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RESEARCH PAPER

Variable Z_o applied to the optimal design of multi-stub matching network and a meander monopole

NIHAD DIB[1], ASHRAF SHARAQA[2] AND RICHARD A. FORMATO[3]

Variable Z_o*, a new concept in antenna design and optimization, is applied to two optimization problems: a multi-stub matching network (MSMN) using biogeography-based optimization (BBO), and an ultra wideband meander monopole antenna (MMA) using central force optimization (CFO). BBO is a newly-proposed stochastic global search and optimization evolutionary algorithm (EA) used to determine MSMN stub lengths and locations for optimum (minimum) reflection coefficient. CFO is a deterministic EA used to optimize the MMA's impedance bandwidth (IBW) while maintaining good average gain without considering the radiation pattern in detail. Two cases are investigated for both problems: (a) fixed characteristic impedance* Z_o*, and (b) variable characteristic impedance. In the first case,* Z_o *is a fixed user-specified parameter (the traditional methodology), whereas in the second, it is a true variable quantity whose value is determined by the optimization methodology, which is a new technology. Variable* Z_o *is a fundamentally different design approach in optimization problems. BBO's fixed* Z_o *results for MSMN are compared to published data computed using Nelder–Mead optimization with BBO exhibiting better performance. BBO's results are improved even more using Variable* Z_o *technology. A similar performance improvement is seen for Variable* Z_o *applied to the CFO-optimized MMA.*

Keywords: *Variable* Z_o, Matching networks, Monopole antenna, Optimization, Biogeography-based optimization, Central force optimization

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I. INTRODUCTION

Traditional antenna system design and optimization methods begin by assuming a *fixed* value for the feed system characteristic impedance or radio frequency source internal impedance Z_o, but doing so automatically excludes all matching networks and antennas whose performance is better with a different value of Z_o. *Variable* Z_o addresses this limitation by making Z_o a true *variable* quantity whose value is determined *by* the design or optimization methodology. *Variable* Z_o produces better networks and antennas by introducing another degree of freedom into the design or optimization space, thereby making it easier to meet any set of performance objectives. As examples of *Variable* Z_o's effectiveness, this paper describes a multi-stub matching network (MSMN) designed using biogeography-based optimization (BBO) and an ultra wideband (UWB) meander monopole antenna (MMA) optimized using central force optimization (CFO).

[1] Electrical Engineering Department, Jordan University of Science and Technology, P.O. Box 3030, Irbid 22110, Jordan
[2] Communication and Security Projects Division, WorleyParsons Arabia Ltd., P. O. Box 31699, Al-Khobar 31952, Saudi Arabia
[3] Consulting Engineer and Patent Attorney, P.O. Box 1714, Harwich, MA 02645, USA
Corresponding author:
N. Dib
Email: nihad@just.edu.jo

Matching networks are important in all communication systems because they maximize power delivered to the load, improve signal-to-noise ratio (SNR), and reduce the amplitude and phase errors in power distribution networks by minimizing the reflection coefficient [1]. An extremely low voltage standing wave ratio (VSWR) often is a requirement in broadcast applications, sometimes ≤1.05:1, where even slight amplitude and phase errors result in loss of signal fidelity. To that end, the MSMN is a commonly employed matching device usually designed using the Smith chart or an analytical solution to determine the stubs' lengths and positions [1]. Unfortunately, as the number of stubs increases, so does the complexity of this process, and at some point it becomes unwieldy. An alternative approach is to use optimization techniques that minimize the reflection coefficient in a specific frequency range [2, 3].

BBO is a newly proposed global optimization evolutionary algorithm (EA) [4] based on the science of biogeography (study of the natural geographic distribution of plants and animals). BBO has been demonstrated to be an effective optimization technique compared to other methodologies [4–6]. It has been successfully applied across a range of engineering problems, for example: optimal power flow [7, 8]; optimal Yagi–Uda antenna design [9]; optimization of linear and circular antenna arrays [10–13]; and calculation of the resonant frequencies of rectangular and circular microstrip patch antennas [14, 15]. BBO's robustness and effectiveness against complex problems have been further improved by hybridizing BBO with other optimization techniques, thereby taking advantage of the best features of both algorithms [16, 17].

The first optimization problem considered in this paper is the design of an optimized MSMN comprising stubs placed at specific distances from the load [18, 19], the design variables being the stubs' locations and the lengths. BBO with fixed and *Variable* Z_o is used to determine these values by minimizing the reflection coefficient in a specific frequency range. A multi-stub configuration is optimized, which is a significant extension of previously published work that considered only single- and double-stub configurations [2, 3].

With respect to the MSMN design, the objectives are twofold: demonstrating BBO's effectiveness as a design tool; and comparing BBO results using fixed and *Variable* Z_o with results available in the literature. It should be emphasized that *Variable* Z_o concept has not been applied to MSMN design previously. BBO with *Variable* Z_o achieves almost exactly the desired VSWR response, whereas BBO (or other methods) with fixed Z_o does not perform nearly as well. A similar approach is taken with respect to the MMA. The MMA is optimized for impedance bandwidth (IBW) using CFO using both fixed and *Variable* Z_o [20]. The MMA example again demonstrates that *Variable* Z_o provides much better results than the fixed Z_o case.

This paper is organized as follows: Section 2 presents the MSMN problem. In the same section, the BBO technique is briefly described (detailed information is available in the above-cited references with basic BBO Matlab code available in [21]), and two examples are presented. Section 3 describes the MMA design problem. Section 4 is the conclusion.

II. MULTI-STUB MATCHING NETWORK

In this section, *Variable* Z_o is applied to a BBO-optimized MSMN. The obtained results are compared to optimization results for the MSMN using BBO along with the standard approach of fixing Z_o. The *Variable* Z_o MSMN exhibits much better performance.

A) Optimization methodology

BBO is a metaphor drawn from the science of biogeography, which studies nature's geographical distribution of plants and animals. Mathematical biogeography models are based on the metaphor of extinction and migration of species between neighboring islands. An "island" is any habitat (area) that is geographically isolated from other habitats. Islands that are more suitable for habitation have a high "habitat suitability index" (HSI), which is treated as a dependent variable because it correlates with many factors such as rainfall, temperature, diversity of vegetation and topography, and so on. Another important BBO variable is the "suitability index variable" (SIV), which generally characterizes an island's habitability and is treated as an independent variable. The BBO algorithm consists of three steps: (1) creating a set of solutions to the problem, where they are randomly selected, and then applying (2) migration and (3) mutation steps to reach the optimal solution.

BBO is applied to global search and optimization by starting with a random population of candidate solutions represented by an array of integers as follows:

$$Habitat = [SIV_1,\ SIV_2, SIV_3, \ldots, SIV_N]. \quad (1)$$

Each integer represents an independent suitability index variable (SIV), while the value of the BBO fitness function is the dependent variable habitat suitability index (HSI). HSI and SIV therefore are related by:

$$fitness(Habitat) = HSI = f(SIV_1,\ SIV_2, SIV_3, \ldots, SIV_N). \quad (2)$$

In the second step, the migration step, equations (3) and (4) are used to evaluate the immigration rate (λ) and the emigration rate (μ) of each solution, respectively, which are shown in Fig. 1, and which are used to probabilistically share information between habitats with probability P_{mod} (P_{mod} known as the "habitat modification probability").

$$\lambda_s = I\left(1 - \frac{S}{S_{max}}\right), \quad (3)$$

$$\mu_s = E\left(\frac{S}{S_{max}}\right), \quad (4)$$

where S is the number of species in the habitat; S_{max} the maximum possible number of species; and I and E, respectively, the maximum possible immigration and emigration rates. It is assumed that all solutions have identical rate curves with $E = I = 1$, which normalizes λ and μ to the interval [0, 1] (no net change in number of species in an island, only movement between islands). The pseudocode in Fig. 2 summarizes BBO's migration process.

Finally, the mutation step tends to increase the diversity among the population and gives the solutions the chance to improve themselves by achieving better fitness. Performing mutation on a solution is done by replacing it with a new solution that is randomly generated. Figure 3 shows the pseudocode for the mutation process, whereas Fig. 4 shows a flow chart of the main steps of the BBO.

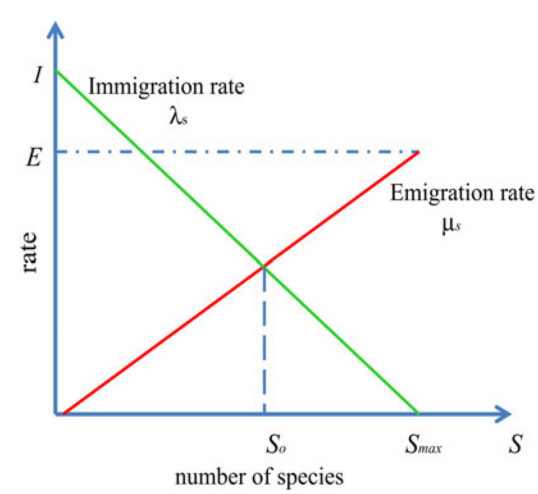

Fig. 1. Species model of a single BBO habitat.

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```
For i = 1 to G (where G is the number of islands)
   If rand > P_mod
         Continue
   End
         For j = 1 to N (where N is the number of variables)
               Select an SIV_j in H_i with probability ∝ λ_i
               If an SIV_j is selected to be modified
                  For k = 1 to G
                        Select H_k with probability ∝ μ_k
                        If H_k is selected
                              Replace the SIV_j in H_i with an SIV_j from H_k
                        End
                  End
               End
         End
End
```

Fig. 2. Pseudocode for BBO Migration Operator.

B) Formulation of the MSMN problem

Figure 5 is a schematic representation showing an N-parallel (shunt) MSMN that matches an arbitrary load impedance Z_L to a transmission line with characteristic impedance Z_o (impedances and admittances being related as $Z_L = 1/(Y_L)$ and $Z_o = 1/(Y_o)$). In addition to their positions and lengths, the stubs can be either open-circuited or short-circuited at their ends. In a perfectly matched system, the total input impedance Z_N (shown in Fig. 5) is equal to Z_o resulting in no reflected power. Thus, the design objective is to determine the stub locations, lengths, and terminations that best achieve this matching condition.

The first step is developing an expression for the total input admittance connected to the transmission line, which may be done recursively as follows [18]:

For the first stub ($n = 1$),

$$Y_1 = Y_1^d + Y_1^s, \tag{5}$$

$$Y_1^d = Y_O \frac{1 - \Gamma_1 \exp(-2\,\gamma\, d_1)}{1 + \Gamma_1 \exp(-2\,\gamma\, d_1)}, \tag{6}$$

$$\Gamma_1 = \frac{Y_o - Y_L}{Y_o + Y_L}, \tag{7}$$

$$Y_1^s = Y_o \frac{1 - \Gamma_1^s}{1 + \Gamma_1^s}, \tag{8}$$

where Γ_i^s is the reflection coefficient at the ith stub (see below).

For the nth ($n = 2, \ldots, N - 1$) stub,

$$Y_n = Y_n^d + Y_n^s, \tag{9}$$

```
For i = 1 to G (where G is the number of islands)
      For j = 1 to N (where N is the number of variables)
            If P_mutate > rand   (P_mutate is a user defined parameter)
                  Replace the SIV_j in H_i with a randomly generated SIV
            End
      End
End
```

Fig. 3. Pseudocode for BBO Mutation Operator.

$$Y_n^d = Y_O \frac{1 - \Gamma_n \exp(-2\,\gamma\, d_n)}{1 + \Gamma_n \exp(-2\,\gamma\, d_n)}, \tag{10}$$

$$\Gamma_n = \frac{Y_o - Y_{n-1}}{Y_o + Y_{n-1}}, \tag{11}$$

$$Y_n^s = Y_o \frac{1 - \Gamma_n^s}{1 + \Gamma_n^s}. \tag{12}$$

Furthermore, for the last stub ($n = N$),

$$Y_N = Y_N^d + Y_N^s, \tag{13}$$

$$Y_N^d = Y_O \frac{1 - \Gamma_N \exp(-2\,\gamma\, d_N)}{1 + \Gamma_N \exp(-2\,\gamma\, d_N)}, \tag{14}$$

$$\Gamma_N = \frac{Y_o - Y_{N-1}}{Y_o + Y_{N-1}}, \tag{15}$$

$$Y_N^s = Y_o \frac{1 - \Gamma_N^s}{1 + \Gamma_N^s}. \tag{16}$$

In the above equations, Γ_n^s depends on the type of the stub as follows:

$$\Gamma_n^s = -\exp\left(-2\gamma l_n^s\right), \quad n = 1, 2, \ldots, N, \quad \text{if the stub is terminated in a short circuit,} \tag{17}$$

$$\Gamma_n^s = \exp(-2\gamma l_n^s), \quad n = 1, 2, \ldots, N, \quad \text{if the stub is terminated in an open circuit.} \tag{18}$$

The transmission line's propagation and phase constants, respectively, are

$$\gamma = \alpha + j\beta, \tag{19}$$

$$\beta = \frac{2\pi}{\lambda} = \frac{2\pi f}{v}. \tag{20}$$

Summarizing the notation, Y_L is the load admittance, Y_o the transmission lines' characteristic admittance, Y_n the admittance just to the left of the nth stub, Y_n^d the admittance just to the right of the nth stub, and Y_n^s the stub input admittance. Γ_n is the reflection coefficient between the characteristic admittance (Y_o) and the admittance Y_{n-1}, and Γ_n^s is the stub reflection coefficient. d_n is the distance between nth and $(n - 1)$th stubs, and l_n^s is the stub length. γ is the propagation constant, α being the attenuation constant, β the phase constant, λ the wavelength, v the phase velocity, and f the frequency, all in consistent units. As shown above, the last calculated input admittance is Y_N which is obtained by recursively computing the admittances starting from Y_1 to Y_{N-1}.

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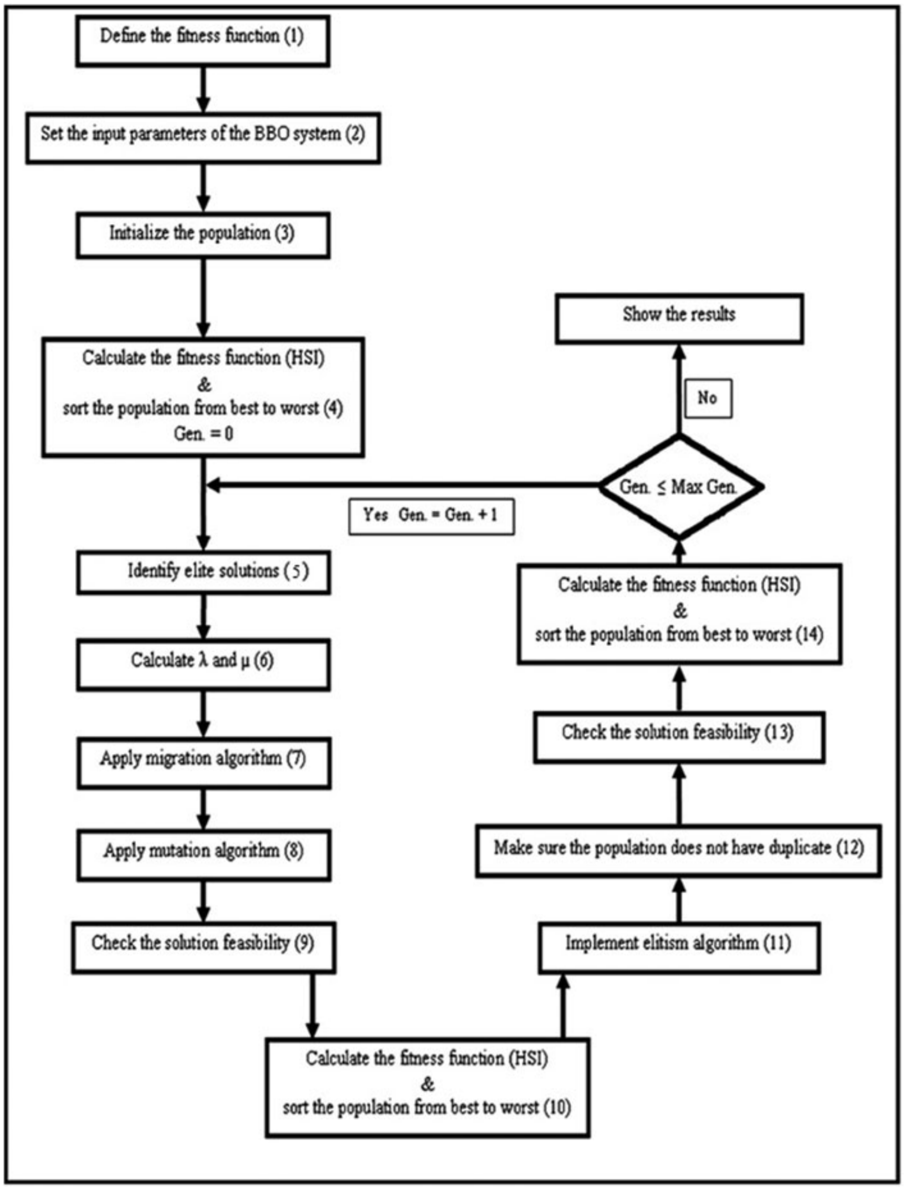

Fig. 4. Flowchart of the main steps of the BBO algorithm.

The final result is the overall input reflection coefficient between the total input admittance and the characteristic admittance of the feeding line, which is given by

$$\Gamma = \frac{Y_o - Y_N}{Y_o + Y_N}. \qquad (21)$$

The optimal match between the load impedance Z_L fed by a transmission line with characteristic impedance Z_o is achieved by minimizing Γ in equation (21). This will be accomplished using BBO as described in the next section. Note that the optimization problem is simplified somewhat by assuming that all components are lossless, and that all stubs are either short-circuited or open-circuited, so that the optimization (decision space) parameters are only the distances between the stubs and their lengths (d_n, l_n^s) which are assumed here to be in the range (1 mm, 100 mm).

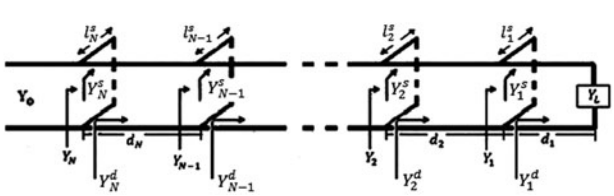

Fig. 5. General N parallel stubs connection.

C) Examples

The matching networks that consist of a single stub or double stubs are designed to operate at a single frequency, not over a band of frequencies [1]. But many modern communication applications require a wide bandwidth to improve transmission quality and data rate. Consequently, in the MSMN examples presented here, three, five and seven short-circuited stub configurations are optimized to obtain as nearly as possible a desired standing wave ratio (SWR) in a specific frequency range. The same problem addressed in [18] is considered here, so that results can be compared directly.

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Following [18], SWR and the fitness function to be minimized by BBO are defined as:

$$SWR = \frac{1 + |\Gamma|}{1 - |\Gamma|}, \quad (22)$$

$$fitness = \sum (\Gamma(f) - \Gamma_d(f))^2, \quad (23)$$

$$\Gamma_d = 0.05 \left(\frac{2}{B}\right)^{2m} (f - f_o)^{2m} \quad (24)$$

subject to $f = [1.1 \text{ GHz}, 1.3 \text{ GHz}]$ with 0.05 GHz increment.

The reflection coefficient Γ appears in equation (21). Γ_d is the desired reflection coefficient; B the bandwidth (here 0.2 GHz); f_o is the band's center frequency; and exponent m is a parameter that has been set to unity following [18]. The load impedance $Z_L = 150 - j60\ \Omega$ is the same value used in [18] (note that Z_L is assumed to be constant because the frequency range is relatively small). Two cases are considered: (a) optimization with fixed characteristic impedance $Z_o = 50\ \Omega$; and (b) optimization with *Variable* Z_o as described in [20]. In *Variable* Z_o methodology, instead of fixing a value forZ_o, the feed system characteristic impedance (or the source internal impedance if there is no feed system) is considered as a *variable* quantity whose value is determined *by* the optimization methodology, which in this case is BBO (although any design or optimization methodology may be used because *Variable* Z_o is not in any way methodology-specific).

Tables 1 and 2, respectively, summarize the BBO-optimized MSMN results for the fixed and *Variable* Z_o cases. The corresponding SWR plots appear in Figs 6 and 7. The best design values provide SWR close to the desired SWR curve, which minimizes the fitness function. Figure 6 also includes the results presented in [18] that were computed using Nelder–Mead (NM) optimization method. The BBO curve is closer to the desired SWR than the NM curve, thus demonstrating BBO's effectiveness in solving the MSMN problem.

Turning to Fig. 7, it is apparent that *Variable* Z_o markedly outperforms fixed Z_o for all stub configurations. Using *Variable* Z_o achieves almost exactly the desired response. In addition, only three stubs are required to get very close to the desired response, whereas using seven stubs with fixed Z_o gives in an inferior SWR. Of course, the tradeoff in using *Variable* Z_o is that the feed system impedance is not the "standard" value of 50Ω. But, as a practical matter for the MSMN, any impedance that is appropriate from a fabrication perspective is acceptable, and typical values range from 20 to 150 Ω. In this example, *Variable* Z_o's optimized impedance values ranged from 128 to 143 Ω as shown in Table 2. *Variable* Z_o is an attractive new concept that holds out the possibility of considerably better performance played against a non-standard feed system impedance. Whether or not that tradeoff is desirable is case specific, but it always merits consideration because the end result very well may be much better.

As another example, four and six stub MSMN configurations are BBO-optimized using fixed and *Variable* Z_o. In this case, the load is chosen to be $Z_L = 100 - j80\ \Omega$ (a value used as an example in [1]). The optimized stub parameters appear in Tables 3 and 4 for the fixed and *Variable* Z_o cases, respectively, with the corresponding SWR plotted in Figs 8 and 9. As before, the SWR improvement using *Variable* Z_o is dramatic. Much better SWR performance is obtained with *Variable* Z_o for both the four and six stub cases, and the optimized impedances are quite reasonable at 122 and 131.44 Ω, respectively.

II. UWB MEANDER MONOPOLE

In this section, *Variable* Z_o is applied to a CFO-optimized MMA. These results are compared to optimization results for the MMA using CFO and the standard approach of fixing Z_o. The *Variable* Z_o MMA exhibits much better performance.

A) Optimization methodology

CFO is a deterministic optimization algorithm that has been applied to a variety of antenna problems as well as recognized benchmark functions [22–28]. As an example of applying *Variable* Z_o to a simple antenna optimization problem, CFO/*Variable* Z_o was applied to the design of a MMA on a PEC (perfectly electrically conducting) ground plane. Other examples employing Yagis and loaded bowties appear in [20, 29, 30, 31], which also discuss *Variable* Z_o in greater detail.

One of the major advantages of a deterministic algorithm is that it always returns the same result with the same setup parameters. This attribute makes optimizing an antenna much easier, because changes in antenna performance cannot be the result of the optimizer's inherent randomness (for example, a Genetic Algorithm or Particle Swarm Optimization, both of which are stochastic). Determinism is especially important in defining the "fitness function" against which the antenna is optimized (see [32] for a discussion of this question).

Table 1. BBO-optimized MSMN with fixed Z_o.

No. of stubs	l^s_n (mm) ($n = 1, \ldots, N$)	d_n(mm) ($n = 1, \ldots, N$)	Z_o (Ω)
3 stubs (BBO)	25.8780, 71.7040, 63.0050	40.9360, 35.0490, 4.4154	50
5 stubs (BBO)	26.2340, 69.4090, 66.4230, 63.2840, 65.7320	40.3660, 38.4780, 1.0000, 1.0000, 57.0650	50
7 stubs (BBO)	26.0320, 70.3970, 63.5120, 61.5720, 58.6640, 58.6850, 56.2940	40.7010, 32.9400, 3.2024, 1.0000, 1.0000, 50.0450, 40.6000	50
7 stubs (NM) [18]	24.5371, 63.3895, 65.3817, 61.4128, 60.2661, 60.3690, 64.2648	39.9823, 38.8459, 5.8387, 4.0774, 65.0554 95.5695, 40.3593	50

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Table 2. BBO-optimized MSMN with Variable Z_o.

No. of stubs	l_n^s (mm) ($n = 1, \ldots, N$)	d_n (mm) ($n = 1, \ldots, N$)	Z_o (Ω)
3 stubs	69.0572, 68.7359, 52.7715	50.5720, 11.3606, 83.8700	136.23
5 stubs	72.0921, 53.8166, 60.6398, 64.6650, 61.6489	57.1220, 87.4881, 1.0000, 19.1351, 54.8924	142.76
7 stubs	49.7555, 69.4932, 70.0624, 68.6797, 56.5486, 60.5086, 64.3324	24.2944, 30.2883, 19.4462, 41.3052, 1.0000, 76.9993, 72.4037	128.00

B) MMA fitness function

The general objective of the MMA optimization is maximum IBW with good gain without regard to the detailed radiation pattern. The MMA fitness function therefore was chosen to be the weighted gain-VSWR quotient defined as

$$F = \sum_{i=1}^{N} \frac{w_g(f_i) \cdot G_{\max}(f_i)}{w_{VSWR}(f_i) \cdot VSWR//Z_o(f_i)}, \quad (25)$$

$$\text{where } w_g(f_i) = \frac{(w_g^{max} - w_g^{min})(f_U - f_i)}{f_U - f_L} + w_g^{min},$$
$$w_{VSWR}(f_i) = \frac{(w_{VSWR}^{max} - w_{VSWR}^{min})(f_U - f_i)}{f_U - f_L} + w_{VSWR}^{min}. \quad (26)$$

The MMA fitness was evaluated at N equally spaced frequencies between lower and upper frequency limits f_L and f_U. The antenna's performance was evaluated using the Numerical Electromagnetics Code Ver. 4.2 [33–35]. Total power gain (same as directivity in this case) was computed in NEC's standard spherical polar coordinates at 10° increments in the polar angle θ for two values of the azimuth angle ϕ, broadside ($\phi = 0^\circ$) and endfire ($\phi = 90^\circ$) to the MMA (see Fig. 10 for geometry). G_{max} is the maximum gain over these angles. $VSWR//Z_o$ is the voltage SWR relative to the feed system characteristic impedance Z_o.

The MMA gain-VSWR quotient contains frequency-dependent weighting coefficients w_g for gain and w_{VSWR} for VSWR. Each of these coefficients decreases linearly with increasing frequency. Of course, the antenna designer is free to choose any form for the fitness function, and changing its form changes the design or, in the case of optimization, the decision space's topology, so that the antenna(s) meeting the performance objectives or doing so optimally will be different in the different landscapes. In the MMA example, the fitness function was chosen empirically for its simplicity, as were the linearly tapered weights.

C) Deterministic algorithms and *Variable* Z_o

Variable Z_o is particularly useful when used in conjunction with deterministic design or optimization algorithms. The concept underlying *Variable* Z_o is extraordinarily simple, and it is rather surprising that it has been overlooked through decades of network and antenna design and optimization. All the usual approaches start with an assumed value for Z_o (even if multiple procedures are employed using different parametric values). But, fixing Z_o inevitably makes it more difficult to meet the specific network or antenna performance goals because that very assumption automatically excludes every better design obtained with some other value of Z_o.

An antenna's performance is determined by its current distribution, which, in turn, determines its input impedance. The objective therefore is discovering an antenna structure whose current distribution meets minimum user-specified performance goals (design) or best meets them (optimization). The current distribution that meets this objective is entirely independent of the feed system characteristic impedance. By constraining a design or optimization methodology to produce only current distributions that are matched to Z_o to the degree possible eliminates all other distributions that do a better job of meeting the performance goals. By contrast, allowing Z_o to "float" as a true variable quantity places no constraint on allowable current distributions. Once an acceptable

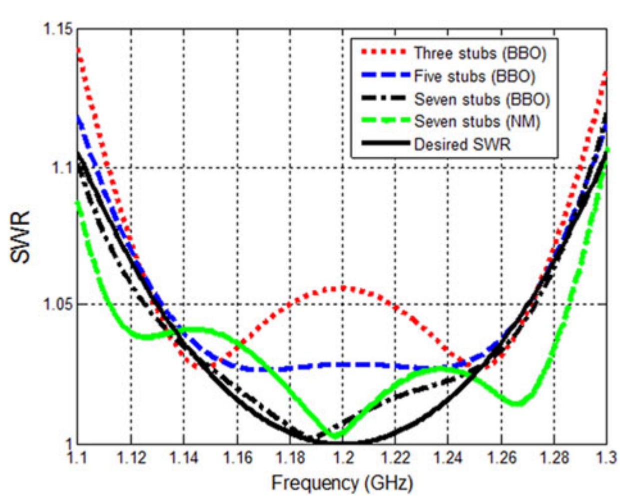

Fig. 6. Standing wave ratio versus frequency for fixed Z_o.

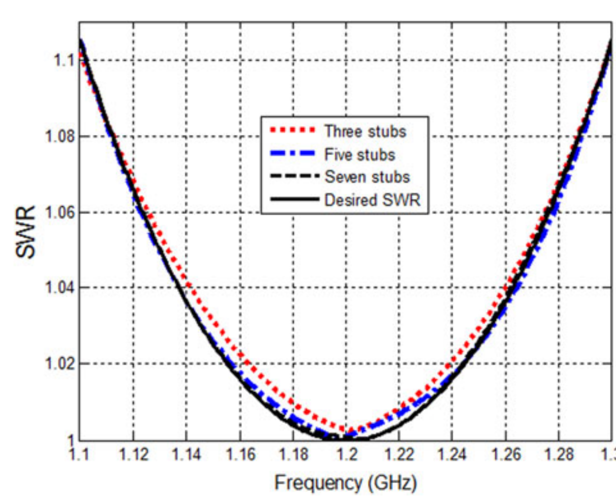

Fig. 7. Standing wave ratio versus frequency for variable Z_o.

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Table 3. BBO-optimized 4 and 6 stub MSMN using fixed Z_o.

No. of stubs	l_n^s (mm) ($n = 1, \ldots, N$)	d_n (mm) ($n = 1, \ldots, N$)	Z_o (Ω)
4 stubs	26.9320, 73.1720, 59.1470, 65.8100	56.0980, 31.3660, 1.0000, 9.7269	50
6 stubs	26.2830, 70.4710, 62.4100, 66.4460, 63.3240, 66.2120	55.6390, 34.4010, 1.0000, 1.0000, 22.8490, 39.6890	50

Table 4. BBO-optimized 4 and 6 stub MSMN using *Variable* Z_o.

No. of stubs	l_n^s (mm) ($n = 1, \ldots, N$)	d_n (mm) ($n = 1, \ldots, N$)	Z_o (Ω)
4 stubs	35.5799, 66.2327, 63.2205, 60.4992	71.7795, 30.9036, 1.0000, 50.7021	122
6 stubs	38.4000, 63.6000, 65.2000, 65.3000, 64.3000, 61.9000	74.2000, 29.5000, 4.1000, 1.0000, 35.2000, 43.3000	131.44

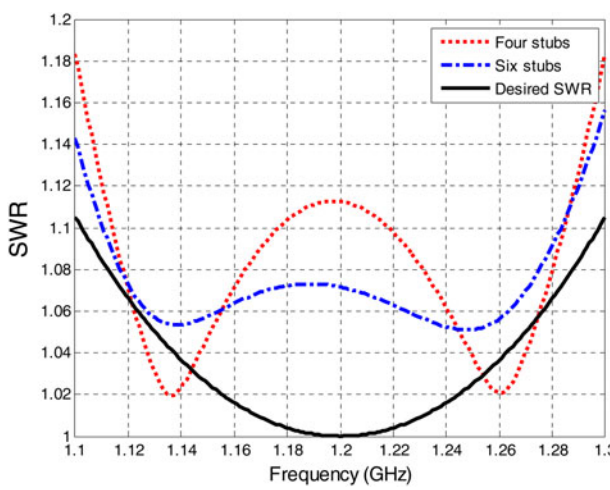


Fig. 8. Standing wave ratio versus frequency for fixed Z_o.

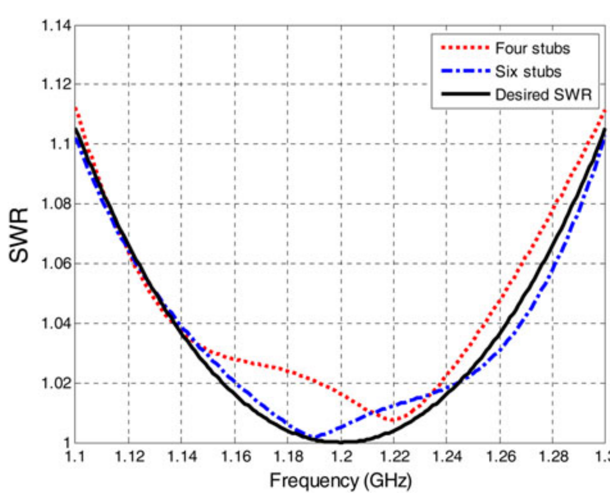


Fig. 9. Standing wave ratio versus frequency for variable Z_o.

distribution or the optimal distribution is discovered, the value of Z_o is determined automatically by the distribution.

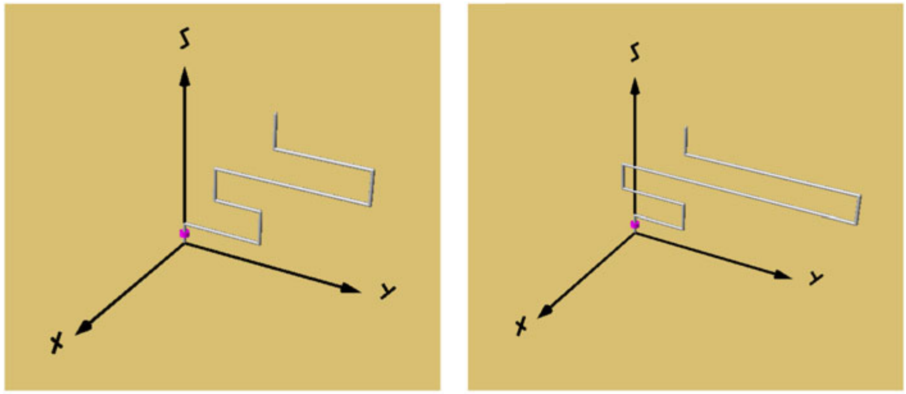
Variable Z_o technology can be applied to any antenna or network design problem against any fitness function or set of performance goals (although *Variable* Z_o may be especially useful for improving antenna IBW). *Variable* Z_o moreover is a "product by process" approach that can be used in conjunction with any design or optimization methodology, deterministic ones like CFO; stochastic algorithms such as Particle Swarm, Ant Colony, Group Search Optimization, Differential Evolution, or Genetic Algorithm; analytic approaches such as extended Wu–King impedance loading [26]; even "seat of the pants" design or optimization based on experience, intuition, or a "best guess." The specific design or optimization methodology is entirely irrelevant to the novelty and utility of treating Z_o as a design *variable* instead of a fixed parameter.

D) MMA geometry

Variable Z_o's effectiveness is demonstrated by CFO-optimizing the MMA with and without *Variable* Z_o. The *Variable* Z_o run allowed variable $25 \le Z_o \le 500\ \Omega$, while for the fixed Z_o run $Z_o = 50\ \Omega$. The antenna was optimized between 2 and 12 GHz with a height constraint of a $\lambda/4$ at 2 GHz and maximum width $\lambda/2$. Perspective views of the optimized MMA geometries visualized using 4NEC2 [36] appear in Fig. 10. The corresponding NEC input files defining these geometries appear in Fig. 11. The two antennas are quite different, yet the only difference in the optimization setup is allowing Z_o to vary in one case, while it was fixed in the other. All CFO parameters were otherwise the same.

The value of Z_o determined to be optimum by CFO is $Z_o = 263.91\ \Omega$. Of course, feeding this MMA from a $Z_o = 50\ \Omega$ feed, which is the most common feed system characteristic impedance, requires a ~5:1 broadband transformer or matching network. Low-loss UWB matching systems are readily available, so that implementing this MMA should be straightforward. But, if it happens that the optimized value of Z_o is unacceptably high or low, then *Variable* Z_o still can be used simply by restricting Z_o's range to acceptable values.

The effect of *Variable* Z_o methodology is evident in the NEC4.2-computed MMA data. The two parameters of interest, VSWR and maximum gain, are plotted in Figs 12 and 13, respectively. *Variable* Z_o performance is plotted in red, while the fixed Z_o curve is black. The *Variable* Z_o MMA is obviously superior to its fixed Z_o counterpart, especially with respect to VSWR, which is much lower and flatter across the entire UWB spectrum (3.1–10.6 GHz). Similarly, the maximum gain is generally higher at most frequencies, and the minima generally are no lower than the fixed Z_o antenna's.



a b

Fig. 10. (a) *Var* Z_o MMA Geometry (axis 0.05 m). (b) Fixed Z_o MMA Geometry (axis 0.05 m).

```
CM File: MEANDER.NEC
CM MEANDER LINE ON PEC GND PLANE
CM Zo=263.91 ohms
CM Note: All dimensions are in METERS.
CE
GW1,9,0.,0.,0.,0.,0.,.006,.00025
GW2,9,0.,0.,.006,0.,.022,.006,.00025
GW3,9,0.,.022,.006,0.,.022,.015,.00025
GW4,9,0.,.022,.015,0.,.009,.015,.00025
GW5,9,0.,.009,.015,0.,.009,.024,.00025
GW6,9,0.,.009,.024,0.,.05,.024,.00025
GW7,9,0.,.05,.024,0.,.05,.033,.00025
GW8,9,0.,.05,.033,0.,.025,.033,.00025
GW9,9,0.,.025,.033,0.,.025,.042,.00025
GE1
GN1
EX 0,1,5,1,1.,0.
FR 0,1,0,0,2000.,0.
RP 0,10,2,1001,0.,0.,10.,90.,100000.
XQ
EN
```

a

```
CM File: MEANDER.NEC
CM MEANDER LINE ON PEC GND PLANE
CM Zo=50 ohms
CM Note: All dimensions are in METERS.
CE
GW1,9,0.,0.,0.,0.,0.,.006,.00025
GW2,9,0.,0.,.006,0.,.016,.006,.00025
GW3,9,0.,.016,.006,0.,.016,.014,.00025
GW4,9,0.,.016,.014,0.,-.004,.014,.00025
GW5,9,0.,-.004,.014,0.,-.004,.022,.00025
GW6,9,0.,-.004,.022,0.,.065,.022,.00025
GW7,9,0.,.065,.022,0.,.065,.03,.00025
GW8,9,0.,.065,.03,0.,.016,.03,.00025
GW9,9,0.,.016,.03,0.,.016,.038,.00025
GE1
GN1
EX 0,1,5,1,1.,0.
FR 0,2,0,0,2000.,4.545455
RP 0,19,19,1001,0.,0.,5.,10.,100000.
XQ
EN
```

b

Fig. 11. (a) *Var* Z_o MM NEC File. (b) Fixed Z_o MMA NEC File.

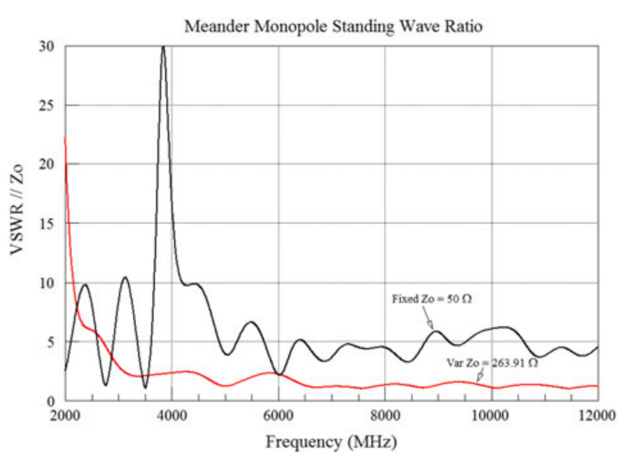


Fig. 12. Meander monopole VSWR

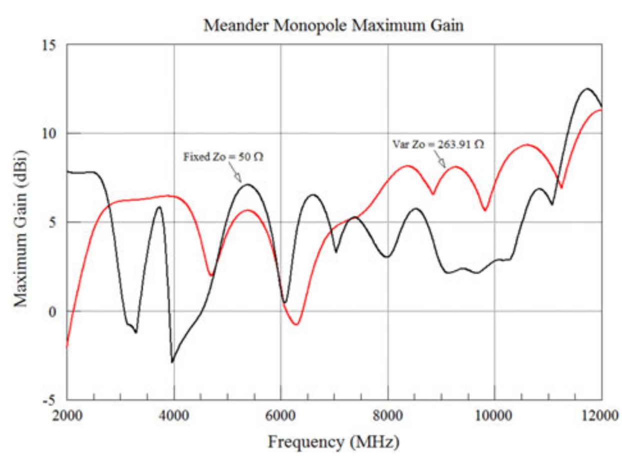


Fig. 13. Meander monopole Max Gain

IV. CONCLUSIONS

In this paper, proprietary *Variable* Z_o technology [31] was employed with the new evolutionary optimization technique BBO to design a MSMN against an optimized reflection coefficient and with CFO to design an optimized MMA. Optimized MSMN stub lengths and positions were determined for a microwave circuit by minimizing the reflection coefficient, and results were compared to published data. The networks were optimized against a desired standing wave ratio profile over a range of frequencies. BBO was used in two cases: fixed Z_o and *Variable* Z_o. A substantial improvement in MSMN performance was obtained using *Variable* Z_o methodology, which appears to have a wide range of applicability for network and antenna design and optimization. BBO has been shown to be an effective optimization methodology, especially when combined with *Variable Z_o*, and future work will apply this technique to various other types of antennas. Of particular interest could be segmented wire wideband monopole antennas [37].

Variable Z_o has been shown to be a simple and effective methodology for creating networks and antennas designed or optimized against any set of performance objectives. Its use is straightforward, and it is universally applicable regardless of the design or optimization methodology being used. *Variable Z_o* is a proprietary [31] technology, and *Variable Z_o*, *Var Z_o*, *VZ_o*, and "*Variable Z_o Inside*" are trademarks and service marks of Variable Z_o, Ltd., P.O. Box 1714, Harwich, MA 02645, USA.

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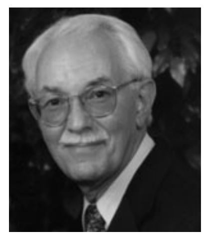
Nihad I. Dib obtained his B.Sc. and M.Sc. degrees in Electrical Engineering from Kuwait University in 1985 and 1987, respectively. He obtained his Ph.D. degree in EE (major in Electromagnetics) in 1992 from University of Michigan, Ann Arbor. Then, he worked as an assistant research scientist in the Radiation Laboratory at the same school. In September 1995, he joined the EE Department at Jordan University of Science and Technology (JUST) as an assistant professor, and became a full professor in August 2006. His research interests are in computational electromagnetics, antennas, and modeling of planar microwave circuits.

Ashraf Hamdan Sharaqa received his B.Sc. degree in Electrical Engineering from Birzeit University (BZU), Birzeit, Palestine in 2009. In 2010, he joined the Master program in the Electrical Engineering Department at Jordan University of Science and Technology (JUST) majoring in Wireless Communications and he worked as teacher and research assistant at the same school. He received the M.Sc. degree in 2012. In October 2012, he joined the Communication and Security Projects Division at WorleyParsons Arabia Ltd., Saudi Arabia, as a radio engineer. His research interests include the analysis and design of antennas and microwave circuits, optimization algorithms and their application in electromagnetics, and wireless communications.



Richard A. Formato is a Consulting Engineer and Registered Patent Attorney. He received his JD from Suffolk University Law School, Ph.D. and M.S. degrees from the University of Connecticut, and M.S.E.E. and B.S. (Physics) degrees from Worcester Polytechnic Institute. In the early 1990s, he began applying genetic algorithms to antenna design and developed YGO3 freeware (Yagi Genetic Optimizer). His interest in optimization algorithms led to the development of Central Force Optimization and Dynamic Threshold Optimization. Variable Z_o antenna technology was invented in a true "aha" moment when he realized that an antenna's feed system impedance should be treated as a true optimization variable, not as a fixed parameter.

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