

Optimizing Current Conveyors by Evolutionary Algorithms Including Differential Evolution

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Abstract—An optimization system based on two multi-objective evolutionary algorithms NSGA-II and MOEA/D is presented for sizing analog integrated circuits. The proposed system uses HSPICE as circuit evaluator and its usefulness is highlighted by sizing mixed-mode analog circuits composed of unity-gain cells. That way, the circuits are optimized in voltage- and current-mode in three parameters: gain, bandwidth and offset, and by including as constraint that all transistors are in saturation operation. Comparison of performances between NSGA-II and MOEA/D with and without differential evolution (DE) as genetic operator in the optimization of two current conveyors are given by using standard CMOS integrated circuit technology.

I. INTRODUCTION

Evolutionary algorithms (EAs), even mixed with other artificial intelligence techniques, are used in optimization tools for analog circuits because it is easy to change the number of objectives or variables with different magnitudes. Additionally, they can take into account constraints under user defined limits between design variables and circuit performances [1].

Multiobjective circuit optimization can be performed by applying EAs such as the Non-Dominated Sorting Genetic Algorithm (NSGA-II) [2] for the design of reconfigurable analog circuits [3], [4]. The Multiobjective EA based on Decomposition (MOEA/D) [5], has been used in [6], which exploits its capabilities of preserving diversity and consistent convergence while is easier to implement and takes less consumption time than NSGA-II. Also, we can find Particle Swarm Optimization [7], which can be adapted to deal with multiobjective optimization problems. Recently, the well known Simulated Annealing method [8], has highlighted the usefulness of including differential evolution (DE) for circuit optimization.

This paper shows the performance of two EAs, NSGA-II and MOEA/D, including DE as genetic operator [9] for the gain, band width and offset optimization of second generation current conveyors (CCII)s. The improvement including DE is appreciated when compared with one point cross-over (CR) as genetic operator.

II. MULTI-OBJECTIVE OPTIMIZATION

NSGA-II and MOEA/D works with multi-objective optimization by minimizing (or maximizing) a problem of the form [10]:

$$\begin{aligned} &\text{minimize } F(\mathbf{x}) = (f_1(\mathbf{x}), f_2(\mathbf{x}), \dots, f_m(\mathbf{x}))^T \\ &\text{subject to } h_k(\mathbf{x}) \geq 0, \quad k = 1 \dots p, \\ &\text{where } \mathbf{x} \in X. \end{aligned} \quad (1)$$

where $X \subset \mathbb{R}^n$ is the decision space for the variables, $\mathbf{x} = (x_1, \dots, x_n)$ is called the decision vector and n is the number of variables. $F(\mathbf{x})$ is the objective vector, $f_j(\mathbf{x}) : \mathbb{R}^n \rightarrow \mathbb{R}$, $j = 1 \dots m$ ($m \geq 2$) are objective functions and $h_k(\mathbf{x})$, $k = 1 \dots p$ are performance constraints. Very often, since the objectives in (1) contradict each other, no point in X minimizes all the objectives simultaneously. The best tradeoffs among the objectives can be defined in terms of Pareto optimality [4].

A. NSGA-II Algorithm

This is an algorithm based on Pareto ranking. First it is necessary to build two populations (P_o and Q_o) each one of size N . The NSGA-II procedure in each generation consists of rebuilding the current (t) population (R_t) from the two original populations (P_t and Q_t).

Next, through a nondominated sorting procedure all solutions in R_t are ranked and classified in a family of sub-fronts [2]. In the next step, it is necessary to create from the current population R_t (previously ranked and ordered by sub-front number) a new offspring (P_{t+1}), the objective will be to choose from a population of size $2N$, N solutions which belong to the first sub-fronts. In this manner, the last sub-front could be greater than necessary, then a measure (*distance*) preserving diversity is used by selecting the solutions that are far from the rest.

B. MOEA/D

The basic idea of MOEA/D is the decomposition of a multiobjective problem in scalar optimization subproblems by a *weights vector* [5]. This vector associates a weight (λ) for each subproblem that is considered as a single solution in the

population and is going to try to improve by itself and to its nearby (*neighborhoods*).

In each generation there is a population of N solutions $\mathbf{x}^1, \mathbf{x}^2, \dots, \mathbf{x}^N \in X$ where $\mathbf{x}^i = (x_1^i, \dots, x_n^i)$ is the current solution to the i_{th} subproblem. After the initialization of the parameters the first step in MOEA/D is related to define the N spread weights vector (to each solution corresponds one λ_i). Therefore, it is possible to define a number (T) of neighborhoods for each λ_i . One way can be by using a parameter H in a sequence, as described by $\{0/H, 1/H, \dots, H/H\}$.

In the procedure it is necessary to generate a new solution \mathbf{y} which will be compared with all its neighborhood by applying a decomposition approach ($g[\mathbf{x}^i | \lambda_i, \mathbf{Z}^*]$) such as the *Tchebycheff Approach* and each neighbor worse than this new solution will be replaced by it in an external population (EP) which is used to store non-dominated solutions.

In the Tchebycheff Approach, the scalar optimization problem is described by $g(\mathbf{x}^i | \lambda_i, \mathbf{Z}^*) = \max\{\lambda_i | f_j(\mathbf{x}^i) - z_j^* \}$, where $1 \leq i \leq N$, $1 \leq j \leq m$ and $\mathbf{Z}^* = \{z_1^*, z_2^*, \dots, z_m^*\}^T$ are the best current objective functions found [10].

C. Differential Evolution

Differential evolution (DE) consists of randomly choosing three solutions [8]: $\mathbf{x}^a, \mathbf{x}^b$ and \mathbf{x}^c from $\{\mathbf{x}^1, \mathbf{x}^2, \dots, \mathbf{x}^N\}$. A new solution $\mathbf{x}_{new} = x_1^{new}, x_2^{new}, \dots, x_n^{new}$ is generated as:

$$x_\iota^{new} = x_\iota^a + R \cdot (x_\iota^b - x_\iota^c), \quad \iota = 1, 2, \dots, n. \quad (2)$$

where R is a constant factor which controls the amplification of the differential variation, in this work it is $R = 0.5$.

III. PROPOSED SYSTEM

The proposed optimization system works on a MATLAB code and the circuit simulations are made with HSPICE by modifying each transistor width (W), and recollecting results from the output listing. The evaluations are made by using the .MEAS statement which prints user-defined electrical specifications of a circuit, and the results could be manipulated in a post-processing step [11]. The library shown in Table I is included to perform AC and DC analysis. With the aim to compare the behavior of both optimization methods, two genetic operators are used: one-point cross-over (CR) and DE.

TABLE I
MEASUREMENTS LIBRARY EXAMPLE

.LIB MEASLIB	* Library name
.AC dec 100 100 1G	* Executing an AC Analysis
.TF V(X) VIN	* Calculating DC parameters
.NET V(X) VIN	* Calculating AC parameters
.MEAS AC AV MAX Vdb(X) FROM=100 TO=100	*Calculating Gain in dB
.MEAS AC bwy TRIG vdb(X) at=100 TARG vdb(X)	
	VAL='av-3' cross=1 *Calculating f_{-3dB}
.DC VIN 1.5 -1.5 .01	*Executing a DC Analysis
.MEAS DC OFFS TRIG V(x) at=0 targ v(x) val=0 cross=1	*Calculating offset
.ENDL MEASLIB	

IV. CIRCUITS UNDER OPTIMIZATION

Figure 1(a) depicts a Positive Second Generation Current Conveyor (CCII⁺) [7] which accomplishes $V_X = V_Y$ and $I_Z = I_X$. Next, Fig. 1(b) depicts a Negative Second Generation Current Conveyor (CCII⁻) [12] which accomplishes $V_X = V_Y$ and $I_Z = -I_X$. Both circuits are biased with $I_{ref} = 50\mu A$, $-V_{ss} = V_{dd} = 1.5V$, and it is assumed that all the MOSFETs have the same transistor length ($0.7\mu m$), then the transistor sizing is made by varying the transistor widths from $0.35\mu m$ to $300\mu m$. For each electrical measurement there is a load capacitor of 1pF and the HSPICE simulations are performed with a LEVEL 49 standard CMOS Technology of $0.35\mu m$. Table II shows the codification of W of the transistors for CCII⁺ ($n = 2$) and CCII⁻ ($n = 8$).

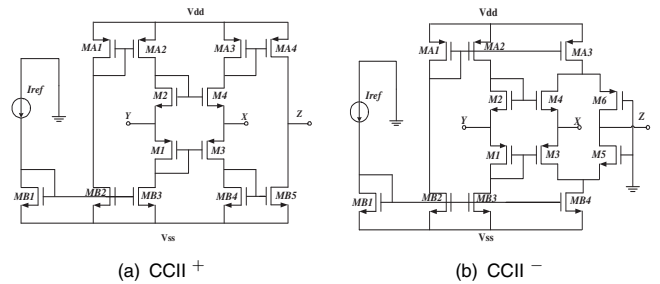


Fig. 1. Tested Circuits

TABLE II
VARIABLES FOR THE CCII⁺ IN OPTIMIZATION PROCESS

Variable Name	Transistors	
	CCII ⁺	CCII ⁻
W_1	$MA_1, \dots, MA_4, M_1, M_3$	MB_1, MB_2, MB_3
W_2	$MB_1, \dots, MB_5, M_2, M_4$	MB_4
W_3	-	MA_1, MA_2
W_4	-	MA_3
W_5	-	M_1, M_3
W_6	-	M_2, M_4
W_7	-	M_5
W_8	-	M_6

V. RESULTS

The circuits are optimized in 6 runs (in a dual processor 2GHz, RAM 2GHz) with both EA's methods and it was selected an H value of 11, then the population length for both methods is 78. The objectives to optimize are: gain, offset and band width (BW) for voltage and current mode. Gain is the relation between the Y to X voltage transfer, and the X to Z current transfer. Offset is a voltage or current value between Y-X or X-Z, and BW is always expressed in Hertz. For voltage and current optimization of these circuits is desired a gain closer to unity, a minimum offset and a maximum BW.

Figures 2 - 5 depict the last non-dominated solutions for voltage and current optimization for the NSGA-II and MOEA/D approaches. As special case, Figure 2(c) compared with 2(d) shows that DE improves the convergence to a Pareto front. In similar cases are Fig. 3(c) compared with Fig. 3(d) and Fig. 5(d) compared with Fig. 5(c).

Tables III and IV show the results of CPU time per generation, gain, offset and BW results. For CCII⁺ Voltage optimization, NSAG-II(CR) and MOEA/D(DE) found the best values, but for the rest of the results always NSGA-II(DE) and MOEA/D(DE) achieve the best values while CPU time is preserved.

Figure 6 shows the CCII⁺ current optimization for BW by using MOEA/D along the 80 generations with CR and DE; it is possible to see how after applying DE all the runs converged at the same value. Figure 7 shows the same behavior, but this time with the CCII⁻ voltage optimization for Gain by using NSGA-II; after applying DE all the runs converged and in this case, the best value is reached in less generations with DE.

Table V displays the dominance percentage which shows how much the methods in columns are dominated by the methods in rows. For instance, NSGA-II(CR) is dominated 39.87% by NSGA-II(DE) for CCII⁺ current optimization. And MOEA/D(CR) is dominated 10% by MOEA/D(DE) for CCII⁻ voltage optimization. Generally NSGA-II(DE) has similar or large dominance percentage on NSGA-II(CR), and MOEA/D(DE) has similar or large dominance percentage on MOEA/D(CR).

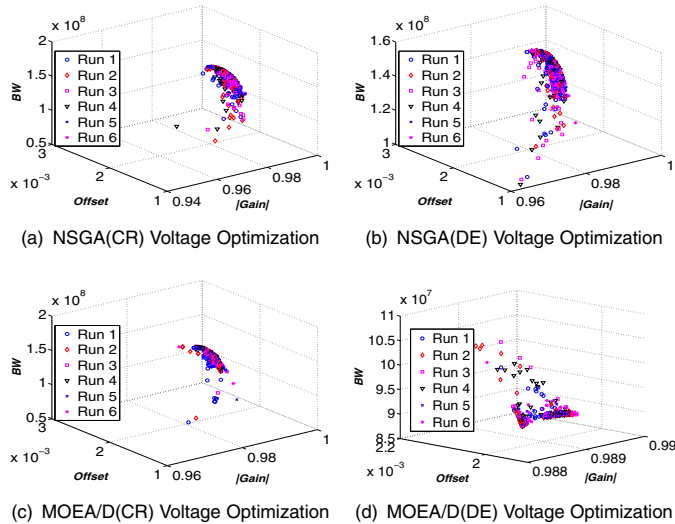


Fig. 2. CCII⁺ Voltage Optimization

VI. CONCLUSION

This work shows the performance of NSGA-II and MOEA/D by applying DE as genetic operator for the optimization of two current conveyors. Gain, band width and offset were the objectives optimized for voltage and current mode ensuring saturation condition.

The discussed results present evidence that in most cases DE improves solution for both EAs. On one hand, DE enhances the convergence to the Pareto front and reduces the objective scattering among different runs. On the other hand, DE preserves the same time efficiency and increases the dominance on NSGA-II and MOEA/D compared with CR.

In this manner we conclude in the usefulness of DE to improve circuit optimization due to the performances enhance-

TABLE III
VOLTAGE OPTIMIZATION RESULTS

	CCII ⁺				CCII ⁻			
	Time (secs)	Gain V/V	Offset Volts	BW MHz	Time (secs)	Gain V/V	Offset Volts	BW MHz
NSGA(CR)								
WORST	46	0.9891	1.0E-3	150	51	0.9816	3.7E-3	152
MEAN	42	0.9892	7.7E-4	153	43	0.9848	2.4E-3	157
BEST	37	0.9892	5.9E-4	154	38	0.9871	1.7E-3	166
NSGA(DE)								
WORST	46	0.9863	1.9E-3	141	48	0.9894	1.2E-3	163
MEAN	40	0.9869	1.8E-3	147	41	0.9899	6.1E-4	165
BEST	35	0.9875	1.5E-3	151	38	0.9905	3.2E-5	166
MOEA(CR)								
WORST	23	0.9870	1.5E-3	153	23	0.9867	6.8E-4	163
MEAN	20	0.9875	1.3E-3	154	20	0.9877	2.2E-4	167
BEST	17	0.9884	1.1E-3	155	18	0.9882	2.5E-5	171
MOEA(DE)								
WORST	23	0.9892	4.3E-4	154	23	0.9895	1.6E-3	162
MEAN	20	0.9892	3.8E-4	154	20	0.9901	3.5E-4	167
BEST	18	0.9892	3.6E-4	155	18	0.9907	0.0E+000	170

TABLE IV
CURRENT OPTIMIZATION RESULTS

	CCII ⁺				CCII ⁻			
	Time (secs)	Gain I/I	Offset Amp.	BW MHz	Time (secs)	Gain I/I	Offset Amp.	BW MHz
NSGA(CR)								
WORST	43	0.9840	9.2E-8	401	45	0.9751	2.0E-7	283
MEAN	38	0.9840	3.2E-8	405	39	0.9868	5.6E-8	345
BEST	33	0.9840	8.2E-9	409	36	0.9902	1.0E-8	427
NSGA(DE)								
WORST	43	0.9800	1.3E-9	283	45	0.9960	1.2E-7	428
MEAN	36	0.9827	2.3E-010	354	39	0.9961	3.6E-8	439
BEST	32	0.9840	4.0E-012	410	35	0.9963	1.3E-9	449
MOEA(CR)								
WORST	21	0.9680	5.5E-8	236	21	0.9892	3.2E-6	277
MEAN	19	0.9788	1.4E-8	334	18	0.9903	6.4E-7	316
BEST	16	0.9840	4.2E-10	404	17	0.9922	1.1E-8	400
MOEA(DE)								
WORST	32	0.9840	1.1E-012	404	21	0.9954	9.4E-9	277
MEAN	20	0.9840	4.2E-013	407	19	0.9961	3.4E-9	311
BEST	16	0.9840	1.9E-013	409	17	0.9965	5.6E-010	329

ment. Future work will be advocated to add more objectives/constraints, calibration of EAs parameters and finally including process variations.

VII. ACKNOWLEDGMENT

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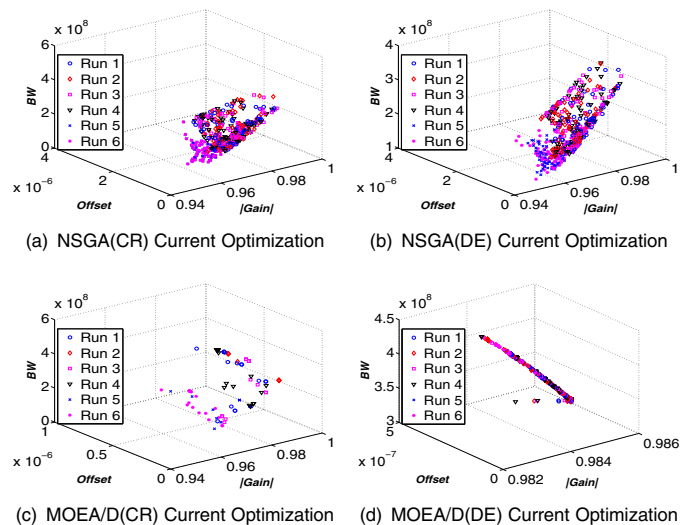


Fig. 3. CCII⁺ Current Optimization

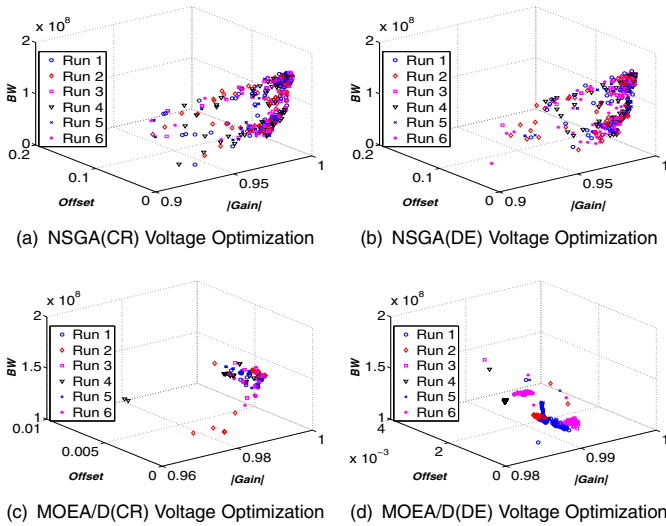


Fig. 4. CCII⁻ Voltage Optimization

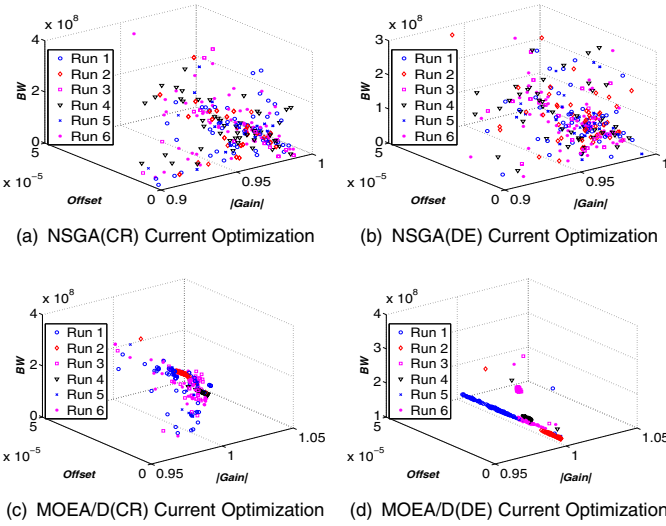


Fig. 5. CCII⁻ Current Optimization

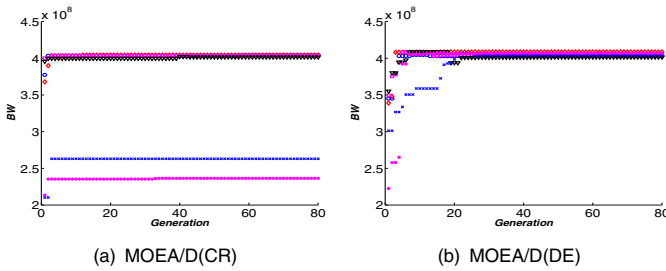


Fig. 6. MOEA/D CCII⁺ Current Optimization for BW

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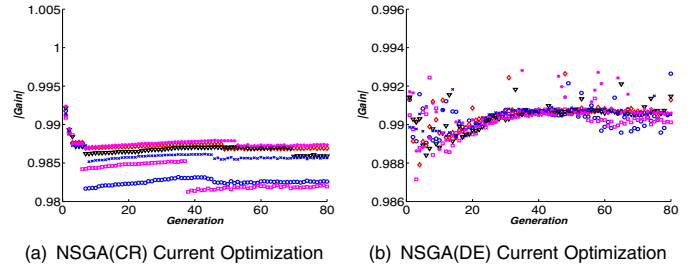


Fig. 7. NSGA-II CCII⁻ Voltage Optimization for Gain

TABLE V
DOMINANCE PERCENTAGE

	NSGA-II(CR)	NSGA-II(DE)	MOEA/D(CR)	MOEA/D(DE)
Voltage Optimization CCII ⁺				
NSGA-II(CR)	-	0.65385	1.8692	0
NSGA-II(DE)	0	-	2.5114	0
MOEA/D(CR)	0	0.77777	-	1.1364
MOEA/D(DE)	0	0.65171	1.6138	-
Current Optimization CCII ⁺				
NSGA-II(CR)	-	0	54.7131	4.338
NSGA-II(DE)	39.8721	-	74.7761	37.8135
MOEA/D(CR)	0	0	-	0.80092
MOEA/D(DE)	41.4092	3.2352	96.2963	-
Voltage Optimization CCII ⁻				
NSGA-II(CR)	-	0	35.8197	1.7964
NSGA-II(DE)	100	-	22.0922	26.0972
MOEA/D(CR)	81.9444	0	-	1.7964
MOEA/D(DE)	40	10.1675	10	-
Current Optimization CCII ⁻				
NSGA-II(CR)	-	1.1364	78.3785	1.2067
NSGA-II(DE)	95.5292	-	93.4963	18.0511
MOEA/D(CR)	16.5727	0	-	1.2067
MOEA/D(DE)	0	8.1395	4.2422	-

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