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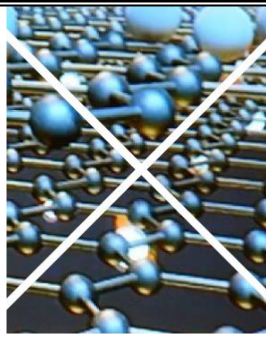

USING SEEKER OPTIMIZATION ALGORITHM TO DESIGN M-STUB IMPEDANCE MATCHING CIRCUITS

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Abstract

This work applies a newly developed evolutionary optimization algorithm named as Seeker Optimization Algorithm for designing broad band matching circuits that maximally match different load impedances to transmission lines in a pre-described range of frequencies. SO algorithm has been verified to be very effective in finding the solutions for such multi-objective functions. Herein the design process aims to select the values and the places of the matching impedances between loads and transmission lines under specific constraints. The obtained results have been compared to those in the literature to verify the enhancement in the performance.

Keyword: Matching network, Optimization, Seeker Optimization Algorithm, Multi-stub System, Tapered Transmission line.

1. Introduction

Nowadays, a wideband lossless design in telecommunication applications becomes a require, and this is why matching networks plays a pivotal role in all communication applications. The main purpose of matching networks is to provide maximum power transfer from source to load, improve the signal to noise ratio, and reduce the amplitude and phase errors in power distribution networks by minimizing the reflection coefficient [1]. One of the most popularly used matching methods is the stub tuning. To find the best values of the desired matching circuit namely lengths and positions of the stubs either the Smith chart or analytical solutions has been used ın the lıtrature [1]. However, when the the number of stubs increases, the process becomes complicated. Whereas such problem could be solved by using the optimization techniques by finding the stubs lengths and positions that minimize the reflection coefficient [2, 3].

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Seeker Optimization (SO) algorithm, which is relatively new proposed optimization technique firstly proposed in 2006 [4] is a promising technique for the real parameter optimization. SO algorithm idea mainly imitate the concept of how the humans act when searching something. This includes the human used memory, experience, and uncertainty reasoning. SO algorithm has recently been applied successfully in solving a lot of electromagnetic problems [5-8].
The main purpose of using the optimization in this work is to find the best parameters to design a matching networks that consist of multi-stubs placed between source and the load [9, 10]. The design parameters to be found are the stubs locations (d) as well as the lengths of the stubs (L). Where, SOA is used to find the appropriate stubs lengths and positions by minimizing the reflection coefficient in a pre-specified frequency range. Nonsimilar to [2, 3] in which only a single and double stubs configurations were designed using optimization methods, a multi-stub configuration is considered here. It should be mentioned here that, the design of stubs using optimization techniques instead of traditional methods is an interesting topic in the optimization applications [2, 3].
The main purposes of thıs paper are to: firstly; approve the capability of using newly devloped optimization techniques in matching applications. Secondly, is to demonstrate the enhancement in the system efficiency by using variable characteristic impedance Z_o over the usage of the fixed characteristic impedance Z_o. Worth mentioning here that the variable characteristic impedance has been also applied successfully in [11,12] to improve antenna bandwidth. To the owther best knowledge this is the first time in the litrature to use the SOA in such proplem solving.

The outlines of this study could be summerized as follows; In section II which has two subsections, in the first one the formulation of the problem has been presented, where in the second subsection the theoretical background of the SO algorithm has been presented. In section 3, three design examples are presented. Finally, Results and possible advanced studies presented and discussed in section 4.

2. Materials and Methods

This section has been divided into two subsections; where the formulation of the problem has been presented in the first subsection and the theoretical background of the SO Algorithm been presented in the other.

2.1 Formulation of the Problems

Figure 1 shows a general N parallel (shunt) stubs that are used to match a predefined load impedance Z_L to a transmission line defined by its characteristic impedance Z_o. Matching stubs could be open-circuited (OC) or short-circuited (SC). The transmission line's characteristic impedance Z_o and admittance Y_o are related as $Z_o = \frac{1}{Y_o}$, and in the same manner the load impedance and the load admittance $Z_L = \frac{1}{Y_L}$. In a perfectly matched system, Z_o and Y_o are complex conjugates resulting in 100% power transfer to the load, and hence the design mainly aims to find the stub best locations and dimensions that fit to the matching condition.

For the first stub:

$$Y_1 = Y_1^d + Y_1^s \tag{1}$$

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

$$\Gamma_1 = \frac{Y_o - Y_L}{Y_o + Y_L} \tag{3}$$

$$Y_1^s = Y_o \, \frac{1 - \Gamma_1^{\,s}}{1 + \Gamma_1^{\,s}} \tag{4}$$

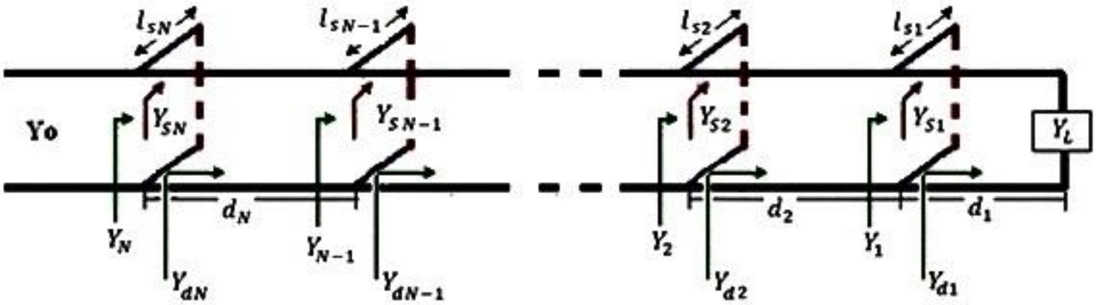

Figure 1. General N parallel stubs connection [9].

To reach the network matching between the load and the transmission line, we need to determine the total admittance calculated from the transmission line end, where this admittance is derived in recursive manner as follows [9]:

For the nth stub:

$$Y_n = Y_n^d + Y_n^s \tag{5}$$

$$Y_n^d = Y_O \frac{1-\Gamma_n \exp(-2\,\gamma\, d_n)}{1+\Gamma_n \exp(-2\,\gamma\, d_n)} \tag{6}$$

$$\Gamma_n = \frac{Y_o - Y_{n-1}}{Y_o + Y_{n-1}} \tag{7}$$

$$Y_n^s = Y_o \frac{1-\Gamma_n^s}{1+\Gamma_n^s} \tag{8}$$

For the last stub

$$Y_N = Y_N^d + Y_N^s \tag{9}$$

$$Y_N^d = Y_O \frac{1-\Gamma_N \exp(-2\,\gamma\, d_N)}{1+\Gamma_N \exp(-2\,\gamma\, d_N)} \tag{10}$$

$$\Gamma_N = \frac{Y_o - Y_{N-1}}{Y_o + Y_{N-1}} \tag{11}$$

$$Y_N^s = Y_o \frac{1-\Gamma_N^s}{1+\Gamma_N^s} \tag{12}$$

where ${\Gamma_n}^s$ is is calculated as per the stub's type (Sunt/series) as per below:

$${\Gamma_n}^s = -\exp(-2\gamma l_n^s) \quad n = 1,2,\dots,N \quad \text{for SC} \tag{13}$$

$${\Gamma_n}^s = exp(-2\gamma l_n^s) \quad n = 1,2,\dots,N \quad \text{for OC} \tag{14}$$

Where,

$$\gamma = \alpha + j\beta \tag{15}$$

$$\beta = \frac{2\pi}{\lambda} = \frac{2\pi f}{v} \tag{16}$$

In the aforementioned equations,

- Y_L = load admittance
- Y_o =characteristic admittance
- Y_n = adjacent admittance to the left of the n^{th} stub
- Y_n^d = adjacent admittance from the right n^{th} stub.
- Y_n^s = stub input admittance.
- Γ_n = reflection coefficient between (Y_o) and (Y_{n-1})
- ${\Gamma_n}^s$ = reflection coefficient from stub n.
- d_n = distance between n^{th} stub and $n-1^{th}$stub,
- l_{sn} = stub length
- γ = propagation constant
- α= attenuation constant, β = phase constant, λ = wavelength, v = phase velocity.
- f is the frequency.

The overall reflection coefficient could be calculated as per the equation17:

$$\Gamma = \frac{Y_o - Y_N}{Y_o + Y_N} \tag{17}$$

To sum up, the best matching is achieved when Γ is minimized. With the assumption that all the components in the systems are lossless (neglecting the losses from the components itself), the parameters to be optimized are the stubs separating distances as well their lengths (d_n, l_n^s).

2.2 Seeker Optimization Algorithm

In engineering, optimization consists of trying variations of parameters and using information gained in different iterations to get the best results, those best results (solution) are relative to the problem in hand, the solving method, and the tolerance allowed. Mathematically, optimization could be defined as adjusting inputs to a mathematical process to find minimum or maximum desired output.

SO algorithm is a new promising technique for the real parameter optimization. Which mainly imitate the concept humans searching. As humans are using their memory, experience, and uncertainty reasoning SO algorithm is working with the same concept. SO algorithm divides the solution set randomly into K sub-populations with the same size, each individual in this sub-populations is called individually as a searcher or equally as seeker, where all those seekers in one sub-population constitute a neighborhood socially sharing searching information among themselves. When the algorithm starts to work, search direction, as well as the radius of the search for each seeker (step length), and trust degree will be determined for each seeker. Every seeker finds its a new position based on three factors: Namely, the seekers social learning, cognitive learning, as well the uncertainty reasoning. SO algorithm operates on a search population of s D-dimensional position vectors [13], that could be considered potential solutions of the optimization problem that we are trying to solve (represented by the fitness function), i.e., $\overrightarrow{x_i} = [x_{i1}, \dots, x_{ij}, \dots, x_{iD}];\ i = 1, 2, \dots, s$

where x_{ij} is the j^{th} element of $\vec{x}_i$ and s is the population size. The flow chart of the seeker optimization is shown in Figure 2. Firstly, it generates s positions that are uniformly distributed and randomly selected in the solution total space (defined by the maximum and minimum values of the parameters). Next step is to calculate the fitness of each seeker, then calculates the search direction $dij(t)$ and the search radius $\alpha_{ij}(t)$, for the i^{th} seeker at time step t. Then the j^{th} element of the i^{th} seeker is calculated as per equation 18 [14]:

$$x_{ij}(t+1) = x_{ij}(t) + \alpha_{ij}(t) d_{ij}(t) \quad (18)$$

To avoid converging to a local minimum, SOA uses an inter sub population strategywhich described by:

$$x_{k_n j,worst} = \begin{cases} x_{lj,best} & if\ R_j \leq 0.5 \\ x_{k_n j,worst} & else \end{cases} \quad (19)$$

Where R_j is a U, R number in the interval [0,1], $x_{k_n j,worst}$ is defined as j^{th} element of n^{th} worst position in k^{th} sub-population, $x_{lj,best}$ is the j^{th} element of the superior position in l^{th} sub-population.

B. Search Direction

An empirical gradient is used when the fitness function can’t be differentiated [15] by in which the direction of increment/ decrement could be determined. In this way, and so seekers are leading their search. In SO algorithm model three different searching manners are used to find the search direction Namely they are called as egotistic, altruistic and proactive.

For Egotistic part, is a totally depending on the seeker itself self-behavior which depends on the seeker self-cognitive learning [16]. And this could be calculated using the equation (20) as:

$$\vec{d}_{i,ego}(t) = sgn(\vec{p}_{i,best}(t) - \vec{x}_i(t)) \quad (20)$$

Secondly, altruistic behavior, where the seekers communicating their neighbors to adjust their behavior and to reach their goal, Mainly, a seeker i in the sub-population is associated with two altruistic directions, i.e., $\vec{d}_{i,alt1}(t)$, $\vec{d}_{i,alt2}(t)$ given by:

$$\vec{d}_{i,alt1}(t) = sgn(\vec{g}_{best}(t) - \vec{x}_i(t)) \quad (21)$$

$$\vec{d}_{i,alt2}(t) = sgn(\vec{l}_{best}(t) - \vec{x}_i(t)) \quad (22)$$

Lastly, seekers also use the proactiveness property, as the seekers are able to use a goal-directed behavior [19]. Also, foreseeing the future behavior depending on their previous behavior [20]. And so, each seeker will be anticipating to change its own search direction according to the seeker itself previous recorded behavior. And so, any seeker i is connected to an empirical direction named as proactiveness direction $\vec{d}_{i,pro}(t)$:

$$\vec{d}_{i,pro}(t) = sgn(\vec{x}_i(t_1) - \vec{x}_i(t_2)) \quad (23)$$

Where $t_1, t_2 \in t, t-1, t-2$ and $\vec{x}_i(t_1)$ has better fitness value than $\vec{x}_i(t_2)$. As per the human reasonable judgment, the real search direction of the i^{th} seeker, i.e., d_i(t) = [d_{i1} , d_{i2}, …, d_{iD}] is based on a compromise among the previously explained four types of the empirical directions. In this work, the j^{th} element of $d_i(t)$ is selected by applying he following selection rule:

$$d_{ij}(t) = \begin{cases} 0 & if\ r_j \le p_j^{(0)} \\ +1 & if\ p_j^{(0)} < r_j \le p_j^{(0)} + p_j^{(1)} \\ -1 & if\ p_j^{(0)} + p_j^{(1)} < r_j \le 1 \end{cases} \quad (24)$$

$p_j^m, m \in (0,1,-1)$ is defined as: in the set $(d_{ij,ego}, d_{ij,alt1}, d_{ij,alt2}, d_{ij,pro})$, let $num^{(m)}$ is the number of "m" then $p_j^{(m)}/4$.

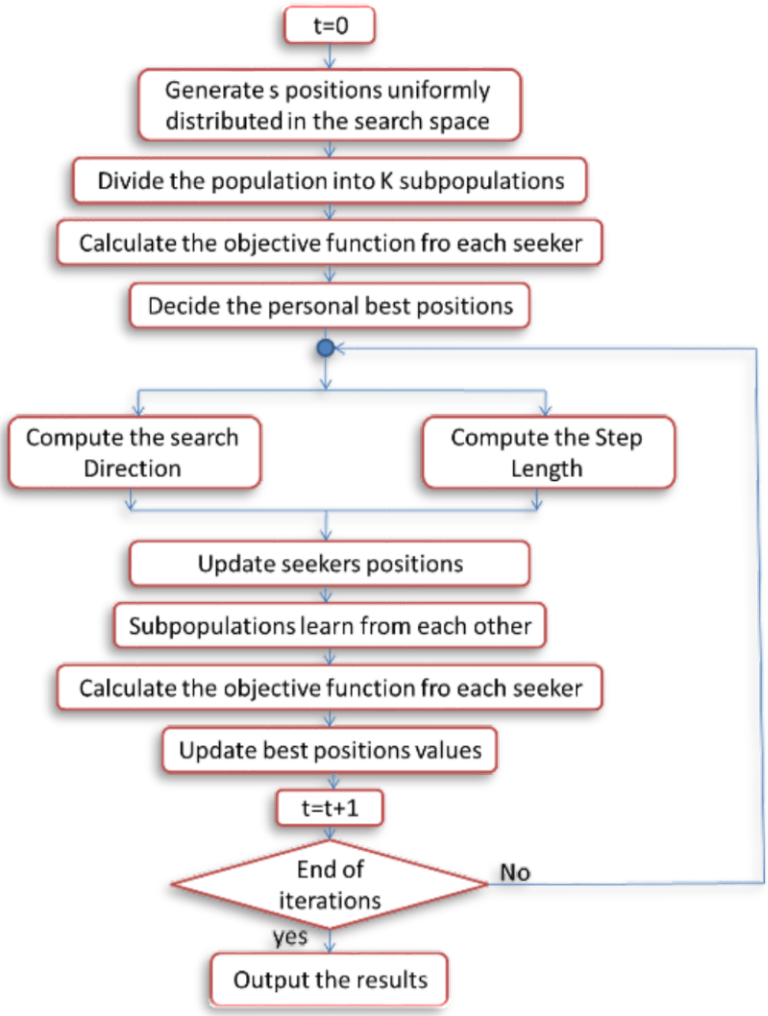

Figure 2. SOA Flow Chart

A. Step Length (search Radious)

Among the whole solution searching space, there are always fitness points that are closer to the extreme point, such that fitness values obtained by using those input variables are connected to their relative distances from the

optimum value, so the search must be intensified in regions with relatively good solutions [17]. Then it will be definitely of great logic to find the better values as moving to the optimum point and vice versa.
During the solving procedure, optimization problems in general have ranges of values obtained in each iteration. To able to design a system that can be applied to a wide range of optimization problems (to make SO algorithm widely used), the obtained fitness values of all the seekers are ordered in descending manner and then turned into the sequence numbers from 1 to s as inputs to a fuzzy reasoning system. A membership function of linear type is usually used in the conditional part, this mathematically represented by:

$$\mu_i = \mu_{max} - \frac{s-I_i}{s-1}(\mu_{max} - \mu_{min}) \quad (24)$$

Where I_i is the sequence number of $\vec{x}_i(t)$ after ordering the fitness values, where μ_{max} is defined as the maximum membership degree value. This value is equal to or little less than 1.0. In this work, $\mu_{max} = 0.95$ and the minimum value $\mu_{min} = 0.0111$ will be considered as often used.

3. Results & Discussion (Numerical Examples)

In this part we will apply the proposed idea over four different types of stubs, namely; Single Stub, Double Stub, Multiple stubs with fixed Z_0 and Multiple stubs with variable Z_0

3.1. Single Stub Example

In this Example a single short-circuited shunt stub is optimized to match a 50 Ω transmission line to a load that could be described numerically as: $Z_L = 60 - j80\ (\Omega)$ at frequency of 2 GHz. Table 1 shows the best optimum solution obtained using the SOA where l_s is defined as the stub length and d is defined as the distance between the stub location and the load. Compared to the results obtained numerically in [1] which also included in the same Table. Figure 3 shows the magnitude of the resulting total reflection coefficient as function of frequency.
According to the results in Table 1, SOA is could simply acieve the tuning instead of using Smith chart or exact expression described in [1]. Also as per the results shown in Figure 3, it could be noticed that that in the second solution a narrower bandwidth has been reached. This is because both l_s and d has larger values for the second solution, which increases the frequency variation of the match.

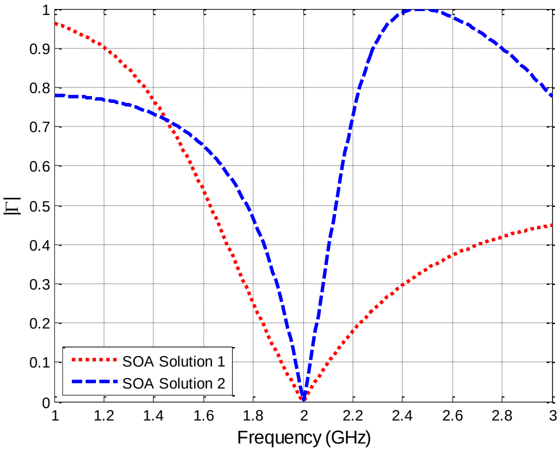

Figure 3. The reflection coefficient magnitudes obtained by SOA versus frequency for a single short circuit shunt stub.

Table 1. Design values obtained by SOA in addition to Pozar's results for a single stub.

Technique	$l_s\ (\lambda)$	$d\ (\lambda)$	Best fitness
SOA (solution 1)	0.0950	0.1104	9.1091e-005
SOA (solution 2)	0.4051	0.2595	2.9145e-005
Pozar (solution 1) [1]	0.095	0.110	-
Pozar (solution 2) [1]	0.405	0.260	-

Table 2. Design values obtained by SOA compared to Pozar's results for double stub matching circuit.

Technique	l_{s1} (λ)	l_{s2} (λ)
SOA (solution 1)	0.1465	0.2042
SOA (solution 2)	0.4819	0.3498
Pozar (solution 1) [1]	0.146	0.204
Pozar (solution 2) [1]	0.482	0.350

3.2.Double Stub Example

In this example we will consider a double stub to match a load of $Z_L = 60 - j80\ (\Omega)$ with TL with characteristic impedance of $Z_o = 50\ \Omega$. Both stubs are open-circuited and $\lambda/8$ −apart. The first stub is located in parallel with Z_L. The optimized parameters in this example are the lengths of the two stubs, so that the results will be easy compared to the example in [1]. Table 2 and Figure 4 shows the results.

3.3. Multi-Stubs Example

In the previous stubs examples, the designed stubs provided matching at a specific frequency, and the aim of the examples to show the accuracy of the obtained solutions compared to the numerical ones. However, in the real time applications a wider bandwidth is required to enhance the transmission in the system. Accordingly, in this example, seven stub of type short-circuited (SC) configuration has been optimized to obtain a pre expressed standing wave ratio (SWR_{desired}) works in a pre-specified frequency range. Standing wave ratio is defined as below:

$$SWR = \frac{1+|\Gamma|}{1-|\Gamma|} \tag{27}$$

Where the fitness objective function are defined as in ref. [9]:

$$fitness = \sum(\Gamma(f) - \Gamma_d(f))^2 \tag{28}$$

$$\Gamma_d = 0.05\left(\frac{2}{B}\right)^{2m}(f - f_o)^{2m} \tag{29}$$

where Γ is given in 17, Γ_d is the desired reflection coefficient, B is the band width, f_o is the middle frequency in the bandwidth, and m is a factor which is chosen here to be unity.

Z_L is assumed to be constant in both the optimization and the plotting of the final results because the frequency range is rather small; $Z_L = 150 - j60\ (\Omega)$.

To achieve the goal of this optimization, two cases have been considered; Thre first one is to run the optimization problem over a fixed characteristic impedance of value $Z_o = 50\ \Omega$, and the other is to run over a varying characteristic impedance [11,12]. In the second case, instead of fixing the value of Z_o, The charastic impedance is considered as a varying parameter with value to be considered as the 15th variable in the optimization process to obtain SWR which is as close as possible to the desired one.

The optimized values determined by SOA for the two cases for the SWR shown in Figures 5 and 6 are tabulated as in Tables 3 and Table 4. The best obtained solving parameters are defined as the ones that give the closest SWR to the desired one, *i.e.*, the minimum value of the fitness function. The results obtained for the seven stubs with fixed Z_o are compared with the results obtained by Nelder-Mead method (NM) [9] in Table 3. From Figure 5, it could be clearly seen that, the SWR obtained using variable Z_o markedly outperforms the fixed one and gives almost exactly the desired response. In real applications, typical values for Z_o are from 20 to 150 Ω. However, most of the microwave equipment uses 50 Ω ports and connectors.

Using the "tic/toc" function in MATLAB environment where the optimization has been performed, the elapsed time has been mesured for each of the aforementioned examples, and the results has been summerized in Table 5.

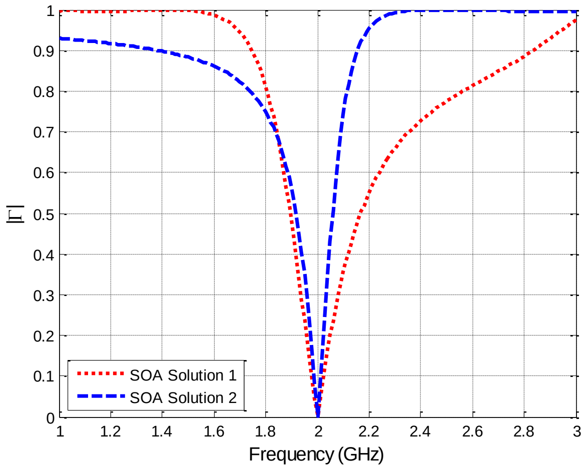

Figure 4. The reflection coefficient magnitude for solutions obtained by SOA vs. frequency for the double stubs matching

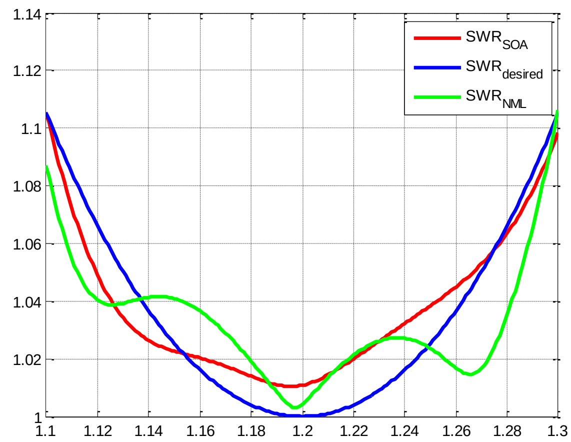

Figure 5. Standing wave ratio for the desired, NML and for the SOA obtained design vs. frequency for fixed $\mathbf{Z_o}$.

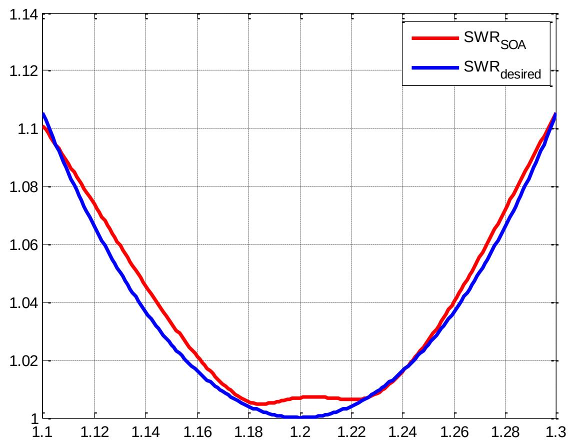

Figure 6. Standing wave ratio for the desired and for the SOA obtained design vs. frequency for variable $\mathbf{Z_o}$.

Table 3. Design values obtained by SOA and NM with fixed $\mathbf{Z_o}$.

Number of stubs	$l_s\ (mm)$	$d_s\ (mm)$	$\mathbf{Z_o}\ (\Omega)$
7 stubs (SOA)	26.996	40.241	50
	59.319	25.527	
	67.848	11.981	
	66.033	1	
	62.996	1	
	62.372	44.973	
	60.313	29.319	
7 stubs (NM) [9]	24.5371,	39.9823,	50
	63.3895,	38.8459,	
	65.3817,	5.8387,	
	61.4128,	4.0774,	
	60.2661,	65.0554	
	60.3690,	95.5695,	
	64.2648	40.3593	

Table 4. Design values obtained by SOA with variable $\mathbf{Z_o}$.

# of stubs	$l_s\ (mm)$	$d_s\ (mm)$	$\mathbf{Z_o}\ (\Omega)$
7 stubs	65.73924	47.46891	142
	69.98455	15.41879	
	60.13989	36.05155	
	59.46959	50.67158	
	56.04904	1	
	63.77201	13.61935	
	63.69742	44.77824	

Table 5. Elapsed time for each run in the numerical examples as calculated in MATLAB.

Number of stubs	Elapsed time for each run (sec.)
Single Stub	44.7807
Double stub	45.5734
Multiple Stub fixed Zo	90.2718
Multiple Stub variable Zo	92.1919

4. Conclusions

In this work, a newly developed optimization technique has been used to design multi-stubs matching system. The SOA has been used to find the optimum lengths and positions of the stubs to provide best matching circuit. Instead of using the recursive numerical calculations, the SO algorithm has been used to minimize the RC. The obtained results for the stubs' locations as well as lengths for single and double stub system were compared and similar to those obtained using numerical/ graphical traditional techniques. For multi-stub matching examples, SO algorithm has been used to obtain the system parameters in a specific frequency range, considering two cases; optimization with fixed and variable Z_o. The obtained results by SOA show the capability of using optimization techniques in matching applications.

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