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Research Article / Araştırma Makalesi

DIFFERENTIAL EVOLUTION OPTIMIZATION APPLIED TO THE PERFORMANCE ANALYSIS OF A MICROWAVE TRANSISTOR

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ABSTRACT

Differential Evolution (DE) is arguably one of the most powerful stochastic real-parameter optimization algorithms in current use. Although the methodology of the DEA is similar to the genetic algorithm, DEA is simpler and has a better convergence rate than the other counterpart Meta-heuristic optimization algorithms. Herein, DE optimization is applied to determining the Feasible Design Target Space of a microwave transistor for use in Low Noise Amplifier (LNA) designs. Thus, a multiobjective cost function including all the performance measure functions of an LNA transistor which are the transducer gain (G_T), Noise Figure (F), input and output Voltage Standing Wave Ratio (V_{in}, V_{out}) is built to determine the source (Z_S) and load (Z_L) terminations to meet the required ($F \geq F_{min}$, GT, $V_{in} \geq 1$, $V_{out} \geq 1$) quadruple within the potential operation bandwidth of the device. A study case is also presented for an LNA transistor NE350184C by applying DE optimization in the determination of their typical performance quadruples together with the source (Z_S) and load (Z_L) terminations.

Keywords: Differential evolution algorithm, metaheuristic algorithms, multiobjective optimization, LNA design.

1. INTRODUCTION

Design of an ultra-wideband (UWB) single stage Low-Noise Amplifier (LNA) is one of the biggest challenges to UWB transceiver integrations. Especially most of the receivers are hand-held or battery- operated devices that requires small size designs and low power consumption alongside of high gain G_T, low noise figure F, low input V_{in} and output V_{out} Standing Wave Ratios with an UWB operation frequency range. Thus, the major challenge in designing a single stage LNA is to enable the active devices which are transistors, subject to the physical limitations and compromise relations among the noise, gain and mismatches at the input and output ports. Therefore performance analysis of a microwave transistor is of primary importance for the LNA design optimization since it facilitates to build all the trade-off relations between the performance ingredients G_T, F, V_{in}, V_{out} within the device's operation domain of bias condition (V_{DS}, I_{DS}) and frequency f. Some recent works in literature for performance characterization of a transistor for a

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pre-determined design strategy using either analytical [1- 5] or numerical [6-10] methods with the Scattering (S-) and Noise (N-) parameters at the chosen operation conditions.

Design optimization of an UWB single stage LNA is a highly nonlinear optimization problem. To tackle complex computational problems, researchers have been looking into nature for years both as model and as metaphor for inspiration. Optimization is at the heart of many natural processes like Darwinian evolution itself. Through millions of years, every species had to adapt their physical structures to fit to the environments they were in. A keen observation of the underlying relation between optimization and biological evolution led to the development of an important paradigm of computational intelligence the evolutionary computing techniques [11 -13] for performing very complex search and optimization.

In this work, DE optimization which is arguably one of the most powerful stochastic real-parameter optimization algorithms in current use, is applied to determining the Feasible Design Target Space of a microwave transistor for LNA designs. For this purpose, a multiobjective cost function including all the performance measure functions of an LNA transistor which are the transducer gain (G_T), Noise Figure (F), input and output Voltage Standing Wave Ratio (V_{in}, V_{out}) is built to determine the source (Z_S) and load (Z_L) terminations to meet the required ($F \geq F_{min}$, G_T, $V_{in} \geq 1$, $V_{out} \geq 1$) quadruple within the potential operation bandwidth of the device. A study case is also presented for an LNA transistor NE350184C by applying DE optimization in the determination of their typical performance quadruples together with the source (Z_S) and load (Z_L) terminations.

The paper is organized as follows: Section 2 presents fundamentals of DE algorithm; in Section 3 the performance measure functions of a microwave transistor are given; section 5 presents a study case on application of DE algorithm for performance analysis of an LNA transistor NE350184C, the paper ends with the conclusions.

2. DIFFERENTIAL EVOLUTION ALGORITHM

The DE algorithm is a population-based evolutionary optimization algorithm developed for the solution of real-valued numerical optimization problems and has been found several significant applications to the optimization problems arising from diverse domains of science and engineering. DE algorithm is originated by Kenneth Price and Rainer M. Storn and first publication of idea of this method was published as a technical report in [15]. Just after inception of this method it has become an attractive field for research and after establishing by Storn in 1997 a website [16] an explosive expansion in differential evolution research took place. Moreover, the current progress in the field of computer computations makes in practice DE a powerful tool for stochastic optimization due to its parallelizable nature from the computational point of view which is used in many optimization problems [17-22]. DE is a method of multidimensional mathematical optimization which belongs to the class of Evolutionary Algorithm (EA). This meta-heuristic method tries to find optimum of the problem by iteratively improving of the candidate solution with respect to value of the objective function. The main difference in constructing better solutions is that genetic algorithms rely on crossover while DE relies on mutation operation. This main operation is based on the differences of randomly sampled pairs of solutions in the population. The algorithm uses mutation operation as a search mechanism and selection operation to direct the search toward the prospective regions in the search space.

2.1. Initialization

The first step is to initialize the population. In general, every member of the population is seeded uniformly within a given space. Most problems are considered to be box constrained since the variables are subject to boundary constraints. This leaves us with the following simple initialization formula for each component:

$$x_{i,0}^{j} = l^{j} + rand \times (u^{j} - l^{j}), \quad j = 1, 2, ..., n \tag{2.1}$$

where rand ϵ [0, 1] is a uniformly distributed random value generated for each j and u^j and l^j are the respective upper and lower limits for the j^{th} variable or component. For certain problems, information might be available that would favor exploration in certain areas. In this case the population can be seeded around these areas of interest.

2.2 Mutation

The defining characteristic of the DE algorithm is the method via which the new trial points are generated. At every generation g, each member of S (S={x_1,x_2,…, x_N} solution space) is targeted to be replaced with a better trial point. Considering x_{ig} as the target point, the corresponding trial point yig is created using the target point and a mutated point $\overset{\Delta}{x}_{i,g}$. For the simplest case, a mutated point is created by adding the weighted difference of two population members to a third. However there are various other possible schemes for generating the mutated points. Some possible mutation schemes for the i^{th} target point are given below:

$$\overset{\Delta}{x}_{i,g} = x_{p(1)} + F \times (x_{p(2)} - x_{p(3)}) \tag{2.2}$$

$$\overset{\Delta}{x}_{i,g} = x_{b} + F \times (x_{p(2)} - x_{p(3)}) \tag{2.3}$$

$$\overset{\Delta}{x}_{i,g} = x_{p(1)} + \lambda \times (x_{b} - x_{p(1)}) + F \times (x_{p(2)} - x_{p(3)}) \tag{2.4}$$

where F and λ are scaling parameters and x_b is the best point in the current population. $x_{p(1)}$, $x_{p(2)}$ and $x_{p(3)}$ are randomly chosen points such that $p(1) \neq p(2) \neq p(3) = i$ i.e. all points are unique and none of these points corresponds to the target point $x_{i,g}$.

There are other variants to the schemes described by equations (2.2) to (2.4). In order to distinguish between different schemes a standard notation is used to indicate the scheme type: DE/a/b/c. The variable "a" specifies the base vector used that will be perturbed is chosen. It can which can either be random e.g. $x_{p(1)}$, as is the case for equation (2.2) and (2.4) or the best vector is the population, x_b, as in equation (2.3). The second variable b indicates how many vector pairs form the difference vectors. For equations (2.2) and (2.3) the value for b is l while for equation (2.4) b is 2. The variable c indicates what type of crossover method is used. Binomial crossover is represented by the abbreviation b in and exponential crossover by exp.

2.3. Crossover

The target or parent point x_{ig} together with the new mutated points $\overset{\Delta}{x}_{i,g}$ are recombined to create the trial point y_{ig}. There are two popular types of crossover methods used with the DE algorithm, namely binomial and exponential. For the purpose of this thesis we only use the binomial method which will be discussed below.

Binomial recombination starts at the first component of the vector and generates a random number rj ϵ [0, 1] for each component. If rj<cr then the j^{th} component of y_{ig} is taken from x_{jig}, otherwise if rj>cr then the component is taken from x_{ig}. This process continues until all components from x_{ig} have been considered. In order to ensure that at least one component in y_{ig} is from x_{ig}, a random integer $I_i \in \{1, 2, ..., n\}$ is generated. The component in y_{ig} corresponding to Ii is taken from x_{ig}. The trial vector can contain components from $x_{i,g}$ at multiple, separated points. Binomial recombination can be mathematically formulated as:

$$y_{i,g}^{j} = \begin{cases} \overset{\Delta}{x}_{i,g} \quad if\ r^{j} \le c_r \ \ or \ \ j = I_i \end{cases} , \quad y_{i,g}^{j} = \begin{cases} \overset{\Delta}{x}_{i,g} \quad Otherwise \end{cases} \tag{2.5}$$

2.4. Acceptance

At each iteration the DE algorithm attempts to replace each point in S with a better point. Therefore at each generation g, N competitions are held to determine the members of S for the next iteration. The i^{th} competition is held to replace $x_{i,g}$ in S. This is done by comparing the function values of the trial points $y_{i,g}$ to those of $x_{i,g}$, the target points. If $f(y_{i,g}) < f(x_{i,g})$ then y_{ig} replaces xig in S, otherwise S retains the original $x_{i,g}$. This can be written mathematically as:

$$x_{i,g}^{j} = \begin{cases} \overset{\Delta}{y}_{i,g} \quad if \ \ f(y_{i,g}) < f(x_{i,g}) \end{cases} , \quad x_{i,g}^{j} = \begin{cases} \overset{\Delta}{x}_{i,g} \quad Otherwise \end{cases} \tag{2.6}$$

The DE algorithm maintains a greedy selection scheme that ensures that the current generation is equal to or better than the previous generation.

2.5. Stop Criteria

The main criterion is that if the current best cost/Fitness value is reached to the requested value and if the maximum iteration limit is reached.

Supportive and optional criteria

- If for the last M iteration the best cost/Fitness value is not changed,

In the next chapter, the DEA is used to determines the optimal design parameters of a SIW antenna for high performance measures such as low input reflection and high gain.

By considering all the above requirements the DE algorithm appears to be one of the most appealing choices as an underlying global optimizer. Next section descripts the DE algorithm.

3. A SMALL – SIGNAL MICROWAVE TRANSISTOR

Fig.1 gives a single transistor LNA being designed by a proper compatible quadrate together with the matching networks providing the required (Z_S, Z_L) termination couple. As seen from fig.1, a transistor used for a small signal amplification can be characterized by a linear two port terminated by the source Z_S and load Z_L impedances, at the input and output ports, respectively.

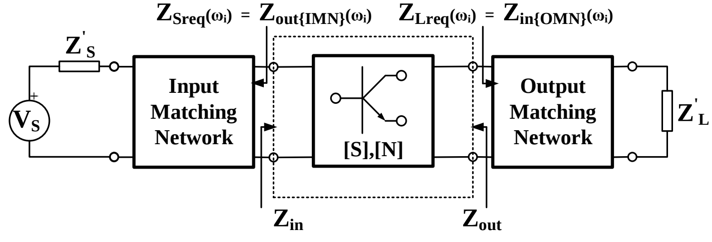


Figure 1. A Single transistor LNA circuit designed by a proper compatible ($F \ge F_{min}$, G_T, $V_{in} \ge 1$, $V_{out} \ge 1$) quadrate and its (Z_{Sreq}, Z_{Lreq}) terminations. [23]

In the Feasible Design Target Space (FDTS), this (Z_S, Z_L) termination couple guarantees a corresponding compatible performance ($F \geq F_{min}$, G_T, $V_{in} \geq 1$, $V_{out} \geq 1$) quadrate. In other words they are a simultaneous solution set of the following highly nonlinear performance equations under the physical realization conditions:

$$F = \frac{(SignalPower/NoisePower)_{input}}{(SignalPower/NoisePower)_{output}} = F(Z_S) = F_{\min} + \frac{R_n \left| Z_S - Z_{opt} \right|^2}{\left| Z_{opt} \right|^2 R_S} \tag{3.1}$$

$$G_T(Z_S, Z_L) = \frac{Power\ delivered\ into the\ Load}{Maximum\ Source\ Power} = \frac{4R_S R_L \left| z_{11} \right|^2}{\left| (z_{11} + Z_S)(z_{22} + Z_L) - z_{12} z_{21} \right|^2} \tag{3.2}$$

$$V_{in} = V_{in}(Z_S, Z_L) = \frac{1+\rho_{in}}{1-\rho_{in}}, \qquad \rho_{in}^2 = \left| \frac{Z_{in} - Z_S^*}{Z_{in} + Z_S} \right|^2 \leq 1 \tag{3.3}$$

$$V_{out} = V_{out}(Z_S, Z_L) = \frac{1+\rho_{out}}{1-\rho_{out}}, \qquad \rho_{out}^2 = \left| \frac{Z_{out} - Z_L^*}{Z_{out} + Z_L} \right|^2 \leq 1 \tag{3.4}$$

The physical realization conditions can be given as

$$\Re e\left\{Z_{in}\right\} = \Re e\left\{ z_{11} - \frac{z_{12} z_{21}}{z_{22} + Z_L} \right\} > 0 \tag{3.5}$$

$$\Re e\left\{Z_{out}\right\} = \Re e\left\{ z_{22} - \frac{z_{12} z_{21}}{z_{11} + Z_S} \right\} > 0 \tag{3.6}$$

$$F \geq F_{\min}, V_{in} \geq 1, V_{out} \geq 1, G_{T\min} < G_T \leq G_{T\max} \tag{3.7}$$

where the conditions given by (5) and (6) ensure the stable operation of the active device, while the inequalities in (7) guaranties the performance ingredients to remain within the physical limitations of the device.

4. STUDY CASE

The following cost functions given in Eqs. (4.1-4.4) are used to perform 2 different optimization problem for a microwave transistors performance characterization. Eqs. (4.1-4.2) are used to determines the optimal Z_S and Z_L values separately while Eq. (3.9) simultaneously perform the search for Z_S and Z_L terminations.

$$\text{Cos}t_1 = f(R_S, X_S, Z_L = Z_{out}^*) = a\left| F - F_{req} \right| + e^{-\frac{G_T}{b}} \tag{4.1}$$

$$\text{Cos}t_2 = g(\overline{Z_S}, R_L, X_L) = c\left| V_{out} - V_{Outreq} \right| + d\left| V_{inopt} \right| \tag{4.2}$$

where F is function of (R_S, X_S), however G_T, Vin and V_{out} are functions of (R_S, X_S, R_L, X_L) as given by Eqs. (3.1-3.4) respectively; Freq, and V_{outreq} are the required noise figure, output VSWR values, respectively. Eq. (4.1) is targetted to obtain the source termination $\overline{Z_S}$ of the maximum gain subject to the required noise Freq, while Eq. (4.2) is aimed at obtaining the load termination Z_L to satify the optimum input mismatching for the requested output mismatching V_{outreq}. a, b, c and d in Eqs (4.1, 4.2) are the user-defined weighting coefficients. If Z_L is wanted for the required (V_{inreq}, V_{outreq}) couple, the Eq. 4.2 can be re-arranged as follows:

$$\mathrm{Cos}t_2 = g(\overline{Z_S}, R_L, X_L) = c\left|V_{out} - V_{outreq}\right| + d\left|V_{in} - V_{inreq}\right| \tag{4.3}$$

In the Eq. (4.4), all the requirements is picked up in a single objective function as follows:

$$\mathrm{Cos}t_3 = f(R_S, X_S, R_L, X_L) = a\left|F - F_{req}\right| + e^{-\frac{G_T}{b}} + c\left\|V_{out} - V_{outreq}\right\| + d\left|V_{in} - V_{inreq}\right| \tag{4.4}$$

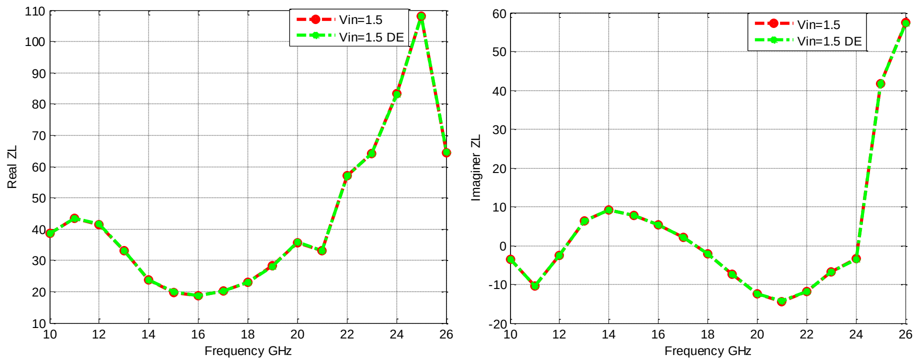
where the optimization problem carried with Eqs. (4.1-4.2) are merged into single cost function. Although by this way optimization process had become faster, the complexity of the problem is significantly increased because the cost given in Eq. (4.4) is a 4 variable optimization while cost functions given in Eqs. (4.1-4.2) are only two variable.

In the following tables and figures, the performance results obtained with DE algorithm for NE350184C transistor are presented. In table 1, the performance results of DE algorithm for different population sizes for each cost function are given.

Table 1. Performance results of Costs for 10 runs.

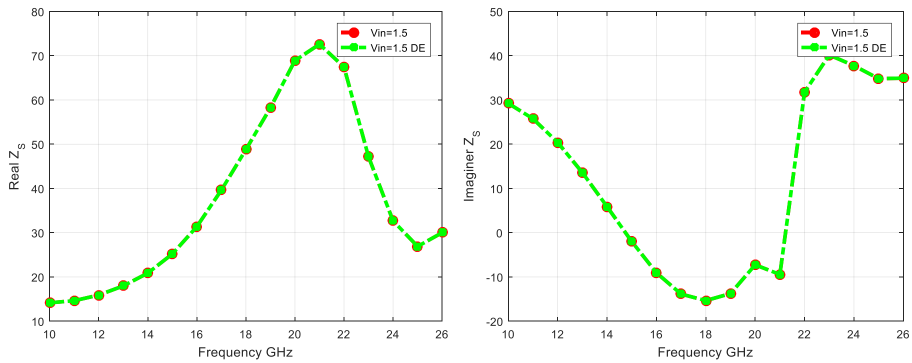
		Cost 1			*Cost 2*			*Cost 3*		
		Max	**Min**	**Mean**	**Max**	**Min**	**Mean**	**Max**	**Min**	**Mean**
Iteration=30 Population=30	**Cost**	2.37	0.27	1.37	0.322	0.303	0.307	4.40	0.67	1.72
	FEN	1633	1656	1651.7	1630	1627	1649.6	1641	1634	1649.4
Iteration=30 Population=50	**Cost**	1.25	0.18	1.09	0.315	0.302	0.304	2.02	0.66	1.25
	FEN	2743	2752	2759.5	2752	2749	2758.5	2757	2748	2748
Iteration=30 Population=100	**Cost**	1.02	0.15	0.48	0.311	0.302	0.303	1.41	0.63	0.894
	FEN	5499	5488	5501.5	5478	5497	5486.5	5474	5505	5499.2

*FEN: Function Evaluation Number



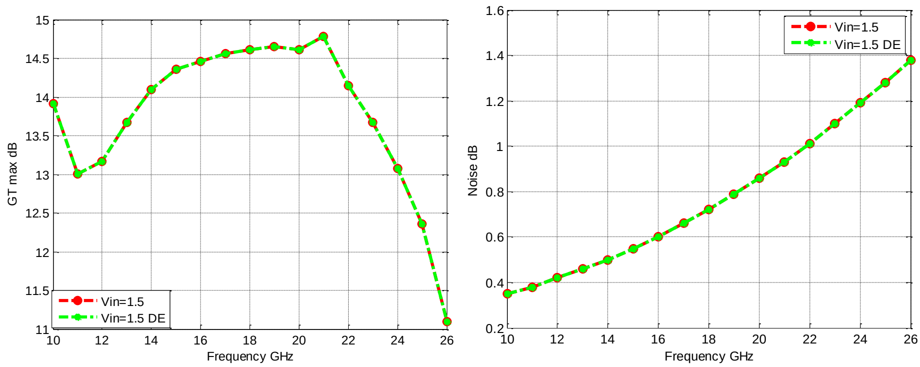
(a) (b)

Figure 2. (a) RL (b) XL Results of NE350184C @ 2V 20mA [Freq = Fmin , Vireq=1.5, Vout=Voutopt ,GTreq = GTmax (f)].



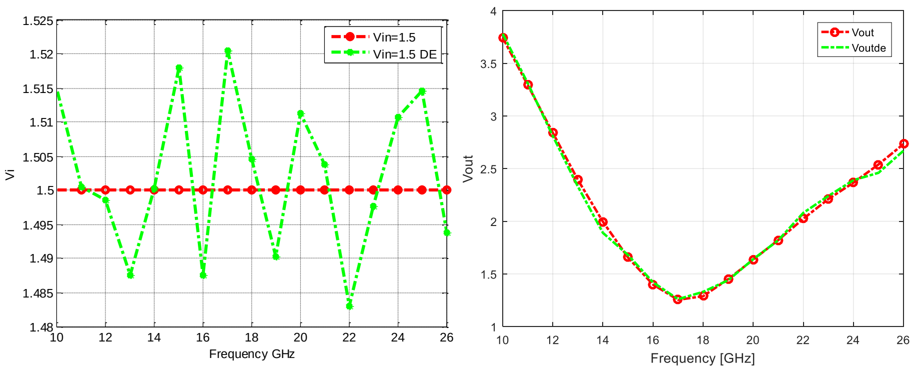
(b) (b)

Figure 3. (a) RS (b) XS Results of NE350184C @ 2V 20mA [Freq = Fmin , Vireq=1.5, Vout=Voutopt ,GTreq = GTmax (f)].



(c) (b)

Figure 4. (a) Gain(b) Noise Results of NE350184C @ 2V 20mA [Freq = Fmin , Vireq=1.5,Vout=Voutopt, GTreq = GTmax (f)].



(a) (b)

Figure 5. (a) Vin (b)Vout Results of NE350184C @ 2V 20mA [Freq = Fmin , Vireq=1.5, Vout=Voutopt, GTreq = GTmax (f)].

5.CONCLUSION

In this work, performance analysis of a LNA transistor is carried out without using any expertise knowledge on microwave device, circuit and noise. For this purpose, highly nonlinear performance measure equations of the transistor are solved with respect to the source Z_S and load Z_L terminations as a constrained multiobjective optimization problem. In this problem, the physical realization conditions are taken account as the constraints of the optimization problem that are the performance limitations and stability conditions of the transistor. Differential Evolution (DE) is used as a fast and accurate and powerful algorithm. The typical LNA transistor NE350184C is presented as a study case by applying DE optimization in the determination of their typical performance quadruples together with the source (Z_S) and load (Z_L) terminations.

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