Optimal Analog Circuit Sizing via Ant Colony Optimization Technique

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Summary
We propose a novel adaptation of the Ant Colony Optimization (ACO) Technique for the resolution of analog sizing optimization problems. The paper details the proposed algorithm and highlights its performances using some mathematical test functions. This novel adaptation of the ACO technique is used for the optimal design of analog circuits, namely, a differential pair current conveyor and an inverted second generation current conveyor. SPICE simulation results are given to show the viability of the proposed algorithm.

Keywords:
Metaheuristic, ACO, Test functions, CMOS, Current conveyors.

1. Introduction

Over the past decade, significant progress has been realized with the appearance of the new generation of powerful and approximate optimization methods, known as metaheuristics [1]. Such methods are used to solve real-world problems by giving approximate solutions within a reasonable amount of time [2]. Some (meta-)heuristics are also proposed in the literature and are used by the designers to optimize the sizing of the analog components automatically, such as Tabu Search (TS) [3,4], Genetic Algorithms (GA) [5], local search (LS) [6], etc…
Recently, a new set of nature inspired heuristic optimization techniques were proposed. These techniques are inventive, resourceful, efficient and easy to use. They are known as SI: 'Swarm Intelligence Techniques'[7,8]. The SI techniques focus on animal conduct in order to develop some meta-heuristics which can mimic their problem resolution abilities, namely Ant Colony Optimization (ACO) [9], Wasp Nets (WN) [8], Bacterial Foraging Optimization (BFO) [10] and Particle Swarm Optimization (PSO) [11, 12].
The ACO technique's basic idea is to imitate the cooperative behavior of ant colonies in order to solve combinatorial optimization problems within an acceptable amount of time. Ant Colonies (AC) is a general purpose heuristic (meta-heuristic) that has been proposed by Dorigo *et al.* in [13,9]. ACO has been successfully used for the optimization of digital circuits [14,15] and its application in the analog design field was recently proposed [16,17].
In this paper we present a novel adaptation of the ACO technique to the optimal sizing of CMOS analog circuits: i.e. a differential pair Class AB current conveyer (diff-CCII) and an inverted second generation current conveyor (ICCII). The proposed method has been validated using some test functions. SPICE simulations are given to show the validity of obtained results.
The remainder of the paper is structured as follows: The second section presents an overview of the ACO technique. The third section deals with the proposed adaptation of the ACO technique for solving combinatorial optimization problems. The fourth section highlights the algorithm viability via some test functions. The fifth section discusses and illustrates the parameterization of the algorithm. The sixth section presents two application examples dealing with the optimal sizing of CMOS current conveyors: A differential pair and an inverted second generation current conveyors. Finally, concluding remarks are given in the last section.

2. Ant colony optimization technique: An overview

ACO technique is inspired by the collective behavior of deposit and monitoring of slopes that is observed in insect colonies [9,18], such as ants. Figure 1 shows an illustration of the ability of ants to find the shortest path between food and their nest. It is illustrated through the example of the appearance of an obstacle on their path. Ants communicate indirectly through dynamic changes in their environment (pheromone trails).
Pheromones are chemical substances that are laid down by ants. Thus, when other ants find the path taken by the former ant, they are no more likely to 'walk randomly', but instead they follow the trail and reinforce it if they eventually find food [19].

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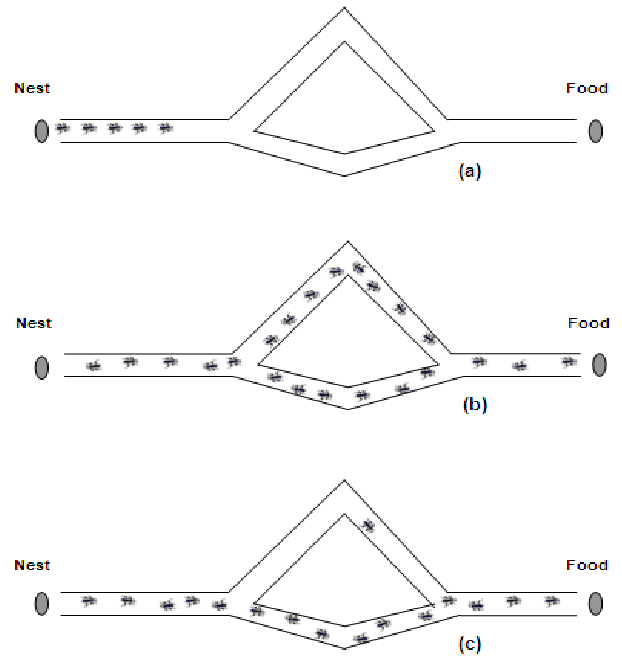

Fig. 1 Self-adaptive behavior of a real ant colony
(a) Q ants go in search of food;
(b) ants follow a path between nest and food source. They; choose, with equal probability, whether the shortest or longest path;
(c) the majority of ants have chosen the shortest path.

ACO was initially used to solve graph related problems, such as the traveling salesman problem [20], vehicle routing problem [21], etc. For solving such problems, ants randomly select the vertex to be visited. When ant k is in vertex i, the probability of going to vertex j is given by expression (1) [9,13,22,23].

$$p_{ij}^{k} = \begin{cases} \dfrac{(\tau_{ij})^{\alpha}.(\eta_{ij})^{\beta}}{\sum_{l \in J_i^k} (\tau_{il})^{\alpha}.(\eta_{il})^{\beta}} & if \quad j \in J_i^k \\ 0 & if \quad j \notin J_i^k \end{cases} \tag{1}$$

where J_i^k is the set of neighbours of vertex i of the k^{th} ant, τ_{ij} is the amount of pheromone trail on edge *(i,j)*, α and β are weightings that control the pheromone trail and the visibility value, i.e. η_{ij}, which expression is given by (2).

$$\eta_{ij} = \frac{1}{d_{ij}} \tag{2}$$

d_{ij} is the distance between vertices i and j.

The pheromone values are updated each iteration by all the m ants that have built a solution in the iteration itself. The pheromone τ_{ij}, which is associated with the edge joining vertices i and j, is updated as follows:

$$\tau_{ij} = (1-\rho)\tau_{ij} + \sum_{k=1}^{m} \Delta\tau_{ij}^{k} \tag{3}$$

where ρ is the evaporation rate, m is the number of ants, and $\Delta\tau_{ij}^{k}(t)$ is the quantity of pheromone laid on edge *(i, j)* by ant k:

$$\Delta\tau_{ij}^{k} = \begin{cases} \frac{Q}{L^k} & \text{if ant } k \text{ used edge } (i,j) \text{ in its tour,} \\ 0 & \text{otherwise.} \end{cases} \tag{4}$$

Q is a constant: 'Quantity of deposit pheromone by the best ant', and L^k is the length of the tour constructed by ant k.

3. Adaptation of the ACO technique

The proposed algorithm consists of constructing a kind of graph which vertices, i.e. nodes, are the discretized variable vectors values. Each ant constructs its path by a random move from a variable value to another, as it is depicted on Figure 2. *V1, V2, V3…VN* are the discrete variable vectors.

Initially, each ant k will randomly choose a path (values of *V1, V2* …), according to the probability given by expression (1) with $\beta=0$, and form a directed graph while randomly generating a rate of pheromone at the constructed graph edges. At each iteration, the path giving the minimum value of the objective function (OF) sees its rate increase, in contrast with the other paths for which pheromone rates are partially evaporated with respect to expression (3).

The proposed algorithm operates as shown in Figure 3. It mainly consists of the following steps:

- Calculation of the movement probability,
- Computation of the 'objective function',
- Save and update of the 'best' result.

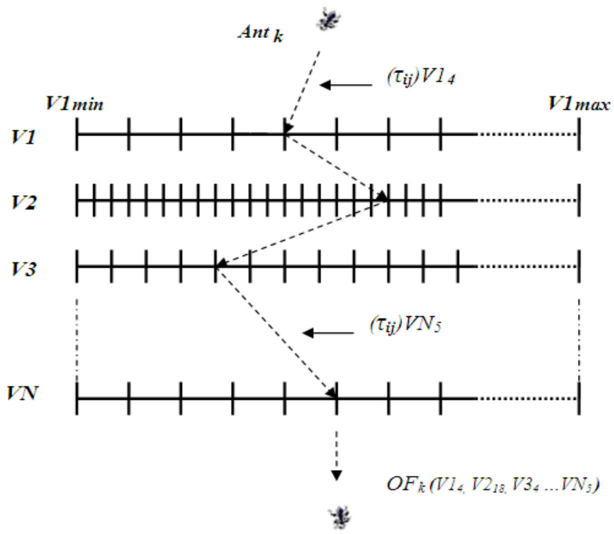

Fig. 2 A pictorial graph showing the mouvement of ants along the virtual graph.

4. Validation by test functions

In order to validate the proposed algorithm, the later was used to deal with some optimization test functions [24].

4.1. Example 1: First test function

The first function is:

$$g(x) = |x| + \cos(x) \tag{5}$$

$x \in [-\infty, +\infty]$

The absolute minimum of the function g is:
$g(0) = 1$, as shown in Figure 4.

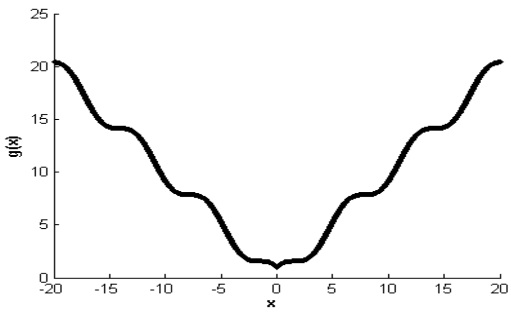

Fig. 4 The function g values *vs*. x for $-20 \leq x \leq 20$

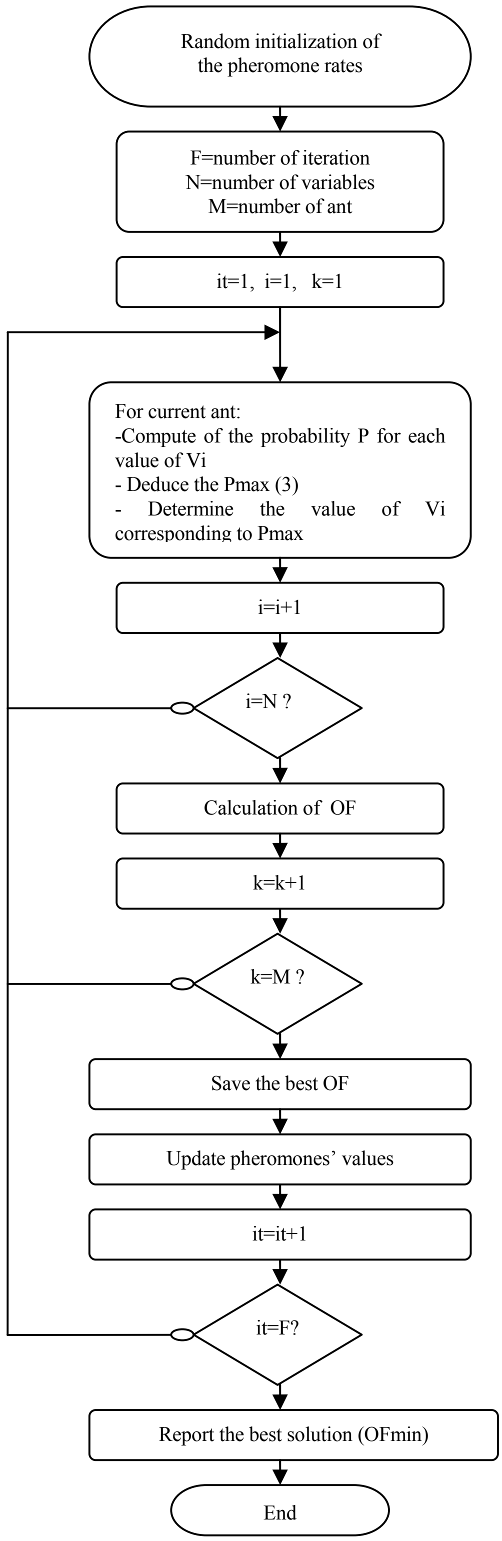

Fig. 3 Flowchart "Adaptation of the ACO technique".

4.2. Example 2: Second test function

The second function is:

$$f(x,y) = x\sin(4x) + 1.1y\sin(2y) \tag{6}$$

where $-\infty \leq x, y \leq +\infty$.
This function has many local minimal points, as shown in Figure 5.

The absolute minimum of the function f is:
$f(9.039, 8.668) = -18.5547$

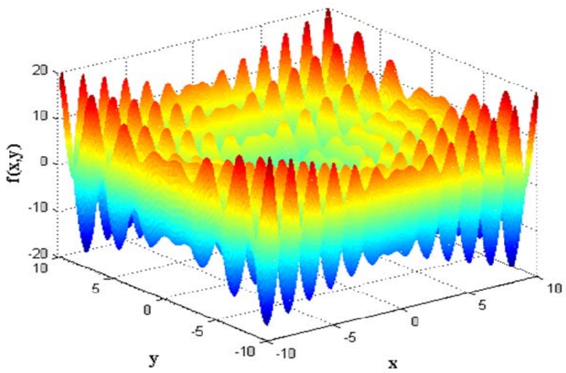

Fig. 5 The function f values *vs*. x,y for $-10 \leq x, y \leq 10$

We applied the proposed MATLAB-implemented ACO algorithm to compute the minima of both functions; the algorithm's parameters are given in Table 1 with a generation algorithm of 1000.

Table 1: Parameters of ACO algorithm

Evaporation rate (ρ)	0.1
Quantity of deposit pheromone by the best ant (Q)	0.2
Number of ants	50

The parameters' range values were discretized with a step that equals 0.0001 for f and g. Obtained results are equal to those expected, i.e. obtained using Matlab software to solve the test problems.

5. Parameterization of the algorithm

In the following we present a study regarding the effect of varying the algorithm parameters (evaporation rate (ρ), quantity of deposit pheromone (Q)). Functions f and g presented in section 4 were considered for this purpose for 20 ants and 500 generations algorithm.

5.1 Evaporation rate and the fitness convergence

The following figure shows the variation of fitness convergence according to the evaporation rate (with quantity of deposit pheromone equal to 0,2) for f and g.

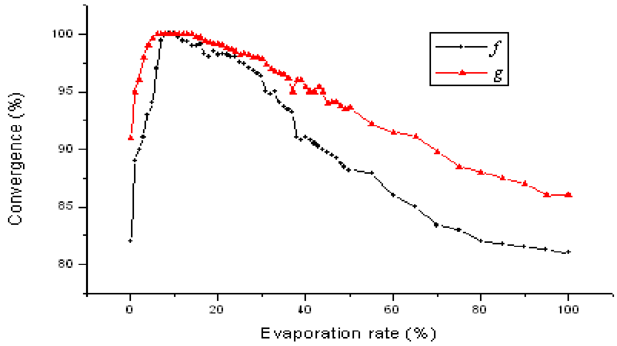

Fig. 6 f and g convergence rate *vs*. evaporation rate.

From these curves we can clearly deduce that the evaporation rate which gives the best convergence of the algorithm is around 10%.

5.2 Quantity of deposit pheromone and the fitness convergence

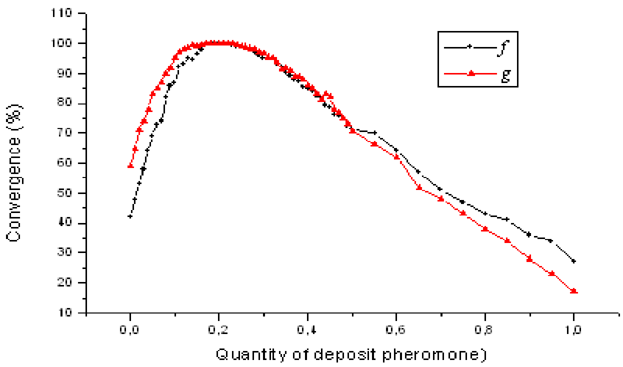

Fig. 7 f and g convergence rate *vs*. quantity of deposit pheromone.

Figure 7 shows the variation of fitness convergence according to quantity of deposit pheromone (with an evaporation rate that equals to 0,1) for f and g.
We note that the amount of deposed pheromone by ants which gives the best convergence of the algorithm is around 0.2.

6. Application to the optimal design of analog circuits

6.1 Differential pair Class AB current conveyer (diff-CCII)

Figure 8 shows the schematic of the diff-CCII circuit [25]. Two objective functions are considered separately: minimizing the input X-pole parasitic resistance (*Rx*) and maximizing the dominant pole (*fp*) value of the current transfer function between X and Z poles. Expressions of *Rx* and *fp* are given by equations (7) and (8), respectively.

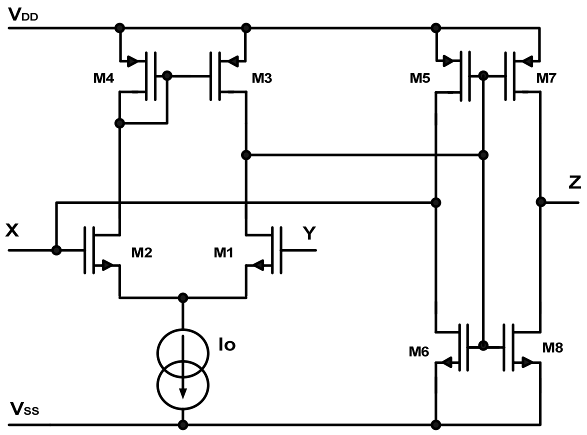

Fig. 8 A differential pair Class AB current conveyor.

$$Rx = \frac{1}{go_P + go_N + \dfrac{gm_N(gm_N + gm_P)}{2go_N}} \tag{7}$$

$$fp = \frac{1}{2\pi}\sqrt{\frac{(gm_P + gm_N)gm_N + (go_N + go_P)^2}{Cgs_N Cgs_P}} \tag{8}$$

where *Cgs*, *gm* and *go* refer, respectively, to the parasitic grid to source capacitance, the transconductance and the conductance of the MOS transistor. Indexes *N* and *P* refer to the NMOS and PMOS channel transistors, respectively.
The proposed algorithm was applied to optimize the MOS transistors sizes: The channels lengths (L_N, and L_p), the gates widths (W_N and W_P) and the value of the bias current (Io). Main considered constraints are ensuring the saturation working mode of all the transistors.
Table 2 shows the optimal sizes obtained by the algorithm using the parameter values listed in Table 1. The average computing time equals 5s for a 1000 generation algorithm, using an Intel Pentium (M) 1.73GHz 794MHz, 1.5Go RAM.
In order to check the convergence rate of the proposed algorithm, a robustness test was performed. i.e. the algorithm was applied a hundred times for optimizing each objective. In Figure 9 we present obtained results for some variables (corresponding to the optimization of *fp*) where one can clearly notice the relatively high convergence ratio to the (same) respective 'optimal' value. Table 3 summarizes and highlights these convergence ratios.

Table 2. Optimal sizes of transistor dimensions and the respective performances for *Rx* and *fp*

	W_N (µm)	W_P (µm)	$L_N = L_P$ (µm)	Io (µA)	*Rx* (Ω)	*fp* (Ghz)
min Rx	42.41	100.00	0.35	15	**3.1**	1.452
max fp	20.00	43.62	0.35	15	11.2	**1.851**

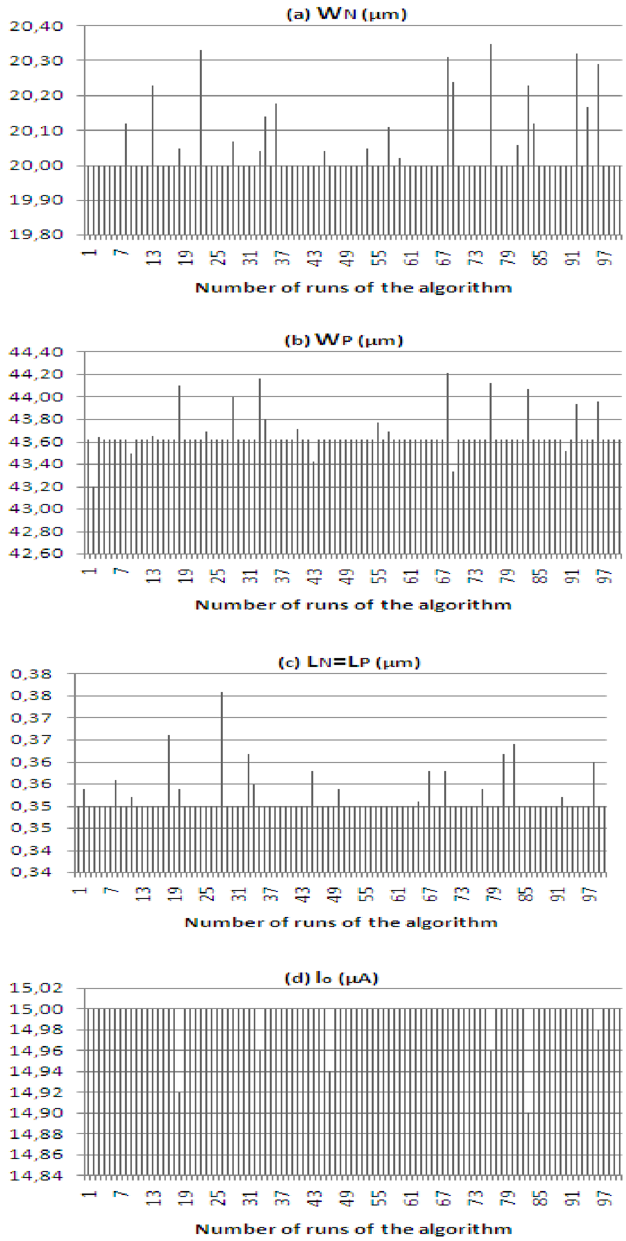

Fig. 9 Results obtained for 100 runs of the algorithm for variables: W_N, W_P, L_N, L_P and Io

Table 3: Convergence ratio (%) to the same 'optimal' parameter's value.

	WN(µm)	WP(µm)	LN(µm)	IO(µA)
Rx (Ω)	81	77	80	93
fp (GHz)	79	80	82	94

Obtained 'optimal' sizings were used to simulate the circuits using SPICE software. The technology under consideration is AMS 0.35µm. VDD/VSS=±1.5V.

Figures 10 and 11 show obtained results. Table 4 gives a comparison of the results obtained using SPICE and Matlab.
We notice that simulation results are in good agreement with the expected ones.

Table 4: Optimal performances of the AB-CCII

	Matlab (ACO)	SPICE
Rx (Ω)	3.1	3.7
fp (Ghz)	1.851	1.882

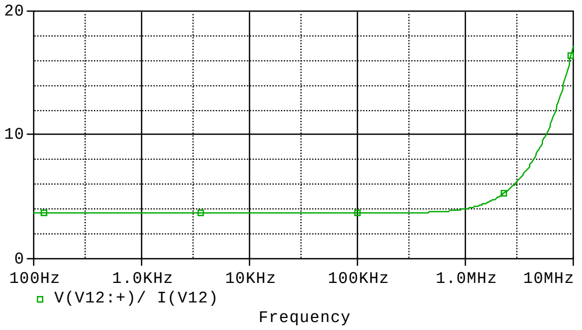

Fig. 10 Rx-pole resistance (Ω) vs. frequency (Hz),

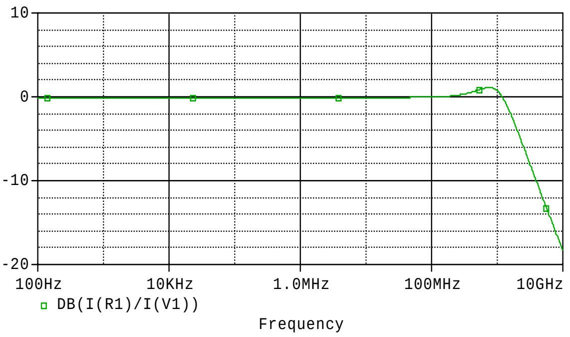

Fig. 11 Current gain (dB) vs. frequency (Hz),

6.2 Inverted second generation current conveyor (ICCII)

The second considered circuit is an inverted CMOS second generation current conveyor (ICCII), it is shown in Figure 12. For comparison reasons, we adopted the weighting technique to combine two objective functions, as presented in [26].
For comparison raisons, with results published in [26], all the NMOS transistors were considered having the same dimensions, ditto for the PMOS transistors.

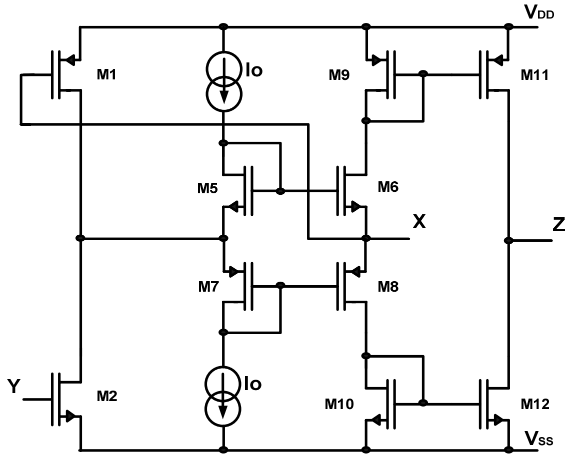

Fig. 12 The inverted second-generation CMOS current conveyor.

The problem consists of minimizing input X-pole parasitic resistance (*Rx*) and maximizing the dominant pole (*fp*) value of the current transfer function between X and Z poles while combining them into a single objective function. Expressions of both objective functions are given by (9) and (10), respectively [26,27]:

$$Rx = \frac{go_p + go_n}{(gm_p + gm_n)(go_p + go_n + gm_p)} \quad (9)$$

$$fp = \frac{1}{2\pi}\frac{gm_p^2.gm_n + gm_p.gm_n^2}{4Cgs_n(gm_p^2 + gm_n.gm_p) + Cgs_p(gm_n^2 + 4gm_n.gm_p)} \quad (10)$$

Actually, the optimization problem was transformed into a monobjective one using the weighting approach (for comparison reasons, as mentioned above). The equivalent objective is given by expression (11).

$$OF = \gamma_1 \dot{fp} + \gamma_2 \dot{Rx} \quad (11)$$

where $\dot{fp}$ and $\dot{Rx}$ represent the normalized values[1] of *fp* and *Rx*, respectively.

[1] The considered objectives are incommensurable. Thus, a normalizing technique was adopted [26]. It consists of bringing the variation range of each objective *fi*, to the range [0,1], as follows:

Table 5 gives optimal sizes corresponding to different values of γ_i and presents comparisons between theoretical (algorithm results) and simulation (SPICE) results. The good agreement between simulation and expected results can be noticed. Also, it is to be noted that the ACO average computing time equals 34s for a 5000 generation algorithm using the parameter values given in Table 1.

Table 5: ''Optimal'' device scaling and performances of the ICCII for different weightings (γ_i)
(Ln=Lp=0.35µm)

OF	*4fp+Rx*	*2fp+Rx*	*fp+Rx*	*fp+2Rx*	*fp+4Rx*
Wn (µm)	3.41	6.24	9.53	13.38	23.40
Wp (µm)	10.00	18.52	28.26	39.87	70.00
Matlab					
Rx *(Ω)*	154.1	90.3	64.4	46.2	24.6
Fp *(GHz)*	2.347	1.731	1.401	1.187	0.887
SPICE					
Rx *(Ω)*	130.4	94.9	72.3	58.8	36.4
Fp *(GHz)*	2.371	1.706	1.392	1.228	0.990

In Table 6 we notice a good percentage of convergence ratio for different weightings (γ_i). 100 runs of the algorithm were considered.

Table 6: Convergence ratio (%) to the same 'optimal' parameter's value.

	4fp+Rx	*2fp+Rx*	*fp+Rx*	*fp+2Rx*	*fp+4Rx*
W_N (µm)	88	89	83	78	82
W_P (µm)	91	94	94	90	93
L_N=L_P (µm)	84	85	87	77	81

The same ICCII was optimized in [26], Table 7 presents performances and sizing given in [26]. It can be clearly noticed that the proposed ACO algorithm globally offers better results in terms of objectives and computation time, as well.

Table 7: Performances proposed in [26]
(Ln=Lp=0.35µm)

OF	4fp+Rx	2fp+Rx	fp+Rx	fp+2Rx	fp+4Rx
Wn (µm)	3.71	6.43	9.80	13.56	23.13
Wp (µm)	11.13	19.17	29.25	40.66	69.08
Spice					
Rx (Ω)	115.3	80.7	61.7	50.5	37.6
Fp (GHz)	2.206	1.695	1.398	1.192	0.913

Figures 13 and 14 show respectively SPICE simulations of Rx and current gain (Iz/Ix) performed using the sizes given in Table 6 with a voltage power supply of $V_{DD}/V_{SS}=\pm1.8V$ and using the AMS 0.35µm technology. We notice that simulation results are in good agreement with those obtained using ACO.

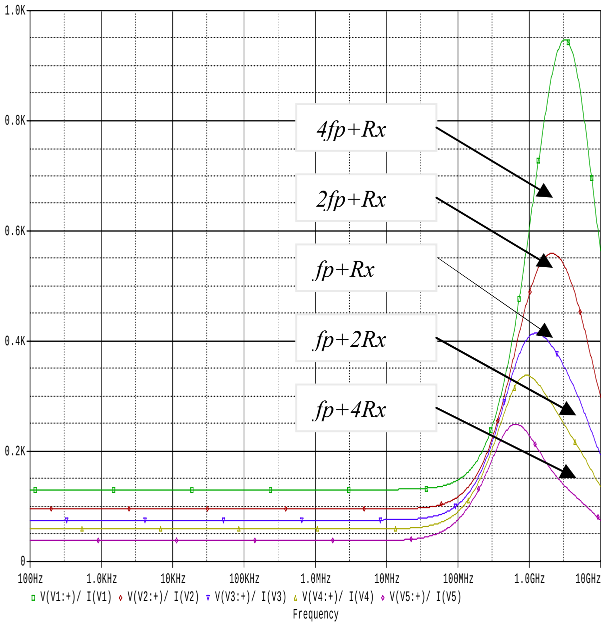

Fig. 13 Rx (Ω) vs. frequency (Hz), for different values of γ_i.

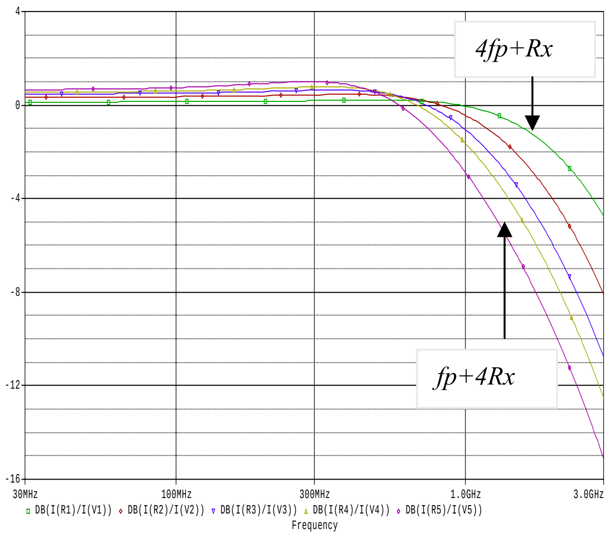

Fig. 14 Current gain (dB) vs. frequency (Hz), for different values of γ_i.

$$f_i \rightarrow \dot{f} = \frac{f_i - f_{i\,\min}}{f_{i\,\max} - f_{i\,\min}}$$

Conclusion

In this brief, a novel adaptation of the ant colony optimization technique for the optimal sizing of analog circuits is proposed. The corresponding algorithm was validated by mathematical test functions and applied to optimize performances of analog circuits, namely two variants of CMOS second generation current conveyors. Optimal parameters of the algorithm were determined using a statistical approach. Reached performances were validated via SPICE simulations. Besides robustness tests are given. It was also shown that the proposed algorithm gives better results in terms of computing time and optimum quality, when compared to already published works.

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