit half thus survives, and its children attempt to evolve to a superior form. Once a new population has been produced, its fitness may be determined.

2.5 Mutation

In natural evolution, mutation is a random process where a gene is altered to produce a new genetic structure. In genetic algorithms, mutation is randomly applied (with a low probability, typically in the range 0.001 to 0.01) to modify elements in the chromosomes. The role of mutation is to enable the recovery of good genetic material that may have been lost through the action of selection and crossover [3]. Many variations on the mutation operator have been proposed, for example, biasing the mutation towards individuals with lower fitness values to increase the exploration in the search without losing information from the fitter individuals [7], or parameterizing the mutation such that the mutation rate decreases with the population convergence [8].

2.6 Termination

Because the genetic algorithm is a stochastic search method, it is difficult to specify convergence criteria. As the fitness of a population may remain static for a number of generations before a superior individual is found, the application of conventional termination criteria becomes problematic. A common practice [4] is to terminate the GA after a pre-specified number of generations and then test the quality of the best members of the population against the problem definition. If no acceptable solutions are found, the GA may be restarted or a fresh search initiated.

3. Optimization of the Geometry of an Array of Five Wire Dipoles

A computer program was developed which incorporated the major features of a GA, as outlined above. In addition, the software was developed to automatically generate input files in NEC format and then run NEC-2 [5] from within the programming environment. For computational speed, an array of five half-wavelength wire dipole antennas was initially chosen to demonstrate the use of a GA for minimizing the normalized error in plane wave synthesis.

The frequency was fixed at 1GHz and a test zone defined as a cube of side length 0.6m (2λ) with the front face positioned 0.4m from the array. Element locations were constrained to the nodes in a two-dimensional grid with 8×8 allowed locations and a spacing of 0.5λ (to avoid overlapping elements). The number of combinations in which it is possible to arrange five elements in the 64 locations, excluding any superpositions of elements and eliminating all patterns that are identical apart from a spatial transformation, is approximately 7.6×10^6 and hence use of an exhaustive search technique for finding an optimum arrangement was infeasible.

For this problem, the parameters to be optimized were the locations of each of the five array elements. A suitable chromosome structure therefore consisted of ten phenotypes as shown below:

$$\text{chromosome} = [(x_1, y_1) (x_2, y_2) (x_3, y_3) (x_4, y_4) (x_5, y_5)] \quad (3)$$

where x_n, y_n are the two-dimensional co-ordinates of the n th array element.

1. Setting the number of bits (genes) per phenotype to be 3 led to a problem space equivalent to an 8×8 grid and a total chromosome length of 30 bits.
2. Setting the restriction that the grid spacing was to be 0.5λ led to a problem space of dimensions $3.5\lambda \times 3.5\lambda$. A phenotype of value 000 was made to correspond to a value of -0.45m and a phenotype of value 111 made to correspond to 0.6m . The asymmetry is a function of the 3-bit resolution and the fact that it was considered desirable that one element had the potential to be located at the problem space origin.
3. The performance of each individual was determined by first calculating the excitation weightings of individual array elements using the synthesis methods described in [2] and then computing the normalized synthesis error (see below). This was adopted as the Objective Function and the results ranked from 'best' (lowest) to 'worst' (highest).
4. Selection of the most fit individuals (those having the lowest numerical value of the normalized synthesis error) was made using the roulette wheel method and using a selective pressure of $B = 2$ for defining the fitness function.
5. The mutation method used was to change the value of a randomly selected gene from a randomly selected chromosome at each generation.
6. The number of chromosomes per population was chosen to be 100 and the algorithm was terminated after 100 generations.

The near field synthesis procedure [2] involves the specification of a three-dimensional mesh of M points within the test zone. A set of excitations for the elements of the illuminating array, $[f]$, is then derived by minimizing the deviations between the resulting electric field values at the nodes of the mesh and the values that would be present if the field distribution was a perfect plane wave. The process may be represented by the matrix equation:

$$[T][f] = [E] \approx [E_0] \quad (4)$$

where $[f]$ is an n -element vector of complex excitations for the n elements of the array, $[E]$ is an M -element vector of the resulting electric field values at the nodes of the grid in the test zone, $[E_0]$ is a similar vector for the desired plane wave and $[T]$ is the interaction matrix, of size $n \times M$. The elements of $[T]$ can be found by using an electromagnetic field computation program, such as NEC. The synthesis algorithm finds values for the elements of $[f]$ that minimize the deviation between $[E]$ and $[E_0]$.

The normalized synthesis error is a measure of the quality of the fit of the synthesized field to the desired distribution. It is the normalized summation of the field deviations at all points in the discretisation mesh used by the synthesis algorithm within the test zone:

$$\text{Synthesis error} = \frac{\sum_{m=1}^M |E_m - E_{0m}|^2}{\sum_{m=1}^M |E_{0m}|^2} \quad (5)$$

where E_m and E_{0m} are arbitrary elements of the vectors $[E]$ and $[E_0]$ respectively.

3.1 Results Using Synthesis Method with Magnitude and Phase Specified

Using the synthesis method with magnitude and phase specified [2], a genetic algorithm, as described in previous sections, was initiated. Figure 1 shows how the synthesis error of the best-fit individual varied with generation. This figure highlights the difficulty in specifying convergence criteria since the synthesis error remains static for an unpredictable number of generations. The optimized element locations are shown in Figure 2 and the computed element excitations are listed in Table 1. The optimized geometry is two-dimensional and symmetrical about the origin with each element spaced at a distance of one wavelength from each other element. The resultant geometry is perhaps intuitively obvious; however, this may not necessarily always be the case for larger arrays or for different array patterns.

A sample of the computed x-component of the electric field in slices throughout the quiet zone is shown in Figure 3 and the resultant synthesis error and the worst case deviation in the field magnitude and phase throughout the entire test volume are also summarized in Table 1. The deviations are calculated with respect to an ideal plane wave.

Table 1 Summary of Element Excitations, Synthesis Error and Maximum Field Deviation for a Genetically Optimized Array using Magnitude and Phase Synthesis

Element Number	Magnitude (dB)	Phase
1	0.00	0.0°
2	-4.90	-41.8°
3	-4.90	-41.8°
4	-3.95	-8.9°
5	-3.95	-8.9°
Synthesis error	0.1530	
Magnitude Deviation	±4.9 dB	
Phase Deviation	±53°	

3.2 Results using Synthesis Method with Magnitude Only Specified

From previous studies [2] it was determined that a synthesis technique with magnitude only specified offered the best method for minimizing the synthesis error. The GA was thus used to determine if a more optimal geometry could be achieved using this procedure. As an aid to assessment of the performance of the genetic algorithm to optimize the plane wave quality, a benchmark problem was

proposed. The *cross* geometry shown in Figure 2 was considered suitable for comparison purposes and optimum element excitations determined, using the magnitude-only synthesis method, for the test zone specified.

Figure 4 shows how the synthesis error of the best-fit individual varied with generation. The synthesis error for the benchmark case is included for comparison purposes. It is clear that the genetic algorithm has been successful in reducing this error. The optimized element locations are shown in Figure 5 and the computed element excitations are listed in Table 2.

Table 2. Summary of Element Excitations and Synthesis Error for Benchmark and Genetically Optimized Arrays using Magnitude-Only Synthesis

Element Number	Benchmark Array (Cross)		Genetic Array	
	Mag (dB)	Phase	Mag (dB)	Phase
1	0.00	0.0°	0.00	0.0°
2	-9.34	-44.6°	0.00	0.0°
3	-9.34	-44.6°	-1.84	-2.9°
4	-8.87	13.6°	-1.84	-2.9°
5	-8.87	13.6°	-8.96	47.3°
Synthesis Error	0.0442		0.0239	
Magnitude Deviation	±4.24 dB		±3.08 dB	
Phase Deviation	±61°		±70°	

A sample of the computed x-component of the electric field in slices throughout the quiet zone is shown in Figure 6 for the benchmark case and in Figure 7 for the best-fit genetically optimized array. The resulting synthesis error and the worst case variation in the field magnitude and phase for the two cases are summarized in Table 2. Comparing the results for the cross geometry with those obtained in Section 3.1, where the excitations had been optimized using the magnitude and phase synthesis method, shows that an improvement in the normalized synthesis error and magnitude deviation is achieved by using the magnitude-only method. However, the phase performance is shown to degrade somewhat.

Comparing the results for the cross array with those for the magnitude-only genetically-optimized design shows that there is an improvement in the field magnitude error at the expense, however, of the phase uniformity. This is not unexpected since the optimization method, in this case, did not take phase into account when computing the synthesis error.

4. Conclusions

Genetic algorithms were shown to be able to derive simplified designs for an illuminating array antenna of a plane-wave generator for electromagnetic susceptibility testing. Traditional designs had used seven elements, whereas genetic optimization showed that adequate performance could, in principle, be achieved with five. The study was undertaken as a proof-of-concept exercise using plain dipoles as the array elements, whereas a practical array would use log-periodic elements. Use of dipoles would cause difficulties in practice due to generation of stray radiation away from the test zone,

but within the test zone itself the behavior of dipole and log-periodic elements would be broadly similar. The two genetically-derived designs studied both reached the optimum configuration in less than 60 generations.

The design that was derived by genetic optimization with magnitude and phase specified was of a cross-shaped configuration that was similar to a thinned version of the traditional hexagonal seven-element design, but inherently more economical due to the use of only five elements. The configuration optimized under a magnitude constraint only was closer in form to a linear array, with the result that phase errors in the test zone reached 70° , although the amplitude distribution was relatively constant, showing a lower maximum deviation than could be achieved with the cross geometry. The excitation pattern for the near-linear array might be seen to have advantages of simplicity in some realizations, in cases where the phase error can be tolerated. However, the cross-shaped geometry is likely to be more generally useful.

References

1. Rousseau, M. and Excell, P.S.: 'Computation of the Field Distribution in a Broadband Compact Range for EMC Applications', IEE Conf. Pub. No. 274, 'Antennas & Propagation', York University, UK, Vol. 1, pp. 395-398, 1987.
2. Excell, P.S., Jackson, N.N. & Wong, K.T.: 'A Compact Electromagnetic Test Range using an Array of Log-Periodic Antennas', IEE Proceedings, Part H, Vol. 140, No. 2, pp 101-106, 1993.
3. Goldberg, D.E.: 'Genetic Algorithms in Search, Optimization and Machine Learning', Reading MA: Addison-Wesley, 1989.
4. Haupt, R.L.: 'An Introduction to Genetic Algorithms for Electromagnetics', IEEE Antennas and Propagation Magazine, Vol. 37, No.2, pp. 7-15, 1995.
5. Burke, G.J. and Poggio, A.J.: 'Numerical Electromagnetics Code (NEC): Method of Moments', US Naval Ocean Systems Center, Rept. No. TD116, 1981.
6. Michalewicz, Z.: 'Genetic Algorithms + Data Structures = Evolution Programs', Berlin: Springer Verlag, 2nd edition, 1992.
7. Davis, L.: 'Adapting Operator Probabilities in Genetic Algorithms', Proceedings of the 3rd International Conference on Genetic Algorithms, pp.61-69, 1989.
8. Fogarty, T.C. 'Varying the Probability of Mutation in the Genetic Algorithm', Proceedings of the 3rd International Conference on Genetic Algorithms, pp. 104-109, 1989.

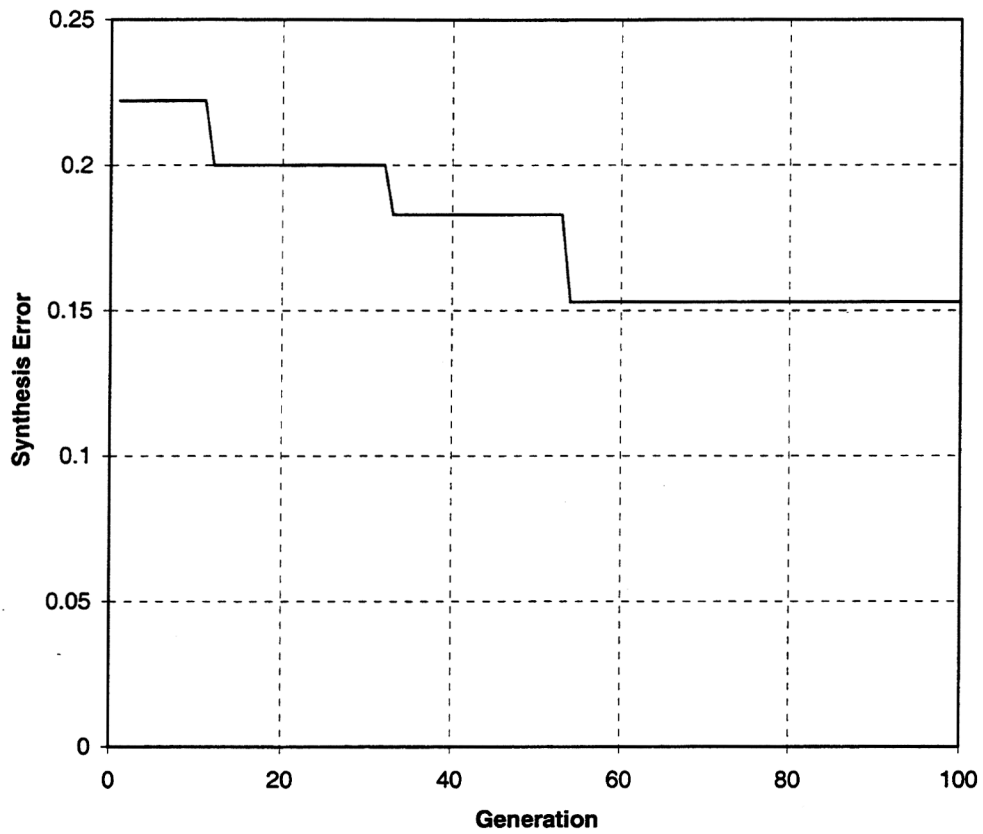


Fig. 1. Variation of best synthesis error with generation: magnitude and phase synthesis method.

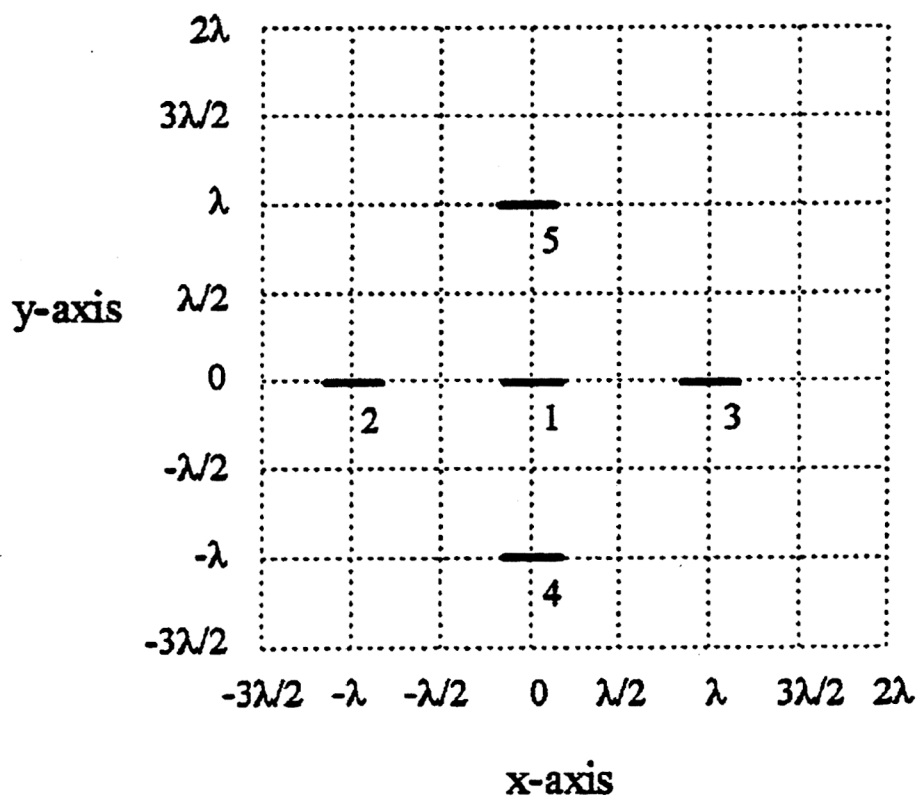


Fig. 2. Genetically optimized element locations using magnitude and phase synthesis method.

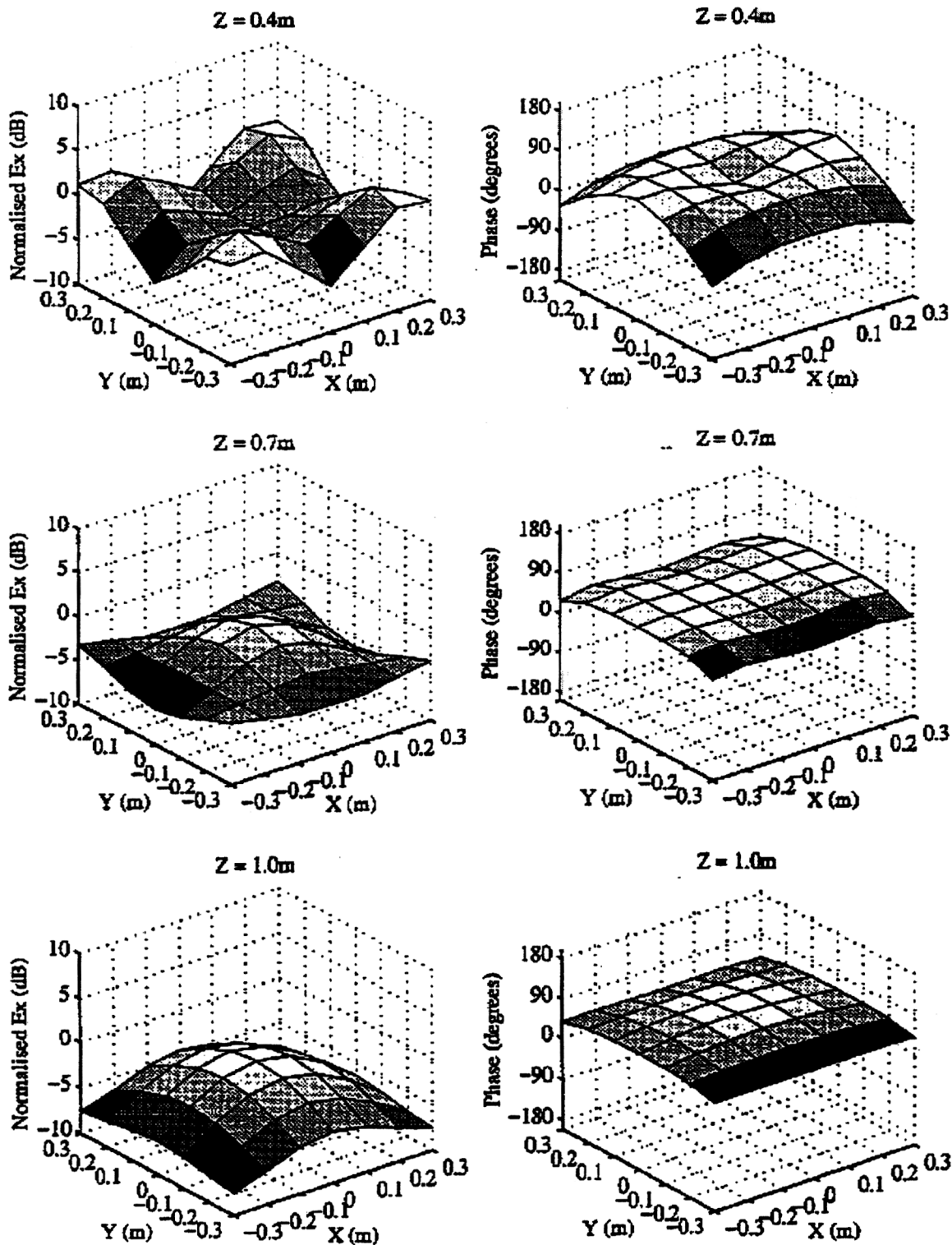


Fig. 3. Magnitude and phase variations of dominant (x) component of computed electric field strength due to array in Fig. 2, synthesized by magnitude and phase method.

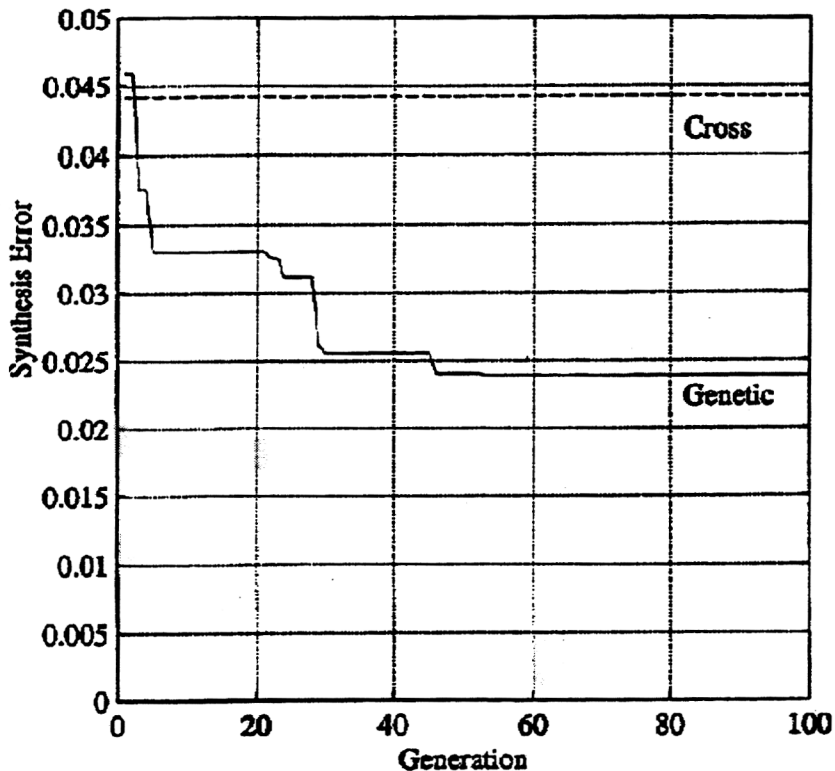


Fig. 4. Variation of best synthesis error with generation: magnitude-only synthesis method

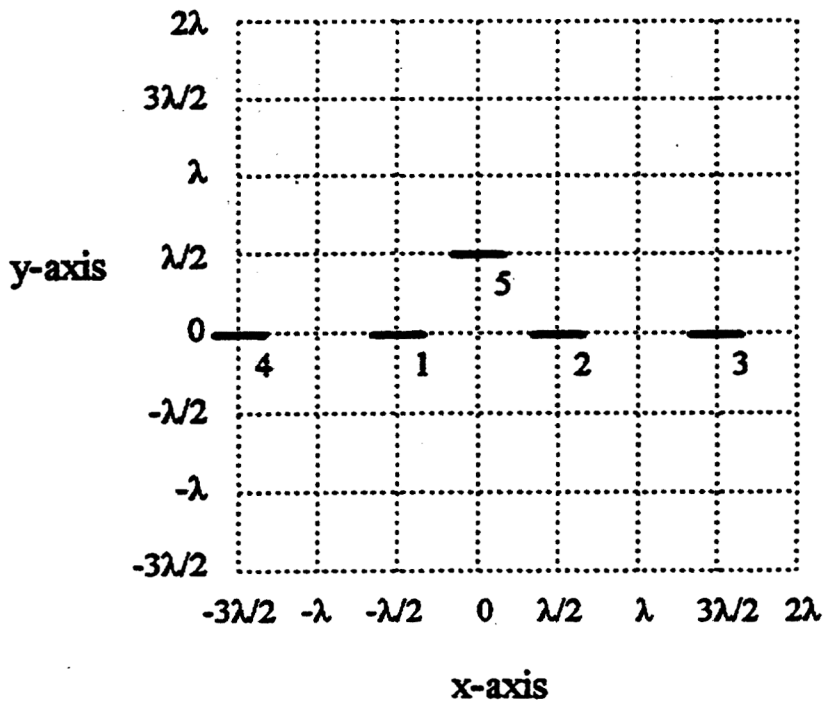


Fig. 5. Genetically optimized element locations using magnitude-only synthesis method.

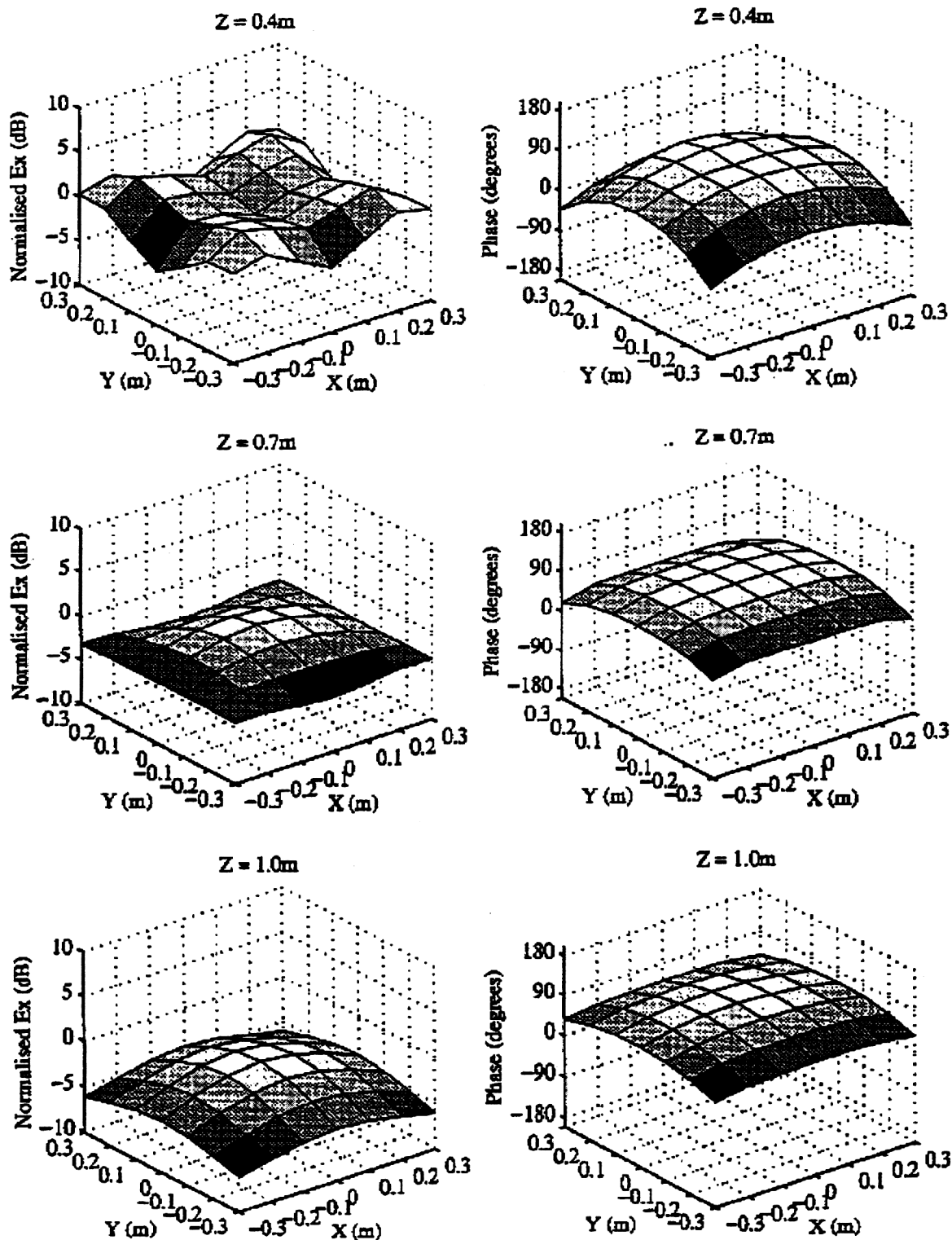


Fig. 6. Magnitude and phase variations of dominant (x) component of computed electric field strength due to cross-shaped array in Fig. 2, synthesized by magnitude-only method.

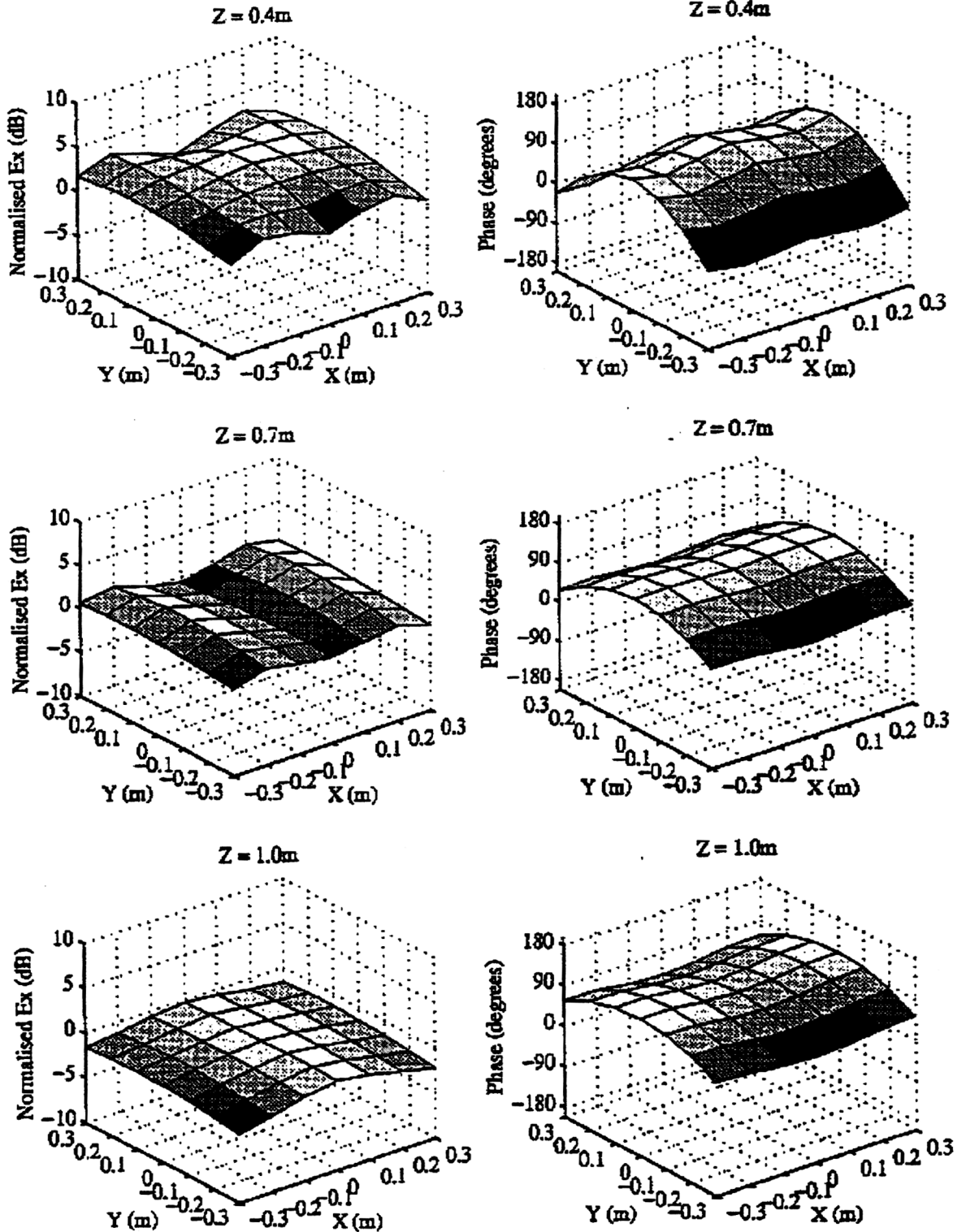


Fig. 7. Magnitude and phase variations of dominant (x) component of computed electric field strength due to near-linear array in Fig. 5, synthesized by magnitude-only method.