Diagnosis of Array Faults from Far-Field Amplitude-Only Data

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***Abstract*—The diagnosis of the faulty elements of a planar array from noisy far-field power pattern data is considered in the case of "on–off" faults. The possible ambiguities of the solutions are considered both in the theoretical and practical sense and are shown to be intrinsically less relevant than in the widely studied continuous case. The probability of the occurrence of the practical ambiguities is inferred from a number of numerical examples and is shown to be negligible in all cases of interest. An effective algorithm is presented here based on an intersection set finding approach and involving the minimization of a suitable objective functional. The global minimization of the functional has been successfully performed by applying a properly modified genetic algorithm. A number of numerical examples shows the effectiveness of the approach whose computational complexity essentially increases linearly with the array size.**

***Index Terms*—Fault diagnosis, phased-array antennas.**

I. Introduction

DETERMINING the faulty elements of an array is a complex problem of practical interest, particularly for large antennas and/or those arrays which cannot be brought to a laboratory for inspection [1].

One kind of fault widely encountered in practical instances is the so-called "on–off" fault, where the faulty element does not radiate at all. Later on we consider only these faults.

One possible solution to the diagnostic problem could be to make use of a network of sensors integrated with the beamforming network, while monitoring the array "status" in real time. However, such an expensive network must be provided at the design stage of the array and may be affected by faults.

Therefore, it is best to perform the antenna diagnosis by measuring the radiated field without removing the array from its working site and without a serious interruption of its normal operating conditions. For satellite borne antennas, the choice of far-field measurements is highly important. In the case of large earth-based antennas, where the far-field measurements can be performed as described in [2] for reflector antennas, this choice proves very convenient from a practical point of view.

Furthermore, to avoid measuring the complex far-field pattern, which requires a reference phase signal and an expensive measurement setup, it is of great practical interest to perform the array diagnosis by exploiting only the amplitude far-field pattern.

At first glance, this goal seems nonrealistic. In fact, the array factor is related to the excitation coefficients by a discrete Fourier transform (DFT) relationship. Accordingly, the diagnosis problem is equivalent to finding a function from the modulus of its Fourier transform, a topic widely dealt with in literature. This does not give unambiguous solutions [3].

The first aim of this paper is to show that this restriction can be practically removed in the case of on–off faults considered here. In particular, it will be shown that the probability of finding an ambiguous solution is drastically smaller than that occurring in the general case. As a result, the diagnosis problem proves unambiguous in the practical sense.

However, this is not enough. One critical point to be considered concerns the ability to effectively explore the solution space without being trapped by false solutions. Since the algorithms based on a deterministic local search criterion stop when a local optimum of the search criterion is found, global minimization algorithms [4] are needed. In particular, for an arbitrary prefixed accuracy, nondeterministic algorithms such as simulated annealing [5] or evolutionary algorithms [6], [7], allow a full exploitation of the solution space in a probabilistic sense and guarantee the attainment of the global optimum of the search criterion asymptotically as the number of trials increases to infinity [4], [6].

In our case, it must be noted that the search space is a discrete one, as the unknowns can assume only one of the two values, i.e., zero or one. However, as is also the case of moderately sized arrays, its cardinality is extremely large (e.g., for an array with 225 radiators it is equal to $2^{225} = 5.4 \cdot 10^{67}$). Accordingly, an effective searching algorithm is necessary. In this paper, we use a (suitably modified) genetic algorithm, which, based on a discrete representation of the unknowns, naturally matches the problem at hand. The extensive numerical analysis presented in this paper shows the effectiveness of this choice.

The statement of the problem is presented in Section II. The analysis of the practical ambiguities is considered in Section III. The diagnostic algorithm is presented in Section IV, where its effectiveness is addressed. Conclusions are drawn in Section V.

II. Statement of the Problem

Let us consider an array of $N \times M$ elements regularly distributed with spacing d_x and d_y along the x and y axes, respectively (see Fig. 1). The nominal excitation coefficients of the array, say $C_{n,m}$, $n = 1, \cdots, N$, $m = 1, \cdots, M$, are assumed

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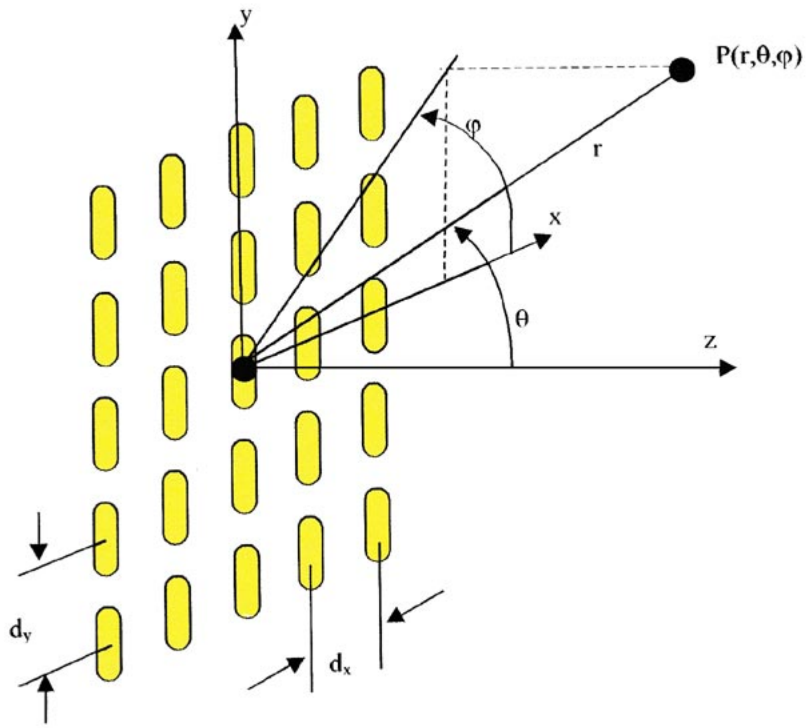


Fig. 1. Geometry of the problem.

to be different from zero and are the components of the excitation matrix $\underline{\underline{C}} = \{C_{n,m}\}_{\substack{n=1,\cdots,N\\ m=1,\cdots,M}}$. The corresponding array factor $F(u, v)$ is given by

$$F(u, v) = \sum_{n=1}^{N} \sum_{m=1}^{M} C_{nm} e^{jnu} e^{jmv} = \mathcal{F}(\underline{\underline{C}}) \tag{1}$$

where $u = kd_x \sin\vartheta \cos\varphi$, $v = kd_y \sin\vartheta \sin\varphi$, $k = 2\pi/\lambda$, λ the wavelength, (θ, φ) the spherical coordinates (Fig. 1), $\mathcal{F}$ the Fourier series associated to $\underline{\underline{C}}$ and a $e^{j\omega t}$ time dependence is subtended.

For the sake of convenience, the excitation coefficients matrix, say $\underline{\underline{C}}^{(g)}$, corresponding to the faulty array, will be expressed in the following as the product (element by element) between $\underline{\underline{C}}$ and the matrix, say $\underline{\underline{C}}^{(b)}$, whose (n, m)th entry is one or zero, according to the status (working or faulty) of the corresponding array element.

In order to account for the noise and measurement errors affecting the power pattern measured, the maximum additive error on the data, say $\varepsilon^2(u, v)$, is introduced. Accordingly, the square amplitude of the array factor actually radiated by the array, say $M^2(u, v)$, belongs to the set

$$\mathcal{Y} = \Big\{ y(u, v) \colon \Big| y(u, v) - \overline{M}^2(u, v) \Big| \leq \varepsilon^2(u, v) \, \forall \, (u, v) \in \Omega \Big\} \tag{2}$$

where Ω denotes the measurement sector in the (u, v) plane and $\overline{M}^2(u, v)$ is the square amplitude measured of the array factor.

However, $M^2(u, v)$ must belong to the set, say $\mathcal{G}$, of the square amplitudes of the array factors $F^{(g)}(u, v)$ associated with the antenna being tested and corresponding to the excitation vector $\underline{\underline{C}}^{(g)} = \{C_{n,m} C_{n,m}^{(b)}\}_{\substack{n=1,\cdots,N\\ m=1,\cdots,M}}$.

Therefore, any point of the intersection set $\mathcal{G} \cap \mathcal{Y}$ can provide an acceptable estimate of the actual array factor and thus of the corresponding excitation coefficients.

III. Occurrence of Ambiguities

In order for a diagnosis technique to be effective, the first property necessary is the uniqueness of the solution. When dealing with this problem, it is convenient first to address the general problem of how to retrieve a matrix $\underline{\underline{A}}$ from the modulus of its Fourier series $F(u, v) = \mathcal{F}\underline{\underline{A}})$ and then the on–off faults case of interest here.

A. Continuous Case

As mentioned in the Section I, this problem does not admit a unique solution, i.e., there are matrices $\underline{\underline{\hat{A}}} \neq \underline{\underline{A}}$ such that $|\mathcal{F}[\underline{\underline{\hat{A}}}]| = |\mathcal{F}[\underline{\underline{A}}]|$, so that ambiguous solutions are indeed possible.

It is convenient to distinguish between trivial and nontrivial ambiguities [8].

Trivial ambiguities occur in the following three cases:

1) $\underline{\underline{\hat{A}}} = c\underline{\underline{A}}(|c| = 1)$;
2) $\underline{\underline{\hat{A}}} | \hat{A}_{n,m} = (A_{N-n,M-m})^*$;
3) $\underline{\underline{A}}$ can be obtained by zero filling a smaller matrix, say $\underline{\underline{\tilde{A}}}$, up to a matrix with dimensions $N \times M$ and $\underline{\underline{\hat{A}}}$ is any other matrix (with dimensions $N \times M$) obtainable from $\underline{\underline{\tilde{A}}}$ by zero filling.

These ambiguities will be referred later on as trivial ambiguities of the first, second, and third kind, respectively.

To discuss nontrivial ambiguities, it is convenient to set $\xi = e^{ju}$, $\eta = e^{jv}$ in (1) and consider $F(u, v)$, as a polynomial in the complex variables ξ, η, say $P(\xi, \eta)$. Nontrivial ambiguous solutions occur when $P(\xi, \eta)$ is a factorable two-dimensional (2-D) polynomial [9], [3].

Since it can be shown that the probability of finding a factorable polynomial is zero,[1] this could appear a slight drawback although not serious. However, as will be discussed later on, the existence of measurement errors makes this kind of ambiguity quite relevant.

In fact, due to measurement error, any matrix belonging to the set $\mathcal{A} = \{\underline{\underline{B}}\colon ||\mathcal{F}(\underline{\underline{B}})|^2 - \overline{M}^2| \le \varepsilon^2\}$ is a possible solution of the problem at hand, but it is acceptable only if it is also close to $\underline{\underline{A}}$.

Now, let us assume that a matrix, say $\hat{\underline{\underline{A}}}_0$, corresponding to a reducible polynomial, belongs to $\mathcal{A}$ so that R matrices, say $\hat{\underline{\underline{A}}}_n$, $n = 1, \cdots, R$, such that $|\mathcal{F}[\hat{\underline{\underline{A}}}_0]|^2 = |\mathcal{F}[\hat{\underline{\underline{A}}}_1]|^2 = \cdots = |\mathcal{F}[\hat{\underline{\underline{A}}}_R]|^2$ do exist. According to the previous considerations, all these matrices are possible solutions. However, if at least one of such matrices is not close to the true solution $\underline{\underline{A}}$, an ambiguous solution occurs and $\underline{\underline{A}}$ cannot be univocally (within the measurement error) determined from the measured data.

This ambiguity, which can be present even if $P(\xi, \eta)$ is not factorable, will be referred to later as a "practical" ambiguity. Furthermore, the probability of its occurrence, which is strictly related to the existence of ambiguities in the ideal case of exact measurements, has a finite value that can be significantly different from zero [8].

B. Discrete On–Off Case

The on–off faults case will now be discussed by showing that the ambiguity problem is more favorable even in the case of exact measurements.

Let us note that the matrix involved in the ambiguity problem discussion is now the faulty excitation coefficient matrix $\underline{\underline{C}}^{(g)} = \underline{\underline{C}} \bullet \underline{\underline{C}}^{(b)}$.

Obviously, the two-level quantized nature of the unknown $\underline{\underline{C}}^{(b)}$ drastically reduces the solution space from C^{N*M} to a set with 2^{N*M} cardinality.

First of all, let us consider the case of trivial ambiguities.

The trivial ambiguities of $\underline{\underline{C}}^{(g)}$ can correspond to faulty arrays, only if they can be put in the form $\underline{\underline{C}} \cdot \underline{\underline{C}}'^{(b)}$ where $\underline{\underline{C}}'^{(b)}$ is a mask matrix, and this can be done if and only if the matrix $\underline{\underline{C}}$ has certain symmetry properties whose occurrence in practice is not very likely.

As a matter of fact, with reference to trivial ambiguities of the second kind (it is easy to verify that trivial ambiguities of first kind never occur), let us remember that we have assumed that the matrix $\underline{\underline{C}}$ has no zero elements.

The matrix $\hat{\underline{\underline{C}}}^{(g)}$ is a solution of the on–off array diagnosis problem if and only if $C_{n,m} = C^*_{N-n, M-m}$ for those n, m such that $C^{(b)}_{N-n, M-m} = 1$. In practice, the number of faulty elements in the array being tested is always a small fraction of the number of array radiators, and so the above symmetry condition is very strong.

In the same way, we can discuss factorable ambiguities.

One necessary condition causing the fault diagnosis problem to be ambiguous is that the faulty excitation coefficients matrix $\underline{\underline{C}}^{(g)}$ belongs to the ambiguity surface (a zero likelihood event), which implies very strong constraints on the matrix $\underline{\underline{C}}$. To highlight this point, let us consider, for example, the case $N = 2$, $M = 3$. Denoting a general $2*3$ matrix as $\begin{bmatrix} a & b & c \\ d & e & f \end{bmatrix}$, the surface ambiguity equation is [8]

$$(af - cd)^2 - (ae - bd)(bf - ce) = 0. \tag{3}$$

When a single fault occurs, for instance, $a = 0$, the fault excitation coefficients matrix belongs to the ambiguity surface if and only if the matrix $\underline{\underline{C}}$ belongs to the surface $(cd)^2 - bd(bf - ce) = 0$. When two faults are present, e.g., $a = 0 = b$, the matrix $\underline{\underline{C}}^{(g)}$ never belongs to the ambiguous surface.

Moreover, even if $\underline{\underline{C}}^{(g)}$ belongs to the ambiguity surface, the problem may prove unambiguous. In fact, it is also necessary that at least one of the ambiguous counterparts of $\underline{\underline{C}}^{(g)}$ is a faulty array, i.e., it can be put in the factorized form $\underline{\underline{C}} \cdot \underline{\underline{C}}'^{(b)}$. Again this is a very unlikely occurrence.

Let us now turn to the problem of practical ambiguities.

Since the presence of practical ambiguities is related to the existence of ambiguities in the ideal case of zero measurement error, it is evident from the above discussion that the practical ambiguity problem is certainly less relevant in the on–off fault array diagnosis problem. In other words, the probability of ambiguous solutions should be drastically reduced to very small values so that the diagnosis problem becomes unambiguous in the practical sense.

In order to show that this is indeed the case, an extensive numerical analysis was performed in a way similar to that followed in [8] in the case of continuous values of the excitation coefficients. From this analysis, the probability of the ambiguous solutions was inferred as discussed in Section III-C.

C. Numerical Investigation of the Ambiguity Problem

Let us denote by

$$\underline{\underline{F}} = \{F(n\pi/N, m\pi/M)\}_{\substack{n=0,\cdots,2N-1 \\ m=0,\cdots,2M-1}}$$

the $2N*2M$ matrix of samples of $F(u, v)$ at twice the Nyquist rate, and with $\underline{\underline{C}}$ the complex matrix of the array excitation coefficients, zero padded to a $2N*2M$ matrix. The spaces of such matrices will be called image space and object spaces, respectively. Following [8], we define the distances[2] δ_i and $\delta_o$in the object and image space, respectively, as (it can be proved that $\delta_i \le \delta_o \le \sqrt{2}$ [8])

$$\delta_o\left(\underline{\underline{C}}', \underline{\underline{C}}''\right) = \left\| \frac{\left(\underline{\underline{C}}', \underline{\underline{C}}''\right)^*}{\left|\left(\underline{\underline{C}}', \underline{\underline{C}}''\right)\right|} \frac{\underline{\underline{C}}'}{\|\underline{\underline{C}}'\|} - \frac{\underline{\underline{C}}''}{\|\underline{\underline{C}}''\|} \right\| \tag{4a}$$

[1]In fact, the set of all factorable polynomials with a given degree is a surface in the space of all polynomials (with the same degree [9]) and, thus, has a zero Lebesque measure.

[2]Strictly speaking a metric in the quotient space of the matrices normalized to their norm.

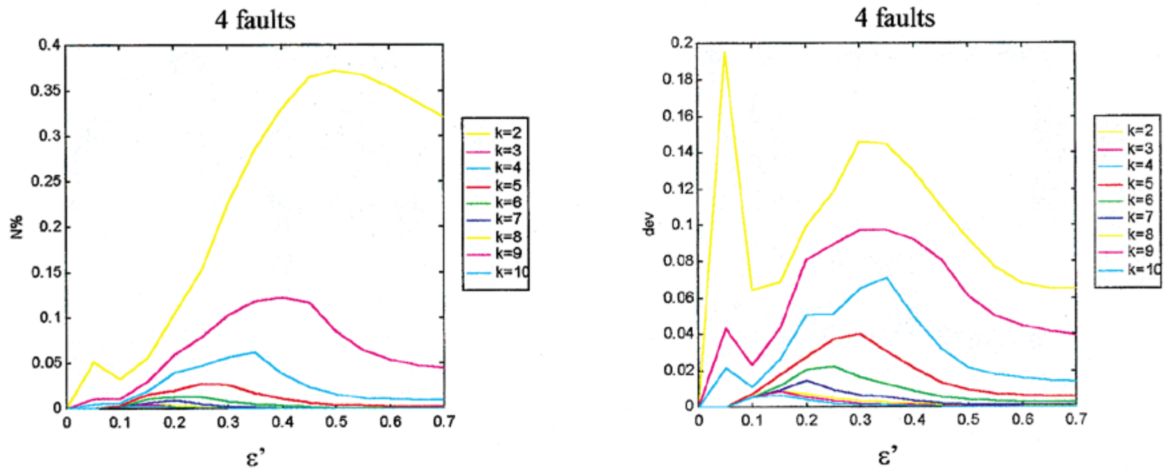


Fig. 2. Percentage of cases for which $\delta_i < \varepsilon'$ and $\delta_o < k\,\delta_i$.

and

$$\delta_i\left(\underline{\underline{F'}}, \underline{\underline{F''}}\right) = \left\| \frac{|\underline{\underline{F'}}|}{\|\underline{\underline{F'}}\|} - \frac{|\underline{\underline{F''}}|}{\|\underline{\underline{F''}}\|} \right\| \tag{4b}$$

where

$$\left(\underline{\underline{C'}}, \underline{\underline{C''}}\right) = \sum_{1 i \delta}^{2N, 2M} C'_{ij} C''^{*}_{ij}, \; \|\underline{\underline{C}}\| = \left[\sum_{1\, ii\delta}^{2N, 2M} C_{ij} C^{*}_{ij}\right]^{1/2}$$

and $(z/|z|)$ is defined equal to one for $z = 0$.

The diagnosis algorithm should find a set of excitation coefficients whose distance δ_o from the true one is as close as possible to δ_i, say less than $k\delta_i$, where k is a factor close to one. Accordingly, among all points of $\mathcal{G} \cap \mathcal{Y}$, only those corresponding to excitations whose distance from the true one (in the object space) is greater than $k\delta_i$ give rise to an ambiguity in the practical sense.

A numerical analysis was performed on a set of 20 matrices of $3*3$ randomly chosen complex coefficients. For each matrix, all possible faulty arrays with two, three, and four faults were considered. For each fault array, its distance from any other possible faulty array, irrespective of the number of faults, was computed both in the object and image space. For space-saving purposes, only the results referring to three faults are reported. Fig. 2(a) and (b) shows the mean value and the standard deviation, respectively, (over the whole set of 20 considered arrays) of the percentage number, say $N\%$, of cases for which δ_i is less than a given value, say ε', and δ_o is less than $k\delta_i$ for several values of k versus ε'.

As can be seen, the probability that δ_o is significantly greater than δ_i is very close to zero for small values of δ_i (as in any practical instance is). The results of the numerical analysis for two and four faults confirm this behavior, especially when the number of faults is not a major fraction of the total number of the array elements.

IV. Diagnostic Algorithm and Numerical Results

For closed-bounded sets, finding a point of the set $\mathcal{G} \cap \mathcal{Y}$ is equivalent to finding a matrix $\underline{\underline{C}}^{(b)}$ minimizing the functional

$$\Psi\left(\underline{\underline{C}}^{(b)}\right) = \left\| |F^{(g)}(u, v)|^2 - P_{\mathcal{Y}}\left(|F^{(g)}(u, v)|^2\right) \right\|_{\mathcal{L}_2} \Big/ \left\| \overline{M}^2 \right\|_{\mathcal{L}_2} \tag{5}$$

where $P_{\mathcal{Y}}$ is the metric projector[3] onto $\mathcal{Y}$ and $\|*\|_{\mathcal{L}_2}$ represents the norm in the space of square integrable functions over Ω, say $\mathcal{L}_2(\Omega)$. Any array factor whose squared amplitude differs from $\overline{M}^2(u, v)$ for less than $\varepsilon^2(u, v)$, $\forall (u, v) \in \Omega$, is an absolute minimum (zero) of the functional (5).

As pointed out in Section I, we used a genetic algorithm, which, generally speaking, successfully obtained the solution of difficult minimization problems with a weak dependence on the complexity of the problem, i.e., the dimensions of the array being tested and with reasonable computing time.

Since the defining space of the functional Ψ is the space of binary matrices, a binary coded genetic algorithm was considered where each chromosome of the population represents one mask matrix. In order to improve the convergence properties of the algorithm, a modified version of a canonical genetic algorithm [10] was adopted.

First of all, an elitist strategy was considered [11], [12]. In addition, a "2-D" crossover was introduced and a quasilinear scaling of the fitness function was applied [10].

In particular, given the mating matrices $\underline{\underline{A'}}$ and $\underline{\underline{A''}}$ and two randomly chosen indexes, say i_0 and j_0, the two "2-D" crossed matrices are defined as

$$B'_{ij} = \begin{cases} A'_{ij}, & \text{for } (i, j) \text{ such that } i \geq i_0,\ j \geq j_0 \\ & \text{or } i \leq i_0,\ j \leq j_0 \\ A''_{ij}, & \text{for } (i, j) \text{ such that } i > i_0,\ j < j_0 \\ & \text{or } i < i_0,\ j > j_0 \end{cases} \tag{6}$$

[3]The metric projector onto $\mathcal{Y}$ associates the point of $\mathcal{Y}$ nearest to x to any point x.

$$B''_{ij} = \begin{cases} A''_{ij}, & \text{for } (i,\, j) \text{ such that } i \geq i_0,\, j \geq j_0 \\ & \text{or } i \leq i_0,\, j \leq j_0 \\ A'_{ij}, & \text{for } (i,\, j) \text{ such that } i > i_0,\, j < j_0 \\ & \text{or } i < i_0,\, j > j_{0_0}. \end{cases} \tag{7}$$

In this way the algorithm explicitly takes into account the 2-D characteristics of the unknown, and so building blocks in the form of submatrices are allowed to grow.

The quasi-linear scaling realizes the following correspondence between the objective functional and the fitness function, say Φ

$$\Phi = \begin{cases} a\Psi + b, & \text{for } a\Psi + b \geq 0 \\ 0, & \text{for } a\Psi + b < 0 \end{cases} \tag{8}$$

where the constants a and b are chosen in order to fix the mean value and obtain $\max(\Phi) = h * \text{mean}(\Psi)$ and where $h > 1$ is a scaling parameter. An appropriate value of h is able to guarantee a constant selection pressure and so to speed up the convergence of the algorithm (by about ten times, in our numerical analysis) with respect to the simple more conventional correspondence: $\Phi = \max(\Psi) - \Psi$.

The minimization genetic algorithm was subjected to an extensive numerical analysis in order to choose the optimal set of parameters and to prove its effectiveness.

In an initial investigation, the excitation coefficients have constant amplitude and a random phase in order to avoid the problem of detecting faults corresponding to coefficients whose amplitude is much smaller than the maximum. The mean number of generations (over ten runs with different initial populations) needed to obtain the solution with a number of faults equal to $0.2 * N * M$ is shown in Table I for four different values of N and M. In the examples worked out, the population consists of 101 chromosomes and a uniformly distributed noise -50 dB under the norm of the square amplitude of the array factor was assumed. Table I shows that the computing time required to find the solution weakly depends on the complexity of the problem. In fact, while the number of possible solutions ($2^{N \times M}$) increases exponentially with the array dimension, the number of generations only shows a linear increase.

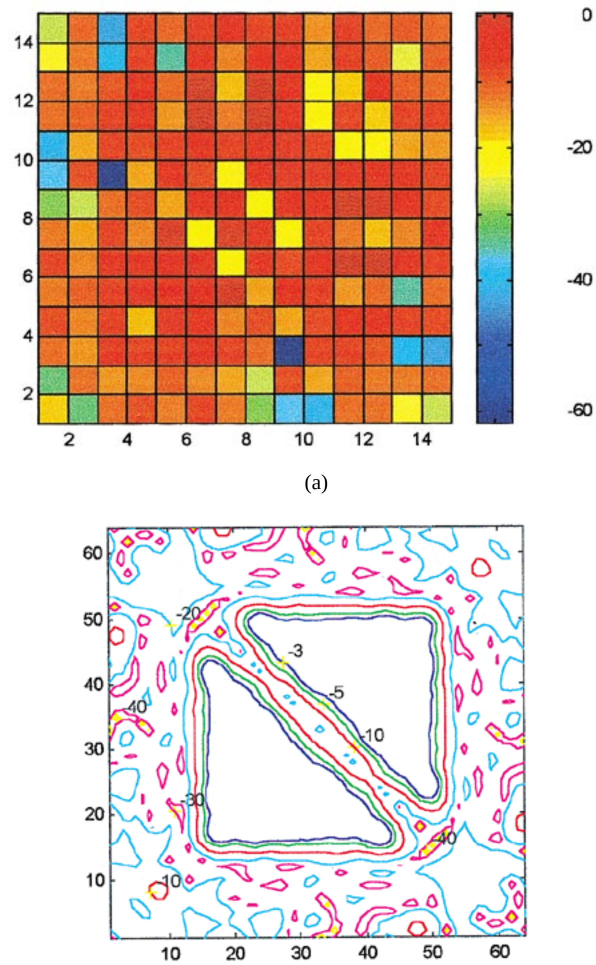
The algorithm was also tested on excitation coefficients matrices of practical interest. The excitation coefficient matrix of $15 * 15$ elements, shown together with the correspondent array factor in Fig. 3, was used for this purpose. In this case, a matrix with a large dynamical range of elements and with symmetry properties is involved. Ten different fault configurations with 20 faults were considered. Ten runs with different initial population were worked out for each fault configuration. The cardinality of the population was always set equal to 101.

In the case of zero measurement error, ambiguity problems never occurred.

When a maximum error equal to -50 dB was present, the algorithm was able to reconstruct the correct fault matrix, apart from the excitation coefficients whose amplitude is much less than the maximum modulus coefficient in the array being tested. Numerical analysis showed that the differences between the computed mask matrix and the true one were generally

TABLE I
MEAN NUMBER OF GENERATIONS NEEDED TO GET THE SOLUTION FOR DIFFERENT ARRAY DIMENSION

DIMENSIONS	MEAN NUMBER OF GENERATIONS
5*5	6.9
10*10	23.1
15*15	47.5
20*20	195.6



(a)

(b)

Fig. 3. Array excitation coefficients and the corresponding array factor.

confined to one or two coefficients whose amplitudes were -40 dB below the maximum one.

The dependence of the mean value of the objective function on the population, its minimum value and its standard deviation at each generation (as a mean of all the ten considered cases) are shown in Fig. 4 versus the number of generations.

V. CONCLUSIONS

In conclusion, it can be said that the on–off diagnosis of a planar array is an affordable task both from the point of view

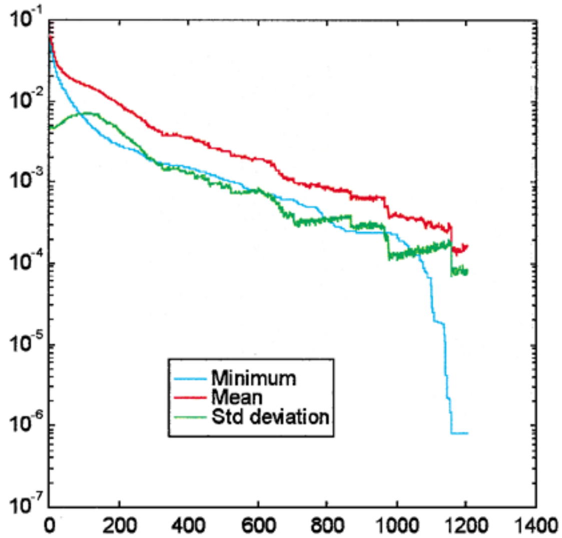


Fig. 4. The minimum value of the objective function over the population, its mean value, and its standard deviation at each generation (as a mean over ten cases and over ten different starting populations for each case) versus the number of generations with a semilogarithmic scale.

of the ambiguity problem and computational effort. The ambiguity problem was shown to be intrinsically less relevant with respect to that encountered in the continuous case. Furthermore, the probability of the occurrence of the ambiguous (in the practical sense) solutions, as inferred from the numerical investigation presented, assumes fairly small values and can be considered negligible in any practical application. The global minimization of the objective functional was successfully performed by applying a (suitably modified) genetic algorithm. The computational effort required proved to be modest in the examples worked out and showed an essentially linear dependence on the size of the array being tested.

The approach and the investigation presented here may also be applied to more general kind of faults, to near-field or Fresnel zone intensity measurement, as well as to cases where the mutual coupling between radiating elements is taken into account.

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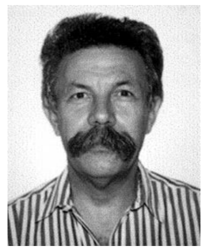

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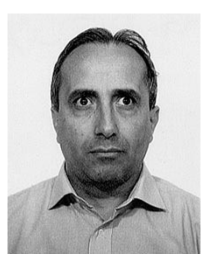

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