Chapter 14
The Backtracking Search for the Optimal Design of Low-Noise Amplifiers

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Abstract The backtracking search algorithm (BSA) was recently developed. It is an evolutionary algorithm for real-valued optimization problems. The main feature of BSA vis-à-vis other known evolutionary algorithms is that it has a single control parameter. It has also been shown that it has a better convergence behavior. In this chapter, the authors deal with the application of BSA to the optimal design of RF circuits, namely low-noise amplifiers. BSA performance, viz. robustness and speed, are checked against the widely used particle swarm optimization technique, and other published approaches. ADS simulation results are given to show the viability of the obtained results.

14.1 Introduction

Radio-frequency circuit (RF) design is a laborious strained and iterative cumbersome task that mainly relies on the experience of the skilled designers. The literature offers a plethora of papers dealing with techniques, approaches, and

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algorithms aimed at assisting the designer in such a cumbersome task, see for instance [22, 47].

Mathematical approaches have been used for alleviating the sizing task of such circuits, and it has already been proven that classical approaches are powerless vis-a-vis these NP-hard optimization problems [23].

Metaheuristics bid interesting and arguably efficient tools for overcoming impotence of the classical techniques. This can be briefly explained by the fact that due to the stochastic aspect of metaheuristics, 'efficient' sweeping of large dimension search spaces can be insured. Furthermore, metaheuristics allow dealing with many objective problems as well as constrained ones [15, 51, 52, 57].

Evolutionary metaheuristics have been used to deal with the optimal design of RF circuits, as well as analog circuits, and a large number of algorithms have been tested [2, 19, 24, 25, 29, 32, 40–44, 47, 50, 53, 54].

Swarm intelligence techniques (SI) have also been used, such as particle swarm optimization techniques (PSO) [20, 21, 38, 55, 56], ant colony optimization techniques (ACO) [3, 5], and bacterial foraging techniques (BFO) [10, 31]. SI metaheuristics are nowadays largely adopted for the resolution of similar optimization problems. Actually, it has been shown that when compared to notorious optimization algorithms, mainly genetic algorithms (GA) [26, 33] and simulated annealing (SA) [35], SI techniques can be much interesting to be used because they can be more robust, faster, and require much less tuning of control parameters, see for instance [48].

Very recently, an evolutionary algorithm's enhanced version has been proposed, and it is called the backtracking search optimization technique (BSA or BSOA), and it has been shown via mathematical test functions and few engineering problems that BSA offers superior qualities [11].

Thus, in this work, we have put BSA to the test. It was used for the optimal sizing of low-noise amplifiers (LNAs), namely an UMTS LNA and a multistandard LNA.

BSA performances were checked with those obtained using conventional PSO algorithm and also with published results (for the same circuits) using ACO and BA-ACO techniques [42] as it is highlighted in the following sections.

The rest of this chapter is structured as follows. In Sect. 14.2, we offer a brief introduction to the considered RF circuits. In Sect. 14.3, the BSA technique is detailed, and a concise overview of the PSO technique is recalled. Section 14.4 presents the BSA obtained results, which provides a comparison with performances from the other techniques. ADS simulation techniques are also given in this section. Finally, Sect. 14.5 concludes this chapter and discusses the reached results.

14.2 Low-Noise Amplifiers

Despite the tremendous efforts on RF circuit design automation, this realm remains very challenging. This is due to the complexity of the domain and its high interaction and dependency on other disciplines, as depicted in Fig. 14.1 [45].

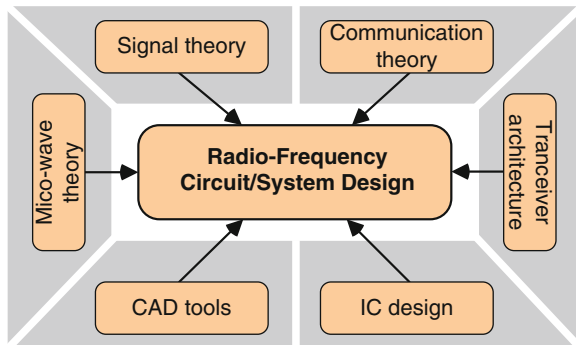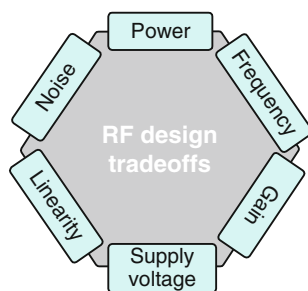**Fig. 14.1** Pictorial illustration of some disciplines involved in the RF design process

Fig. 14.2 RF design tradeoffs

It is to be stressed that one among the most different tasks in this design is the handling of various tradeoffs, known by the famous hexagon introduced in [45], see Fig. 14.2.

The most important block of a front-end receiver is arguably the low-noise amplifier, which principal role consists in amplifying the weak RF input signal fed from the external antenna with a sufficient gain, while adding as less noise as possible, hence its name [1].

Advances in CMOS technology have resulted in deep submicron transistors with high transit frequencies. Such advances have already been investigated for the design of CMOS RF circuits, particularly LNAs [39].

In this work, we deal with two CMOS LNAs, namely a wideband LNA and a multistandard LNA. Both architectures are chosen for comparison reasons with an already published paper [4] regarding performance optimization, as it is detailed in Sect. 14.4.

- A multistandard LNA

The CMOS transistor level schematic of the LNA is shown in Fig. 14.3. It is intended for multistandard applications in the frequency range 1.5–2.5 GHz [8].

In short, this LNA encompasses a cascade architecture for reducing the Miller effect and uses the reverse isolation. M_3, R_2, and R_1 for the biasing circuitry of the input transistor; L_2, C_1, and C_2 allow the input matching.

Fig. 14.3 A multistandard CMOS LNA
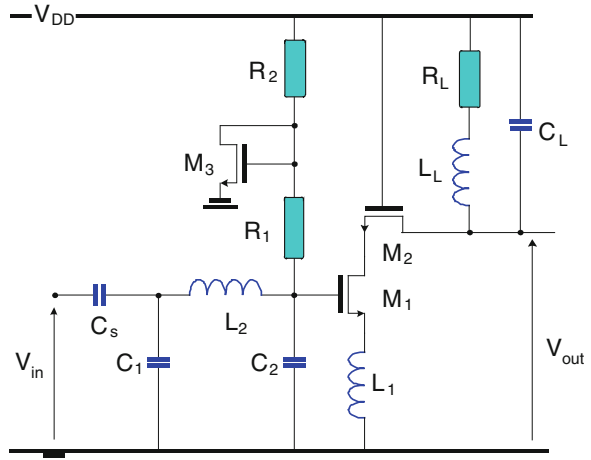
• An UMTS dedicated LNA

Figure 14.4 presents a CMOS LNA, in which topology was optimized in order to be dedicated for UMTS applications. R_1, R_2, and M_3 form the bias circuitry. M_2 forms the isolation stage between the input and the output of the circuit. L_L, R_L, and C_L form the circuit's output impedance.

In Sect. 14.4, we will deal with the optimal sizing of these circuits. Most important performances of such LNAs are considered, i.e., the voltage gain and the noise figure. It is to be noted that the voltage gain is handled via the scattering parameter 'S21' [8]. Corresponding expression (generated using a symbolic analyzer [18]), as well as expressions of the noise figure and the input/output matching conditions, is not provided. We refer the reader to [8] for details regarding these issues.

Fig. 14.4 An UMTS CMOS LNA
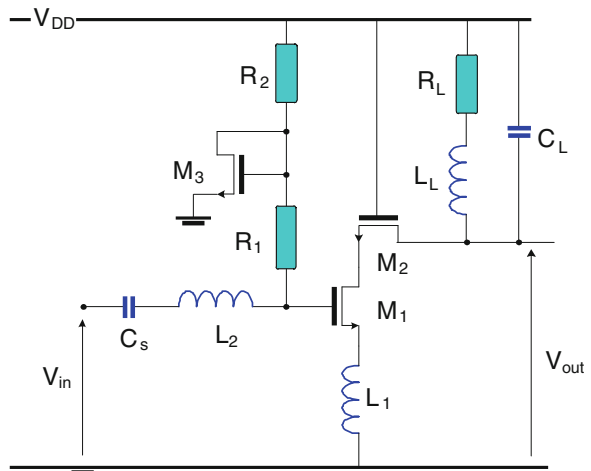
14.3   PSO and BSA Metaheuristics

As introduced in Sect. 14.1, metaheuristics exhibit a wide spectrum of advantages when compared to the conventional mathematical optimization techniques. Metaheuristics are intrinsically stochastic techniques. They ensure random exploration of the parameter search space, allowing converging to the neighborhood of the global optimum within a reasonable computing time. According to [49], the name 'metaheuristics' was attributed to nature-inspired algorithms by Fred Glover [28].

Genetic algorithms [26, 33], which are parts of the evolutionary algorithms, are the oldest most known metaheuristics. A large number of variants of GA were proposed since the introduction of the basic GA (see for instance [15, 51]).

More recently, a new discipline was proposed, so-called swarm intelligence (SI). SI is an artificial reproduction of the collective behavior of individuals that is based on a decentralized control and self-organization [6].

A large number of such systems were studied by swarm intelligence, such as schools of fishes, flocks of birds, colonies of ants, and groups of bacteria, to name few processes [7, 9, 27, 34, 46]. Nowadays, particle swarm optimization may be the most known and the most used technique, particularly in the analog and RF circuits and systems designs, see for instance [13, 20, 21, 37, 48, 55].

More recently, a new improved variant of GA was proposed, and it is called backtracking search optimization technique (BSA) [11]. It offers some interesting features, mainly its robustness (vis-a-vis GA), its rapidity, and the low number of control parameters.

BSA is being used in the fields of analog and RF designs, see for instance [14, 16, 17, 30, 36]. BSA will be used for optimizing performances of both LNAs given in Sect. 14.2.

Presently, PSO is, as introduced above, largely used in design fields; it will also be considered for comparison reasons with BSA.

Furthermore, obtained results are also compared to the ones published in [3], using ant colony optimization (ACO) and backtrack ACO (BA-ACO) techniques.

- PSO technique is inspired from the observation of social behavior of animals, particularly birds and fish. It is a population-based approach that has the particularity that the decision within the group is not centralized [12, 34]. In short, PSO algorithm can be presented as follows.

  The group, which is formed of potential solutions called particles, moves (flies) within the hyper search space seeking for the best location of food (the fitness value).

  Movements of the group are guided by two factors: the particle velocity and the particle position, with respect to Eqs. (14.1) and (14.2).

$$\vec{v_i}(t+1) = \begin{vmatrix} \omega \vec{v_i}(t) \\ +C_1\text{rand}(0,1)(\vec{x_{Pbesti}}(t) - \vec{x_i}(t)) \\ +C_2\text{rand}(0,1)(\vec{x_{Gbesti}}(t) - \vec{x_i}(t)) \end{vmatrix} \qquad (14.1)$$

$$\vec{x_i}(t+1) = \vec{x_i}(t) + \vec{v_i}(t) \qquad (14.2)$$

$\vec{x_{Pbesti}}$ is the best position of particle i reached so far; $\vec{x_{Gbesti}}$ is the best position reached by particle i's neighborhood.

ω, $C_1\text{rand}(0, 1)$, $C_2\text{rand}(0, 1)$ are weighting coefficients. ω controls the diversification feature of the algorithm, and it is known as the inertia weight. It is a critical parameter that acts on the balance between diversification and intensification. Thus, a large value of ω makes the algorithm unnecessarily slow. On the other hand, small values of ω promote the local search ability. C_1 and C_2 control the intensification feature of the algorithm. They are known as the cognitive parameter and the social parameter, respectively.

PSO algorithm is given in Fig. 14.5.

As shown above, PSO algorithm is simple to be implemented and is computationally inexpensive. Thus, it does not require large memory space and is rapid, as well. These facts are on the basis of its popularity.

- BSA (or BSOA) is a new population-based global minimizer evolutionary algorithm for real-valued numerical optimization problems [11]. BSA offers some enhancements over the evolutionary algorithms, mainly the reduction in sensitivity to control parameters and improvement in convergence performances.

  Classic genetic operators, namely selection, crossover, and mutation, are used in BSA, but in a novel way.

  BSA encompasses five main processes: (i) initialization, (ii) selection ①, (iii) mutation, (iv) crossover, and (v) selection ②. BSA structure is simple, which confers low computational cost, rapidity, and necessitates low memory space. Moreover, the power of BSA can be summarized through its control process of the search directions within the parameters' hyperspace.
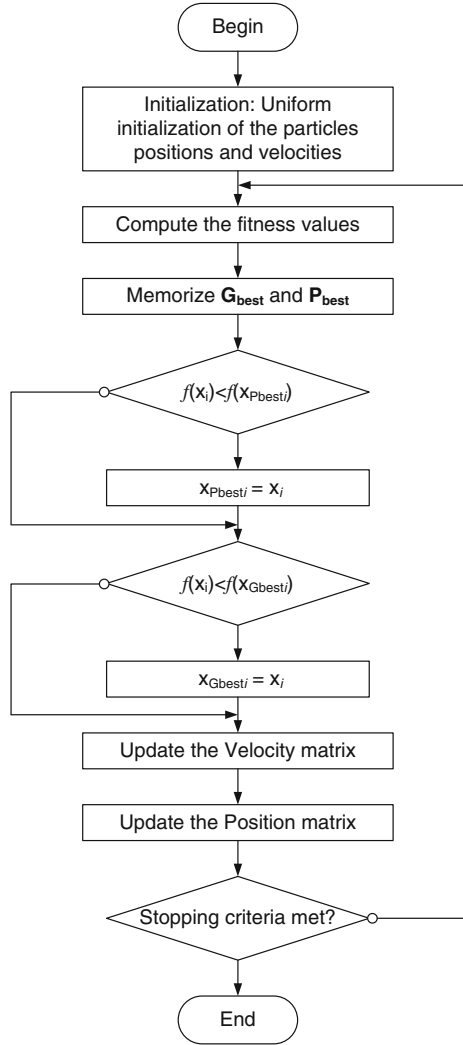 BSA algorithm is given in Fig. 14.6.

  – *Initialization*: The population $\mathbf{P} = (p_{ij})_{(N,M)}$ is initialized via a uniform stochastic selection of particles values within the hypervolume search space, as shown by expression (14.3):

$$p_{ij} = p_{j\min} + \text{rand}(0, 1)(p_{j\text{Max}} - p_{j\min})$$
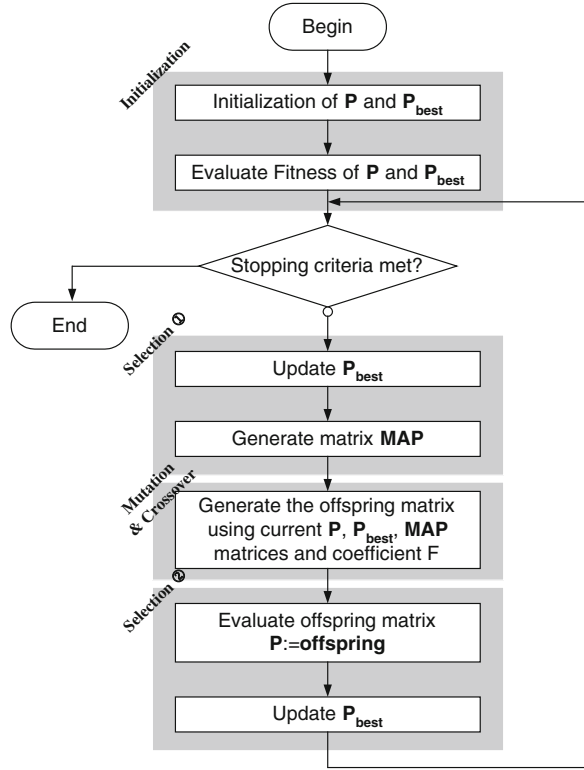$$(i,j) \in \{1, \ldots, N\}x\{1, \ldots, M\} \qquad (14.3)$$

Fig. 14.5 Basic flowchart of PSO

BSA takes benefits from previous experiences of the particles; thus, it uses a memory where the best position of each particle visited so far is memorized. The corresponding matrix noted $\mathbf{P_{best}} = (p_{\text{best}ij})_{(N,M)}$ is initialized in the same way as matrix $\mathbf{P}$:

$$p_{\text{best}ij} = p_{j\text{min}} + \text{rand}(0, 1)(p_{j\text{Max}} - p_{j\text{min}})$$
$$(i, j) \in \{1, \ldots, N\} x \{1, \ldots, M\}$$

$$(14.4)$$

Fig. 14.6 BSA algorithm

- *Selection* ① consists of the update of the $\mathbf{P_{best}}$ matrix,
- *The Mutation* process operates as follows. A mutant **MUTANT** = $(\text{mutant}_{ij})_{(N,M)}$ is generated as shown in Eq. (14.5).

$$\text{mutant}_{ij} = p_{ij} + \mathcal{F}(p\text{best}_{ij} - p_{ij})$$
$$(i,j) \in \{1, \ldots, N\} x \{1, \ldots, M\} \tag{14.5}$$

$\mathcal{F}$ is a normally distributed factor that is used to control the search path, i.e., the direction.
- *Crossover*: It consists in generating a uniformly distributed integer valued matrix **MAP** = $(\text{map}_{ij})_{(N,M)}$. **MAP** elements values are controlled via a strategy that defines the number of particle components that mutate. This is performed via the '*dimension-rate*' coefficient. Matrix **MAP** is used for determining the matrix **P** components to be handled: the offspring matrix.
- *Selection* ② consists of the update of the trial population via $\mathbf{P_{best}}$ matrix.

14.4   Experimental Results and Comparisons

In this section, we will first deal with the application of the BSA technique to some mathematic test functions and give comparison results with the ones obtained by means of PSO regarding the robustness and the algorithm execution time. Then, we will consider the case of both LNAs introduced in Sect. 14.2. It is to be noted that a Core™2 Duo Processor T5800 (2 M Cache, 2.00 GHz, 4.00 Go) PC was used for that purpose.

- **Test functions**

Five test functions were considered: *DeJong's*, *Eason 2D*, *Griewank*, *Parabola*, and *Rosenbrock*.

The corresponding expressions are given by (14.6)–(14.10), respectively. Figure 14.7 shows a plot of these functions.

Both algorithms, i.e., PSO and BSA, were run 100 times. The algorithms' parameters are given in Table 14.1.

$$f(x) = \sum_{i=1}^{n} i x_i^4$$
$$-5.12 \leq x_i \leq 5.12 \tag{14.6}$$

$$f(x) = -\cos(x_1)\cos(x_2)e^{(-(x_2-\pi)^2-(x_2-\pi)^2)}$$
$$-5 \leq x_1 \leq 5, -5 \leq x_2 \leq 5 \tag{14.7}$$

$$f(x) = \frac{1}{4000}\sum_{i=1}^{n} x_i^2 - \prod_{i=1}^{n} \cos\left(\frac{x_i}{\sqrt{i}}\right) + 1$$
$$5.12 \leq x_i \leq 5.12 \tag{14.8}$$

$$f(x) = \sum_{i=1}^{n} x_i^2$$
$$-5.12 \leq x_i \leq 5.12 \tag{14.9}$$

$$f(x) = \sum_{i=1}^{n-1} \left[100(x_{i+1} - x_i^2)^2 + (x_i - 1)^2\right]$$
$$-2.048 \leq x_i \leq 2.048 \tag{14.10}$$

Figure 14.8 gives a whisker boxplot relative to the 100 executions of both algorithms.

Table 14.2 gives the mean execution time of both algorithms with respect to the five considered functions.
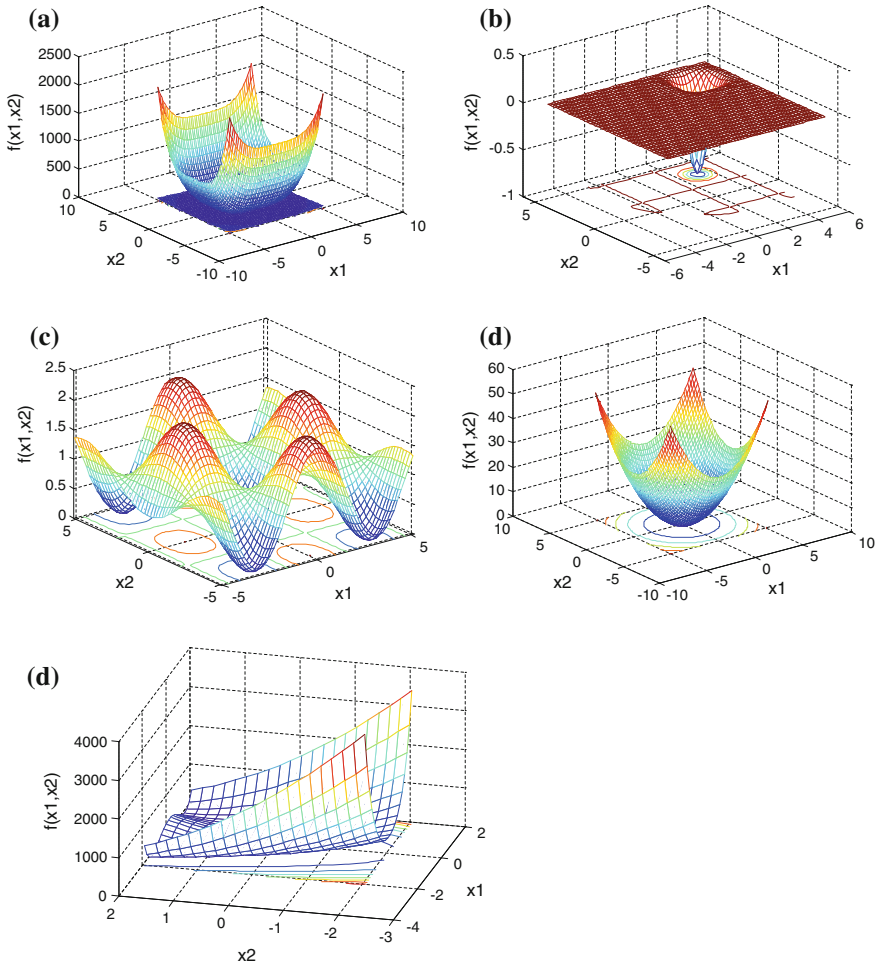
Fig. 14.7 Plots of the five considered functions ($n = 2$). ($x*$ is the minimum of f). **a** DeJong's $x^* = (0, 0)$, $f(x^*) = 0$. **b** Eason 2D $x^* = (\pi, \pi)$, $f(x^*) = -1$. **c** Griewank $x^* = (0, 0)$, $f(x^*) = 0$. **d** Parabola $x^* = (0, 0)$, $f(x^*) = 0$. **e** Rosenbrock $x^* = (1)$, $f(x^*) = 0$

Table 14.1 PSO and BSA algorithms' parameters

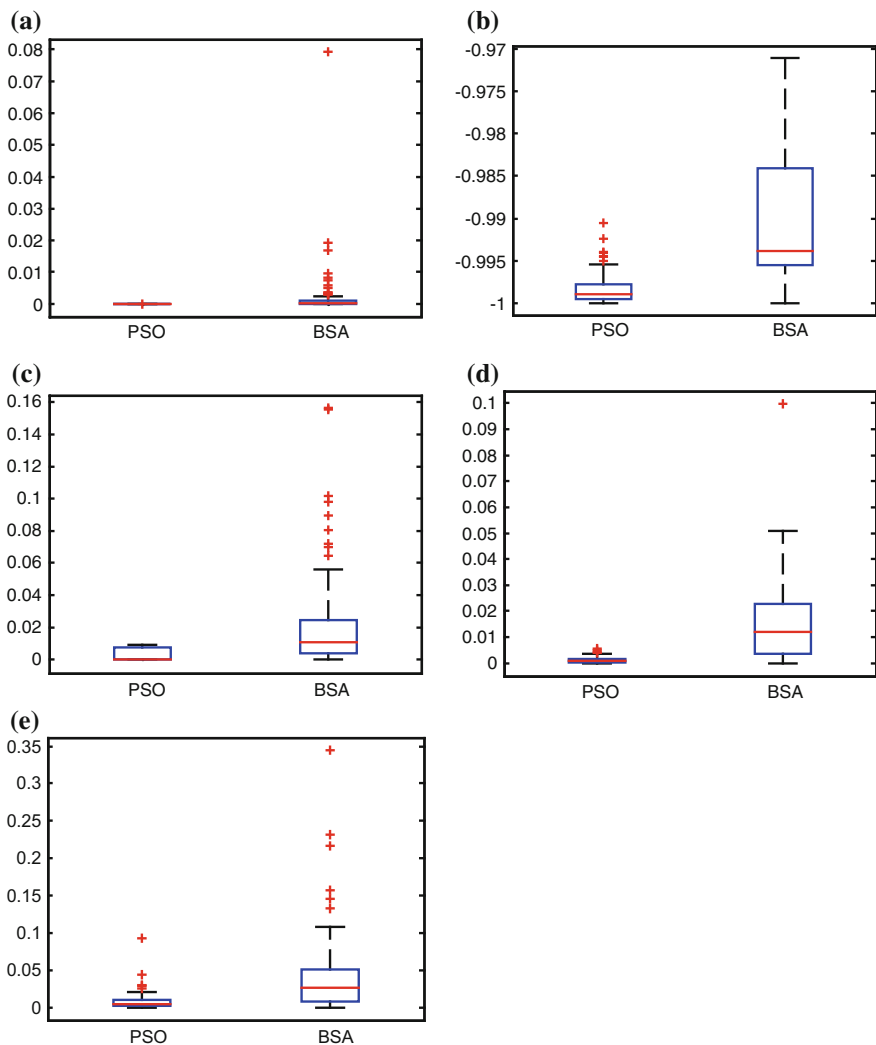| PSO	ω	C_1	C_2
	0.9	2	2
BSA	F	Dimension-rate	
	3	1	

Fig. 14.8 Boxplot of the 100 executions results for both PSO and BSA applied to the five test functions. **a** DeJong's. **b** Eason 2D. **c** Griewank. **d** Parabola. **e** Rosenbrock

Table 14.2 Mean execution time for PSO and BSA (sec.)

Test function	DeJong's	Eason 2D	Griewank	Parabola	Rosenbrock
PSO	24.133	26.848	24.313	25.044	25.219
BSA	0.163	0.292	0.195	0.163	0.170

- **LNAs**

PSO and BSA algorithms were used for optimally sizing both LNAs presented in Sect. 14.2. The same conditions observed above were considered. Tables 14.3 and 14.4 give the circuits' optimized parameters. Moreover, simulations were performed using ADS software to check the viability of these results. Obtained performances are given in Tables 14.5 and 14.6. In addition, these tables present the results published in [4] obtained by application of ACO and BA-ACO techniques.

Table 14.3 Multistandard LNA's optimal parameters' values

	$W_{1,2}$ (μm)/$L_{1,2}$ (μm)	Id (mA)	Cch (pF)	Rch (Ω)	Lch (nH)
PSO	429.98/0.35	96.96	10.00	0.39	0.62
BSA	441.28/0.35	100.00	6.06	0.49	0.90
	Lg (nH)	Ls (nH)	C_1 (pF)	C_2 (pF)	W_3 (μm)/L_3 (μm)
PSO	8.14	0.52	916.90	405.30	40.00/0.35
BSA	10.00	0.35	1000.00	214.00	40.00/0.35

Table 14.4 UMTS LNA's optimal parameters' values

	W_1 (μm)/L_1 (μm)	W_2 (μm)/L_2 (μm)	W_3/L_3 (μm)	Id (mA)	Cch (pF)
PSO	727.41/0.35	995.92/0.35	40.00/0.35	32.33	8.35
BSA	553.19/0.35	513.20/0.35	40.00/0.35	17.7	9.50
	Lch (nH)	Rch (Ω)	Lg (nH)	Ls (nH)	
PSO	0.70	1.24	6.39	0.40	
BSA	0.55	1.20	10	0.27	

Table 14.5 UMTS LNA's optimal performances

S_{21} (dB)	C++ results	ADS simulation results
PSO	16.33	16.46
BSA	16.11	15.64
ACO [4]	16.49	16.47
BA-ACO [4]	16.49	16.36

Table 14.6 Multistandard LNA's optimal performances

S_{21} (dB)	C++ results		ADS simulation results	
	@1.5 GHz	@2.5 GHz	@1.5 GHz	@2.5 GHz
PSO	8.27	11.44	8.78	11.10
BSA	11.56	22.55	8.85	11.02
ACO [4]	10.65	15.48	9.00	11.46
BA-ACO [4]	11.32	18.65	10.68	11.62

Table 14.7 Mean execution time per run

	UMTS LNA (s)	Multistandard LNA (s)
PSO	3.56	2.96
BSA	1.12	0.60
ACO [4]	27.56	38.73
BA-ACO [4]	19.00	31.22

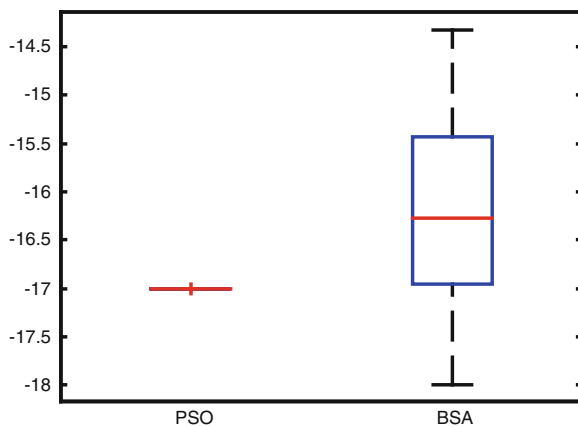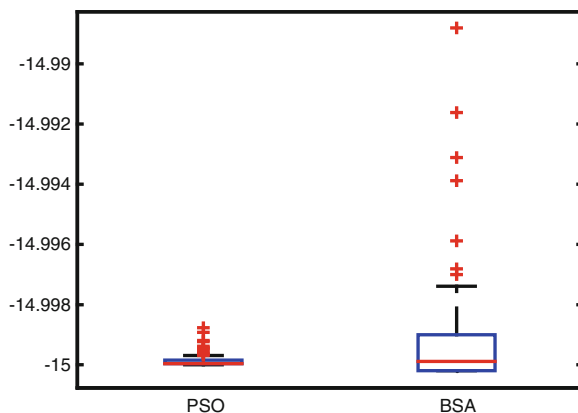**Fig. 14.9** Boxplot for the 100 executions runs for the UMTS LNA using PSO and BSA

Fig. 14.10 Boxplot for the 100 executions runs for the multistandard LNA using PSO and BSA

The mean execution times for both problems are given in Table 14.7. Robustness results are shown in Figs. 14.9 and 14.10.

Simulation results obtained using the 'a priori' optimal parameters for both circuits are depicted in Figs. 14.11, 14.12, 14.13, 14.14, 14.15, 14.16, 14.17, 14.18, 14.19, 14.20, 14.21, 14.22, 14.23, 14.24, 14.25, and 14.26.

Fig. 14.11 ADS simulation results of S21 of the UMTS LNA, using PSO results
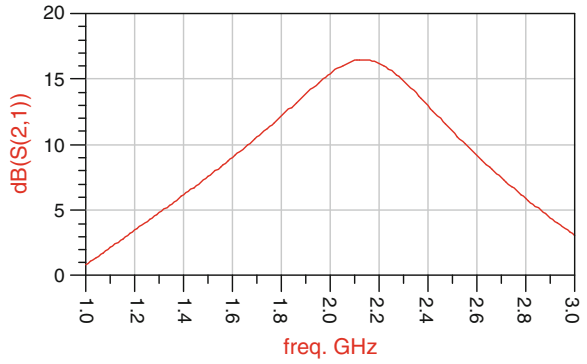
Fig. 14.12 ADS simulation results of S11 of the UMTS LNA, using PSO results
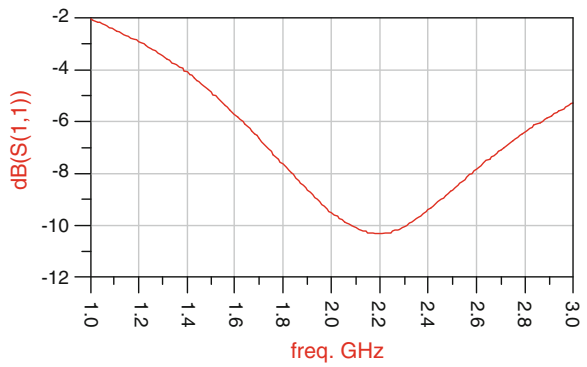
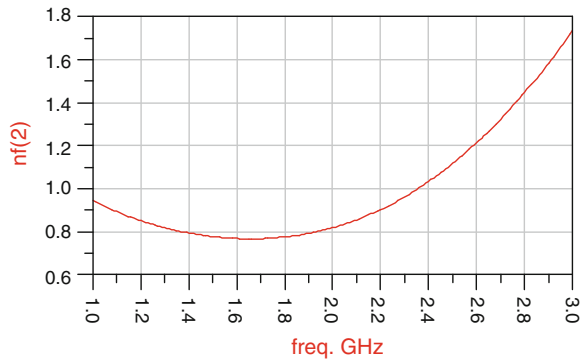**Fig. 14.13** ADS simulation results of the noise figure of the UMTS LNA, using PSO results

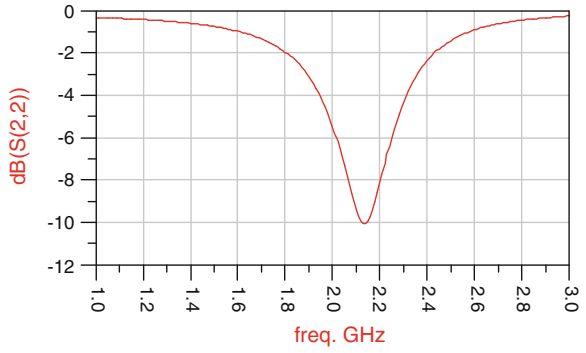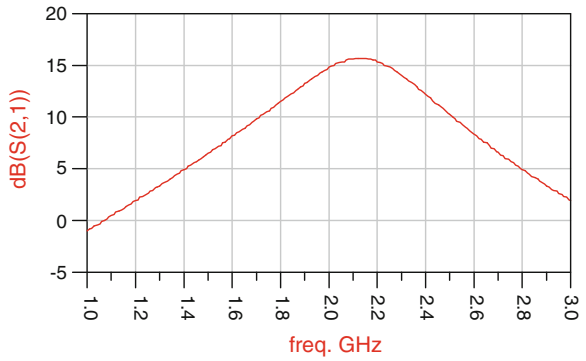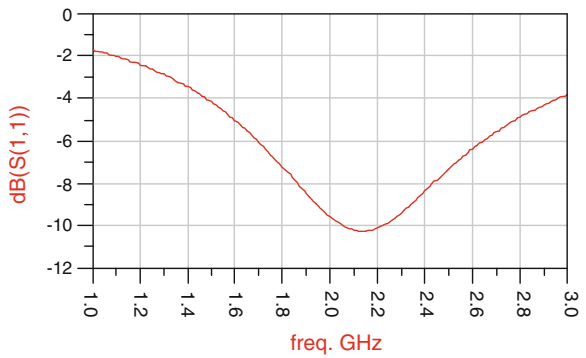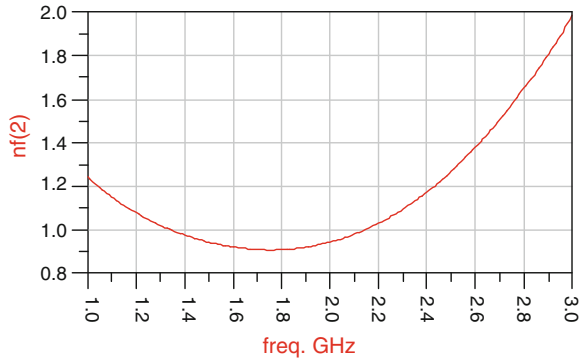**Fig. 14.14** ADS simulation results of S22 of the UMTS LNA, using PSO results

dB(S(2,2))

freq. GHz

Fig. 14.15 ADS simulation results of S21 of the UMTS LNA, using BSA results

dB(S(2,1))

freq. GHz

Fig. 14.16 ADS simulation results of S11 of the UMTS LNA, using BSA results

dB(S(1,1))

freq. GHz

Fig. 14.17 ADS simulation
results of the noise figure of
the UMTS LNA, using BSA
results

Fig. 14.18 ADS simulation
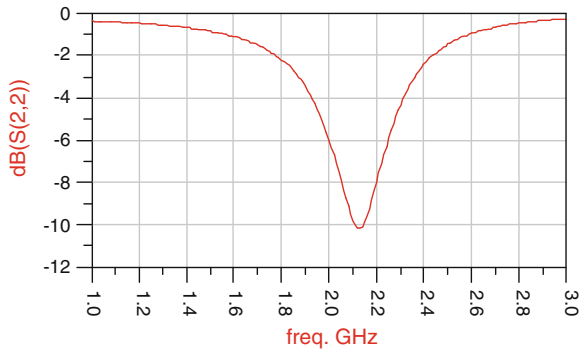results of S22 of the
UMTS LNA, using BSA
results

Fig. 14.19 ADS simulation
results of S21 of the
multistandard LNA, using
PSO results

Fig. 14.20 ADS simulation results of the noise figure of the multistandard LNA, using PSO results
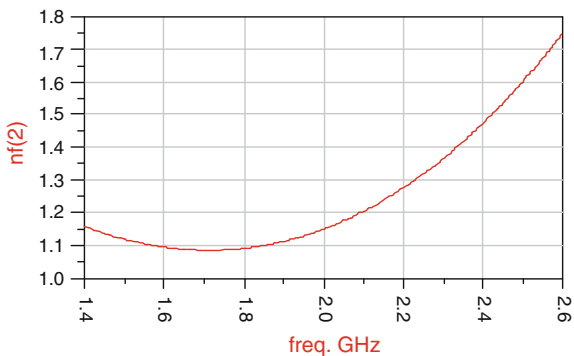

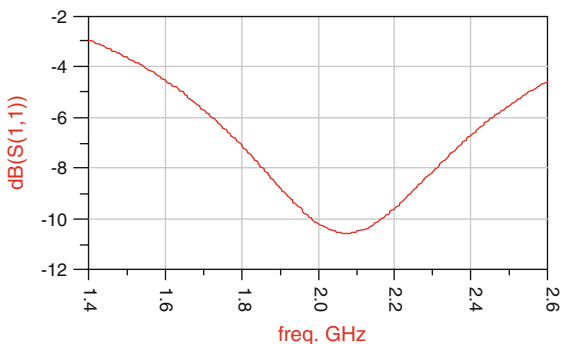**Fig. 14.21** ADS simulation results of S11 of the multistandard LNA, using PSO results

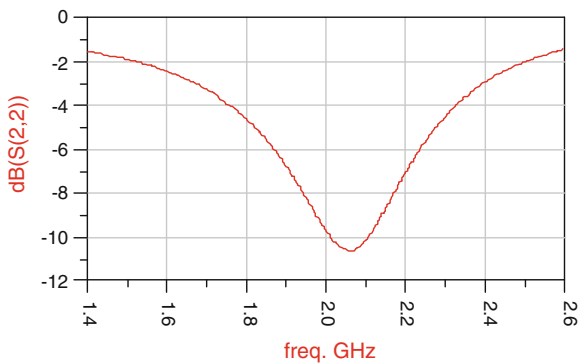**Fig. 14.22** ADS simulation results of S22 of the multistandard LNA, using PSO results

Fig. 14.23 ADS simulation results of S21 of the multistandard LNA, using BSA results
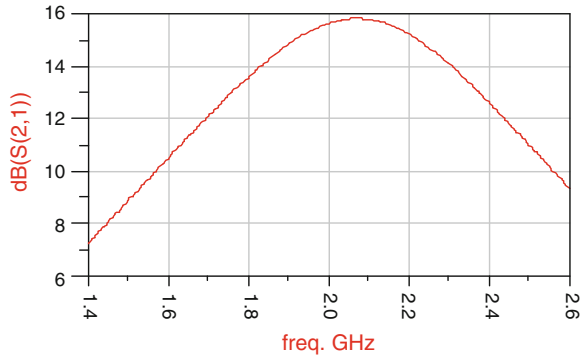
Fig. 14.24 ADS simulation results of the noise figure of the multistandard LNA, using BSA results
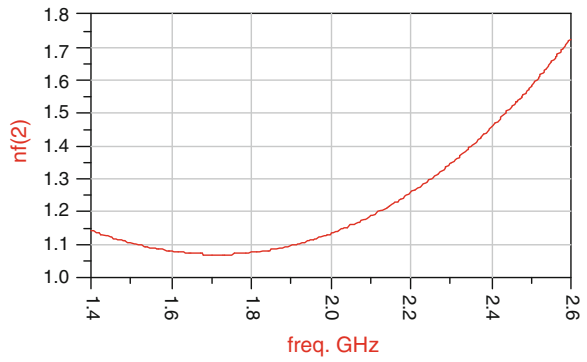
Fig. 14.25 ADS simulation results of S11 of the multistandard LNA, using BSA results
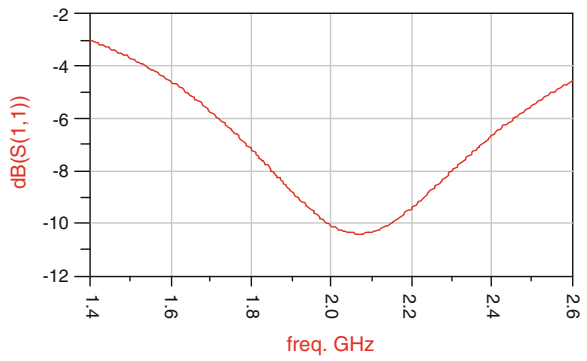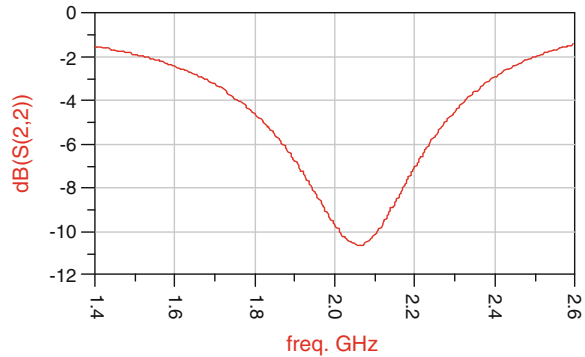
Fig. 14.26 ADS simulation results of S22 of the multistandard LNA, using BSA results

14.5 Discussion and Conclusion

This chapter investigated the application of BSA, the very recently proposed EA technique, on the resolution of RF sizing problems. For comparison reasons, PSO technique was also applied for optimizing these circuits (namely two LNAs). Furthermore, obtained performances were also compared with the already published results dealing with the same circuits but using ACO and BA-ACO, and also the application to the resolution of some test functions.

The obtained results show that BSA outperforms the other optimization techniques in terms of computing time. However, it has been noted that PSO is relatively more robust. Nonetheless, the rapidity of BSA and its good performances make this algorithm a good and interesting technique to be considered within a computer-aided design approach/tool.

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