An Improved ACO Algorithm for the Analog Circuits Design Optimization

Bachir BENHALA
Faculty of Sciences, University of Moulay Ismaïl,
Meknes, Morocco

Abstract— Sizing analog circuits is a complicated and delicate process activity and time consuming task in the entire design, generally based on the experience of the designer. Ant Colony Optimization (ACO) had been recently proposed and successfully applied for finding the optimal performance of analog circuits and hence the transistors sizes for the integrated circuit design. However, this algorithm needs an intensive execution time to converge toward optimal solutions. To improve the speed and even the efficiency of the algorithm, the concept of backtracking search is combined with the ACO algorithm. The performances of the improved ACO algorithm, named BA-ACO, are highlighted through the optimal design of a two stage Operational Amplifier (Op-Amp) and an Operational Transconductance Amplifier (OTA). SPICE simulation results are given to show the validity of the proposed algorithm.

Keywords— *Metaheuristic; Ant Colony Optimization; Backtracking Search Technique; Analog Design; Op-Amp; OTA.*

I. INTRODUCTION

INTEGRATED circuit design is a complicated and delicate process activity due to the number of variables involved, to the number of required objectives to be optimized and to the constraint functions restrictions. Generally, the circuit sizing is carried out thanks to the experiment and the intuition of the designer or according to the approaches based on fixed topologies and/or statistical techniques [1]. However, these techniques are time consuming and do not guarantee reaching the global optimum solution.

To efficiently resolve circuits sizing optimization problems, some (meta-)heuristics and algorithms were proposed in the literature and are used by the designers, such as Tabu Search [2], [3], Simulated Annealing [4], Genetic Algorithms (GA) [4], [5], local search (LS) [6]. However, the metaheuristics that gave the best results are those that are nature inspired. They are inventive, resourceful, efficient, easy to use and known as SI: 'Swarm Intelligence Techniques' [7].The SI techniques focus on animal conduct in order to develop some meta-heuristics which can mimic their problem resolution abilities, namely Wasp Nets (WN) [8], Bacterial Foraging Optimization (BFO) [9], Particle Swarm Optimization (PSO) [10] and Ant Colony Optimization (ACO) [11], [12].

In our previous works, we have presented, successfully, the ACO technique to deal with analog circuits design and sizing [11]–[15]. This optimization technique leads to the best optimum qualities, but the ACO requires a significant execution time compared to other metaheuristics [16], [17].

To enhance the quality of the solution, several modifications to the original ACO were introduced [18]–[23]. Despite these changes, which have improved the performance of the ACO algorithm, they have not tackled the problem of excessive accumulation of pheromone which entraps ACO in local optima.

The BA-ACO presents a way to overcome this problem. By using the principle of the Backtracking algorithm [24] to the ACO, in order to reduce the search space, to solve the problem of excessive accumulation of pheromones which increases the speed of convergence and improves the overall research capacity. The Backtracking technique is a method that optimizes the search by returning back to new selection if it fails to achieve the objectives.

We have presented and applied the BA-ACO successfully for RF circuits [25]. In this work, we focus on the use of the BA-ACO algorithm to solve typical analog circuit sizing problems. The application examples considered is a two-stage CMOS operational amplifier and an Operational Transconductance Amplifier (OTA). The rest of the paper is structured as follows: The second part presents an overview of the BA-ACO technique. The third part deals with the application of the proposed algorithm to the optimal design of two CMOS analog circuits, a sizing/optimization problems are showcased; namely the two stage operational amplifier and an Operational Transconductance Amplifier. Simulation results and a comparison with the basic ACO are provided to show the validity of the proposed algorithm. The fourth section shows the improvements provided by the BA-ACO regarding the robustness and the execution times relative to the application to the optimization problems. Finally, section five provides some concluding remarks.

II. THE BACKTRACKING ANT COLONY OPTIMIZATION TECHNIQUE: AN OVERVIEW

A. The basic ACO algorithm

The ACO is an evolutionary stochastic computational discipline well adaptable for solving hard combinatorial optimization problems. Inspired from the natural behavior of ants in finding the shortest distance between their nests and food sources, it's based on indirect communication within a colony of simple agents, called (artificial) ants which exchange information about good routes through a chemical substance called pheromone that accumulates for short routes and evaporate for long routes [26], [27].

ACO was initially used to solve graph related problems, such as the traveling salesman problem (TSP) [28], vehicle routing problem [29]... 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) [26], [27].

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

where J_i^k is the set of neighbors of vertex i of the k^{th} ant, τ_{ij}^{k} 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:

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

where ρ is the pheromone 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:

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

Q is a constant and L^k is the length of the tour constructed by ant k.

Each ant k will randomly choose a path according to the probability given by expression (1), and form a directed graph while randomly generating a rate of pheromone at the formed 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 which pheromone rates are partially evaporated with respect to expression (3).

The ACO algorithm conducts research intelligently to perform global optimizations, it is characterized by good strength, positive feedback, distributed calculation, and it can easily combine with other algorithms. Therefore, ACO provides a powerful tool for the optimization of many fields [30]. This algorithm did not cease to be developed and improved continuously, but there are still some gaps of consuming time, easy to stagnation and easily fall into local optima [31].

In the ACO algorithm, pheromones are the means for indirect communication between ants; they are the bracket passage of information which directly affects the convergence and the efficient resolution of the ACO algorithm [32].

B. The BA-ACO algorithm

In the ACO algorithm, when a trail is preferred it automatically has continuous accumulation of pheromones as iterations go on. Actually, this easily leads the algorithm to be trapped in a local optimum.

In order to overcome this drawback, the backtracking technique which is an algorithm that is back slightly on decisions to get out of a blocking [25], [33]: Backtrack the pheromone to the initial value each time the algorithm is trapped in a local optimum. The update has to be performed once it is noted that the current 'optimal' value does not change for a certain number of iterations.

The improved algorithm operates according to the ACO technique by including the following detailed points:

- When the optimal value does not change for N-time, the pheromone are updated on the optimal path, in each backtracking period

$$\tau_{ij}(t+\Delta t) = \tau_{ij}(t) - \left(NQ \middle/ L_L \right) \tag{5}$$

where L_L is the length of current local optimal tour.

- When the optimal value does not change for M-time, it gets back to the backtracking point, and it re-initializes the pheromone value.
- To improve the convergence speed, pheromones are updated with respect to updating rules, in the proposed algorithm, using local and global updating rules, as given by expressions (3) and (6), respectively.

$$\tau_{ij}(t+\Delta t) = \tau_{ij}(t) + \left(Q \middle/ L_G \right) \tag{6}$$

where L_G is the length of the current global optimal tour.

The rule of updating pheromones reduces the solution search space, so it can lessen the number of 'bad' solutions reached so far and thus can improve the quality of solutions and enhance the algorithm's performances. The proposed algorithm operates with respect to the flowchart seen in Figure 1.

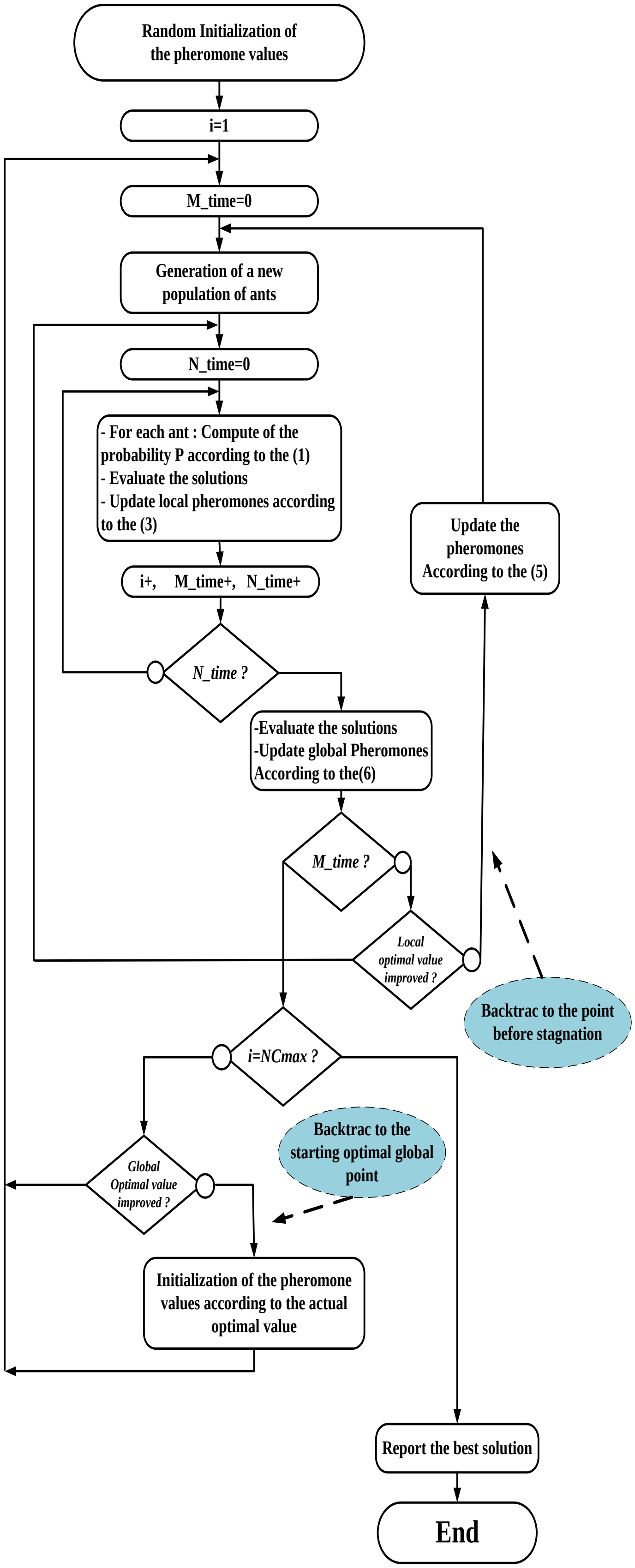

Fig.1 Flowchart "BA-ACO"

III. Application Examples

The abovementioned algorithm was used to optimize performances of two analog CMOS circuits: an Operational Amplifier (Op-Amp) and an Operational Transconductance Amplifiers (OTA). We give optimization results and present comparison with results obtained using the basic ACO technique.

The algorithm's parameters are given in Table 1 with a generation algorithm of 200 (Ncmax). The optimization techniques work on MATLAB codes and are able to link SPICE (using the technology of 0.35 µm CMOS from AMS) to measure performances.

Table 1 The algorithms' parameters

Number of Ants	40
Evaporation rate (ρ)	0.1
Quantity of deposit pheromone (Q)	0.2
Pheromone Factor (α)	1
Heuristics Factor (β)	1
N-time	3% of NCmax
M-time	10% of NCmax

A. Performance optimization of an Op-Amp

In this section we applied the BA-ACO algorithm to perform optimization of a two stage CMOS operational amplifier (Op-Amp), including constraints like saturation conditions [16].

A. 1 Circuit Descriptions

The implementation of a two stage CMOS operational amplifier (Op-Amp) is shown in Figure 2.

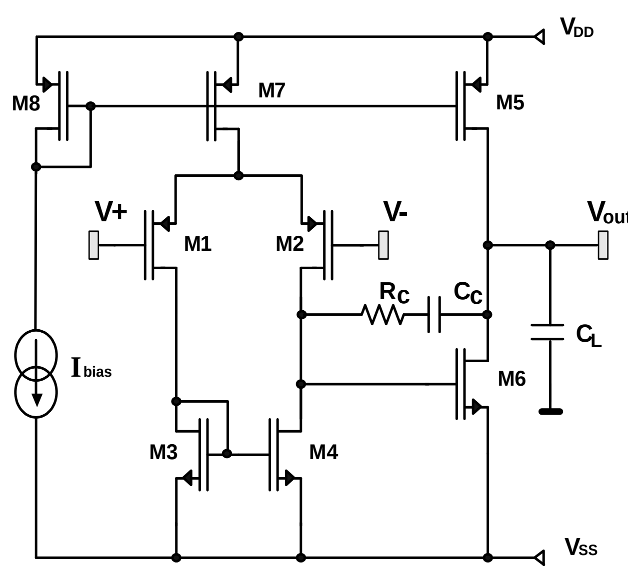

Fig.2 A two stage CMOS operational amplifier (Op-Amp)

The follow parameters are considered fixed, e.g., the compensation resistor (R_C=800Ω), the compensation capacitor (C_C=3pF) and the capacitive load (C_L=10pF). All channel lengths L are considered the same for all the transistors. Performances of an Op-Amp are evaluated via several parameters such as:

- The open-loop voltage gain Av:

$$Av = \frac{2C_{ox}}{(\lambda_n + \lambda_P)^2}\sqrt{\frac{\mu_n \mu_P}{I_1 I_7}\left(\frac{W}{L}\right)_2\left(\frac{W}{L}\right)_6} \tag{7}$$

- The power dissipation P:

$$P = (V_{DD} - V_{SS})(I_{bias} + I_5 + I_7) \tag{8}$$

- The Common Mode Rejection Ratio $CMRR$:

$$CMRR = \frac{2C_{ox}}{(\lambda_n + \lambda_P)\lambda_P}\sqrt{\frac{\mu_n \mu_P}{I_5^2}\left(\frac{W}{L}\right)_1\left(\frac{W}{L}\right)_3} \tag{9}$$

- The die Area A:

$$A \approx \sum_{i=1}^{8} W_i L_i \tag{10}$$

Those expressions (7) and (9) were obtained by considering the small signal equivalent transistor's models. V_{DD} and V_{SS} are respectively the positive and the negative supply voltages; W_1-W_8 and L_1-L_8 are the gates widths and the channels lengths of the transistors M_1-M_8 respectively. I_{bias} is the bias current, C_{ox}, λ_n, λ_p, μ_n and μ_p are technological parameters.

Determining the optimal dimensions of the transistors for a specific design involves a tradeoff among all these performance measures. Each transistor must be in saturation. Expressions (11)-(14) give the corresponding constraints that have to be satisfied when computing optimal sizes of the transistors M_1(and M_2), M_5, M_6 and M_7 respectively.

$$V_{cm,\min} - V_{SS} - V_{TP} - V_{TN} \geq \sqrt{\frac{2I_1}{\mu_n C_{ox}\left(\frac{W}{L}\right)_3}} \tag{11}$$

$$V_{DD} - V_{cm,\max} + V_{TP} \geq \sqrt{\frac{2I_1}{\mu_P C_{ox}\left(\frac{W}{L}\right)_1}} + \sqrt{\frac{2I_5}{\mu_P C_{ox}\left(\frac{W}{L}\right)_5}} \tag{12}$$

$$V_{out,\min} - V_{SS} \geq \sqrt{\frac{2I_7}{\mu_n C_{ox}\left(\frac{W}{L}\right)_6}} \tag{13}$$

$$V_{DD} - V_{out,\max} \geq \sqrt{\frac{2I_7}{\mu_P C_{ox}\left(\frac{W}{L}\right)_7}} \tag{14}$$

where

$$I_5 = \frac{\left(\frac{W}{L}\right)_5}{\left(\frac{W}{L}\right)_8} I_{bias}, \quad I_7 = \frac{\left(\frac{W}{L}\right)_7}{\left(\frac{W}{L}\right)_8} I_{bias}, \text{ and } I_1 = \frac{I_5}{2}$$

while respecting the expression (15):

$$\frac{\left(\frac{W}{L}\right)_3}{\left(\frac{W}{L}\right)_6} = \frac{\left(\frac{W}{L}\right)_4}{\left(\frac{W}{L}\right)_6} = \frac{1}{2}\frac{\left(\frac{W}{L}\right)_5}{\left(\frac{W}{L}\right)_7} \tag{15}$$

where, V_{TP} and V_{TN} are the PMOS and the NMOS threshold voltages, respectively.

The BA-ACO algorithm was applied to optimize the MOS transistors sizes: W_1,…,W_8, L and the value of the bias current I_{bias}.

A. 2 Optimization results

Table 2 gives optimal results obtained using the BA-ACO and the ACO for the parameters and the circuit's performances.

TABLE 2 OPTIMIZATION AND PERFORMANCE RESULTS

Specifications	ACO	BA-ACO
$W_{1,2}$ (µm)	215.08	215.82
$W_{3,4}$ (µm)	260.94	259.13
W_5 (µm)	57.80	58.38
W_6 (µm)	459.47	455.48
W_7 (µm)	50.92	51.02
W_8 (µm)	9.64	9.51
L (µm)	0.35	0.35
I_{bias} (µA)	10.00	10.00
Av (dB)	127.22	127.25
CMRR (dB)	124.72	124.71
A (µm²)	535.4	533.5
P (mW)	1.2	1.2

The optimum channels lengths and gates widths obtained after optimization are used in SPICE simulations to measure the circuit performances. The simulation results are collected in the following table:

TABLE 3 PERFORMANCE AND SIMULATION RESULTS

	Av (dB)	CMRR (dB)	A (µm2)	P (mW)
Opt.	127.25	124.71	533.5	1.2
Sim.	117.94	116.42	---	1.7

B. Performance optimization of an OTA

B.1 Circuit Descriptions

Figure 3 shows the architecture of a Folded Cascode Operational Transconductance Amplifier [11], which has a differential stage consisting of NMOS transistors M_9 and M_{10}. Mosfets M_{11} and M_{12} provide the DC bias voltages to M_1-M_2 and M_3-M_4 transistors. While cascode transistors M_5-M_6-M_7-M_8 are controlled respectively by transistors M_{13} and M_{14}.

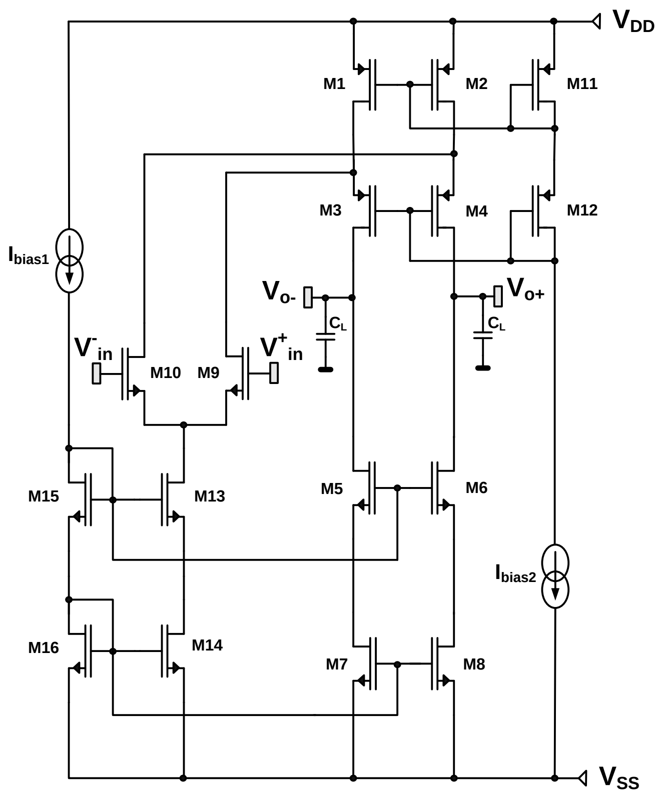

Fig.3 Folded Cascode OTA Topology

The circuit's OFs under consideration are as follows. The open-loop voltage gain (Av), the unity-gain frequency (Fc), the power-supply rejection ratio (PSRR) and the common mode rejection ratio (CMRR):

- Open-loop voltage gain Av:

$$A_v = g_{m9} R_{out} \tag{16}$$

- Unity-gain frequency Ft:

$$Fc = \frac{g_{m9}}{2\pi C_L} \tag{17}$$

- Power-Supply Rejection Ratio PSRR:

$$PSRR^{+} = \frac{(R_1 + R_2 + r_{03})(R_1 + r_{03} + g_{m3} r_{03} R_1)}{(R_2 (1 + g_{m3} r_{03}))} \tag{18}$$

- Common Mode Rejection Ratio CMRR:

$$\mathrm{CMRR} = \frac{R_{out}(1 + 2 g_{m9}(r_{013} + r_{014}))}{2(r_{03} + R_1)} \tag{19}$$

Where:

$$R_{out} = R_2 // (g_{m3} r_{03} R_1) \tag{20}$$

$$R_2 = g_{m5} r_{05} r_{07} \tag{21}$$

$$R_1 = r_{01} // r_{09} \tag{22}$$

g_{m3}, g_{m5} and g_{m9} are respectively the transconductances of transistors M_3, M_5 and M_9. r_{01}, r_{03}, r_{05}, r_{07}, r_{09}, r_{013} and r_{014} are respectively the drain-source resistances of transistors M_1, M_3, M_5, M_7, M_9, M_{13} and M_{14} and C_L is the load capacitance.

In addition to the modeling equations of the different characteristics we need to give the main constraints that have to be satisfied, *i.e.* each transistor should remain in saturation for all possible values of the input common-mode voltage and the output voltage.

These conditions are imposed to ensure that the different transistors are in the inversion mode of operations as follows:

$$V_{DD} - V_{out,\max} \geq \sqrt{\frac{3.I_1}{K_P.\left(\frac{W}{L}\right)_1}} + \sqrt{\frac{2.I_1}{K_P.\left(\frac{W}{L}\right)_3}} \tag{23}$$

$$V_{out,\min} - Vss \geq \sqrt{\frac{I_1}{K_N.\left(\frac{W}{L}\right)_5}} + \sqrt{\frac{I_1}{K_N.\left(\frac{W}{L}\right)_7}} \tag{24}$$

$$V_{DD} - V_{in,\max} + V_{TN} \geq \sqrt{\frac{3.I_1}{K_P.\left(\frac{W}{L}\right)_1}} \tag{25}$$

$$V_{in,\min} - Vss - V_{TN} \geq \sqrt{\frac{I_1}{K_N.\left(\frac{W}{L}\right)_9}} + \sqrt{\frac{2.I_1}{K_N.\left(\frac{W}{L}\right)_{13}}} + \sqrt{\frac{2.I_1}{K_N.\left(\frac{W}{L}\right)_{14}}} \tag{26}$$

The supply voltages used (V_{DD}/V_{SS}) are 1.8V/-1.8V. The capacitive load (C_L=0.1pF) is considered as fixed parameter. The BA-ACO algorithm was used to compute the optimal values of the geometric dimensions of the MOS transistors forming the OTA: W_1,…,W_{16}, L and the value of the bias currents I_{bias1} and I_{bias2}.

B.2 Optimization results

Table 4 gives optimal results obtained using the BA-ACO for the parameters and the circuit's performances.

TABLE 4 OPTIMIZATION AND PERFORMANCE RESULTS

Specifications	ACO	BA-ACO
$W_{1,2,11,12}$ (µm)	46.82	46.85
$W_{3,4}$ (µm)	30.91	30.89
$W_{5,6,7,8,13,14,15,16}$ (µm)	50.00	50.00
$W_{9,10}$ (µm)	50.00	50.00
L (µm)	1.00	1.00
I_{bias1} (µA)	60.00	60.00
I_{bias2} (µA)	90.00	90.00
Av (dB)	84.14	84.16
Fc (MHz)	534	534
CMRR (dB)	94.81	94.82
PSRR (dB)	84.56	84.55

The SPICE simulation results are collected in the following table:

TABLE 5 PERFORMANCE AND SIMULATION RESULTS

	Av (dB)	Fc (MHz)	CMRR (dB)	PSRR (dB)
Opt.	84.16	534	94.82	84.55
Sim.	84.02	507	93.71	79.28

From Tables 2 and 4, we note that the proposed algorithm BA-ACO presents the same quality of the optimum compared to the ACO.

IV. ROBUSTNESS AND COMPUTING TIME

A. Robustness

In order to check and compare the convergence rate of the BA-ACO algorithm, a robustness test was performed. i.e. the algorithm are applied a hundred times for optimizing all the objectives of each circuit. In Figures 4 and 5, we present in a boxplot representation the obtained results (respectively for Op-Amp and OTA) for both the ACO and BA-ACO algorithms.

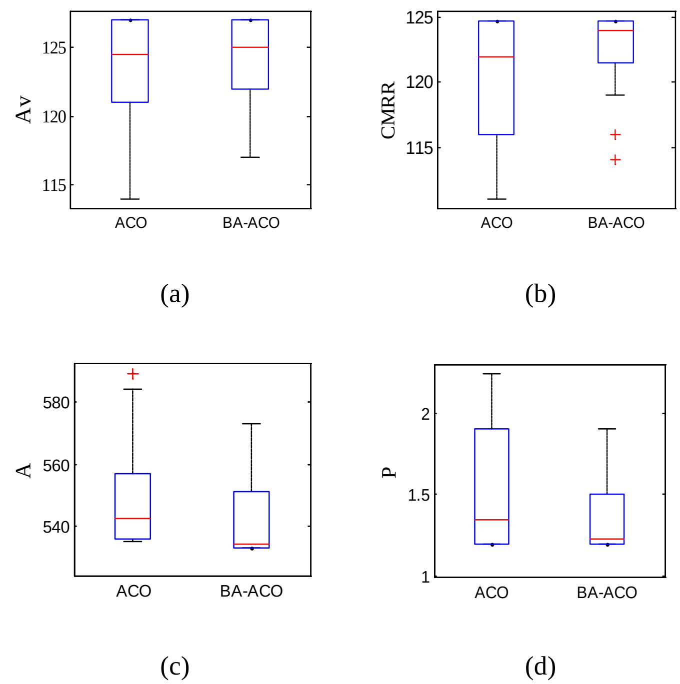

Fig.4 Box plots for 100 runs of the BA-ACO and the ACO algorithms for the Op-Amp

(a) for the Av (dB); (b) for the CMRR (dB); (c) for the A (µm^2); (d) for the P (mW)

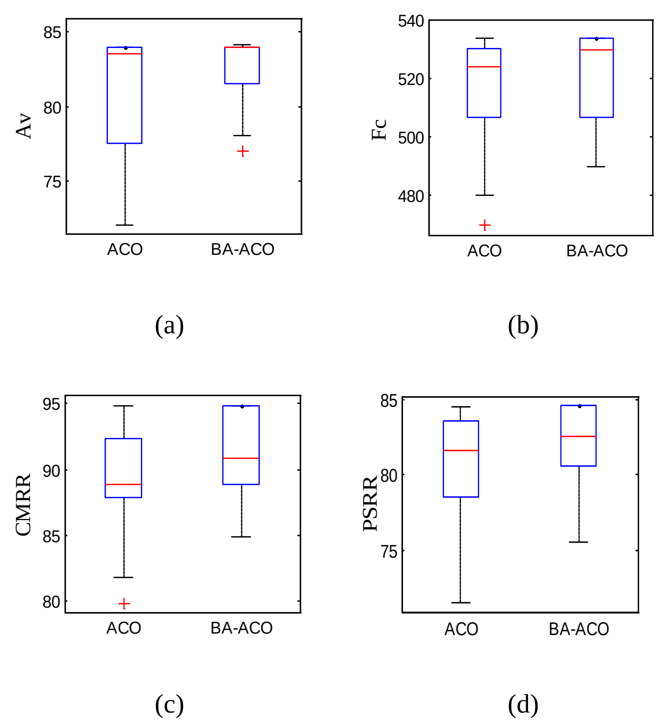

Fig.5 Box plots for 100 runs of the BA-ACO and the ACO algorithms for the OTA

(a) for the Av (dB); (b) for the Fc (MHz); (c) for the CMRR (dB); (d) for the PSRR (dB)

The good convergence ratio can be easily noticed, despite the probabilistic aspect of the two algorithms. We can also notice that the robustness of the BA-ACO algorithm is better than the ACO's one. The convergence rates to the same optimal value for ACO and BA-ACO are shown in the Table 6 which summarizes also the convergence rate improvement.

TABLE 6 CONVERGENCE RATE AND IMPROVEMENT

		Convergence rate (%)		
		ACO	BA-ACO	Improvement
Op-Amp	Av	44	53	20%
	CMRR	37	46	24%
	A	38	46	21%
	P	41	49	19%
OTA	Av	41	50	22%
	GBW	43	51	18%
	CMRR	40	48	20%
	PSRR	37	47	27%

B. Computing time

Table 7 summarizes a comparison between computing times for the ACO and the BA-ACO algorithms. A (2 GHz, 2 Go RAM) core 2 DUO PC was used for this purpose.

TABLE 7 EXECUTION TIME AMELIORATION (%)

	Execution Time (s)		
	ACO	BA-ACO	Improvement
Op-Amp	61.5	44.7	54%
OTA	38.6	31.8	35%

From the above table, we clearly notice that the BA-ACO presents a significant improvement of the execution time.

V. CONCLUSION

The presented work proposes an application of the enhanced version of the classical ant colony optimization technique (ACO) for dealing with the optimal sizing of a CMOS analog circuits. A backtracking technique is integrated into the ACO algorithm in order to improve its performances. The BA-ACO algorithm was successfully applied to optimize performances of a two stage Operational Amplifier and of an Operational Transconductance Amplifier. Performances were compared to the ones obtained by using the classical ACO algorithm, and then checked via SPICE simulations. The optimization results show that the BA-ACO algorithm offers better results in terms of robustness and computing time than the basic ACO technique. Now, we are focusing on transforming the proposed BA-ACO mono-objective algorithm into a multiobjective one.

REFERENCES

[1] F. Medeiro, R. R. MacíasFernández, F.V.R. DomínguezAstro, J.L. Huertas and A. R. Vázquez, "Global design of analogcells using statistical optimization techniques," Analog integrated circuits and signal processing, vol. 6, No. 3, pp. 179–195, 1994.

[2] F. Glover, "Tabu search-part I," ORSA Journal on computing, vol. 1, No. 3, pp. 190–206, 1989.

[3] F. Glover, "Tabu search-part II," ORSA Journal on computing, vol. 2, No. 1, pp. 4–32, 1990.

[4] J. Dreo, A. Pe´trowski, P. Siarry and E. Taillard, "Metaheuristics for hard optimization: Methods and case studies," New York: Springer, 2006.

[5] J. B. Grimbleby, "Automatic analogue circuit synthesis using genetic algorithms," IEE Proceedings-Circuits, Devices and Systems, vol. 147, No. 6, pp. 319–323, 2000.

[6] E. Aarts and K. Lenstra, "Local search in combinatorial optimization," Princeton: Princeton University Press, 2003.

[7] S. Garnier, J. Gautrais and G. Theraulaz, "The biological principles of swarm intelligence," Swarm Intell, vol. 1, pp. 3–31, 2007.

[8] F. T. S. Chan and M. K. Tiwari, "Swarm Intelligence: focus on ant and particle swarm optimization," I-TechEducation and Publishing, 2007.

[9] A. Chatterjee, M. Fakhfakh and P. Siarry, ''Design of Second Generation Current Conveyors Employing Bacterial Foraging Optimization," Elsevier, Microelectronics Journal, vol. 41, pp. 616–626, 2010.

[10] M. Fakhfakh, Y. Cooren, A. Sallem, M. Loulou and P. Siarry, "Analog Circuit Design Optimization through theParticle Swarm Optimization Technique," Springer,Journal of Analog Integrated Circuits & Signal Processing, vol. 63, No. 1, pp. 71–82, April, 2010.

[11] B. Benhala, A. Ahaitouf, M. Kotti, M. Fakhfakh, B. Benlahbib, A. Mecheqrane, M. Loulou, F. Abdi and E. Abarkane, "Application of the ACO Technique to the Optimization of Analog Circuit Performances," book: "Analog Circuits:Applications, Design and Performance", Ed., Dr. Tlelo-Cuautle, NOVA Science Publishers, Inc., Chapter 9, pp. 235–255, 2011.

[12] B.Benhala, A. Ahaitouf, A. Mechaqrane, B. Benlahbib, F. Abdi, E. Abarkan and M.Fakhfakh, "Sizing of current conveyors by means of an ant colony optimization technique," the International Conference on Multimedia Computing and Systems (ICMCS'11), pp. 899–904, April 7–9 Ouarzazate, Morocco, 2011.

[13] B. Benhala, A.Ahaitouf, M.Fakhfakh, A.Mechaqrane and B. Benlahbib, "Optimal analog circuit sizing via ant colony optimization technique," International Journal of Computer Science and Network Security (IJCSNS), vol. 11, No. 6, pp. 223–231, 2011.

[14] B. Benhala, A. Ahaitouf, M. Fakhfakh and A. Mechaqrane, "New Adaptation of the ACO Algorithm for the Analog Circuits Design Optimization," International Journal of Computer Science(IJCSI), vol. 9, Issue 3, No. 2, pp. 360–367,May 2012.

[15] B. Benhala, A. Ahaitouf, A.Mechaqrane and B. Benlahbib, "Multiobjective optimization of second generation current conveyors by the ACO technique," the International Conference on Multimedia Computing and Systems (ICMCS'12), pp. 1147–1151, May 10–12 Tangier, Morocco,2012.

[16] M. Kotti, B.Benhala, M.Fakhfakh, A.Ahaitouf, B.Benlahbib, M.Loulou and A. Mecheqrane, "Comparison between PSO and ACO techniques for analog circuit performance optimization," the International Conference on Microelectronics, IEEE TN CEDA's, ENG-OPTIM'Contest ''Engineering Applications of Optimization Techniques'', 19–22 December, Hammamat, Tunisia, 2011.

[17] A. Sallem, B. Benhala, M. Kotti, M. Fakhfakh, A. Ahaitouf and M. Loulou, "Application of Swarm Intelligence Techniques to the Design of Analog Circuits: Evaluation and Comparison," Analog Integrated Circuits and Signal Processing. Springer, vol. 75, No. 3, pp. 499–516, March 2013.

[18] M. Dorigo, V. Maniezzo and A. Colorni, "The ant system: Optimization by a colony of cooperating agents," IEEE Transactions on Systems, Man and Cybernetics, Part B, vol. 26, pp. 29–42, 1996.

[19] M. Dorigo and L. Gambardella, "Ant colony system: A cooperative learning approach to the traveling salesman problem," IEEE Transactions on Evolutionary Computation, vol. 1,pp. 53–66, 1997.

[20] T. Stützle and H. Hoos, "Max-Min ant system," Future Generation Computer Systems vol. 18, pp. 889–914, 2000.

[21] Z. Song, H. Di-Bo and Z. Ze-Kui, “Ant colony algorithm with dynamic transition probability,” Control and Decision, vol.23, No.2, pp.225–228, 2008.

[22] H.M. Naimi and N. Taherinejad, “New robust and efficient ant colony algorithms: using new interpretation of local updating process,” Expert Systems with Applications, No.36, pp. 481–488, 2009.

[23] B. Yingzhou, Z. Peng, Z. Zhi and D. Lixin, “A novel pheromone update with important solution components,” 6th International Conference on Natural Computation (ICNC), vol. 5, pp.2551–2555, 2010.

[24] W. Li and L. Dong, “Special factor backtracking algorithm for optimizing,” International Conference on Intelligent Computing and Integrated Systems (ICISS), pp.27–30, 2010.

[25] B. Benhala, M. Kotti, A. Ahaitouf and M. Fakhfakh, “ Backtracking ACO for RF-Circuit Design Optimization,” book: "Performance Optimization Techniques in Analog, Mixed-Signal, and Radio-Frequency Circuit Design", Edt. M. Fakhfakh, E. Tlelo-Cuautle, M.H. Fino, IGI-Global, Chapter 7, pp. 158-179, 2015.

[26] M. Dorigo, G. DiCaro and L. M. Gambardella, “Ant algorithms for discrete optimization,” Artificial Life Journal, vol. 5, pp. 137–172, 1999.

[27] M. Dorigo and S, Krzysztof, “An Introduction to Ant Colony Optimization,” a chapter in Approximation Algorithms and Metaheuristics, a book edited by T. F. Gonzalez, 2006.

[28] Y. Jinhui, S. Xiaohu, M. Maurizio and L.Yanchun, "An ant colony optimization method for generalized TSP problem", Progress in Natural Science, Vol. 18, pp 1417–1422, 2008.

[29] B. Yu, Z. Yang and B. Yao, "An improved ant colony optimization for vehicle routing problem", European Journal of Operational Research Vol. 196, pp. 171–176, 2009.

[30] A. Colorni, M. Dorigo and V. Maniezzo, “Distributed optimization by ant colonies,” Proceedings of the 1st European Conference on Artificial Life, pp.134–142, 1991.

[31] S. Guo and Y. Meng, “An improved entropy-based ant colony optimization algorithm,” International Conference on Computer Application and System Modeling, (ICCASM), vol.15, pp.1548–1550, 2010.

[32] M. Daniel and M. Martin, “Ant colony optimization with global pheromone evaluation for scheduling a single machine,” Applied Intelligence, vol.18, pp.105–111, 2003.

[33] Z. Liu, T. Liu and X. Gao, “An Improved Ant Colony Optimization Algorithm Based on Pheromone Backtracking,” IEEE 14th International Conference on Computational Science and Engineering (CSE), pp. 658–661, 2011.

Bachir BENHALA In 1992 he received the teaching degree in Electronic Engineering from the ENSET of Mohammedia (Morocco). In 2007, he received his Master’s from the Faculty of Science and Technology (FST) of Fez, and he received his PhD degree in 2013 in Electronics and Microelectronics. He is currently an Assistant Professor at the Faculty of Sciences of University of Moulay Ismaïl in Meknes, Morocco. He has authored and co-authored more than 30 papers in universally referenced journals. His research interests include metaheuristic optimization techniques, analog design automation, and digital/analog VLSI architectures.