# Intelligent Optimization of CMOS Operational Amplifier using 3D Ant Colony Optimization

Samir Barra

*Abstract* — **This paper presents the use of an artificial intelligence (AI) tool based on ant colony behavior to design an operational amplifier circuit. The ant colony optimization (ACO) is implemented in a hybrid evolutionary sizing method to automate analog circuit design. This new meta-heuristic approach that combines the artificial intelligence of an ant colony and the 3D matrix method is developed to determine the optimal dimensions and the main influencing performances of fundamental analog circuits and, including operational amplifiers (op-amps). The proposed methodology uses ACO and Cadence Spectre as dimensioning techniques and implementation platform, respectively. The Three Dimensions (3D) ACO algorithm is successfully used for analog circuit sizing, and the obtained results demonstrate its effectiveness in sizing basic and more complicated analog circuits.**

*Index Terms* — **Analog Integrated Circuit; Ant Colony Optimization; Operational Amplifier Design; Artificial Intelligence.**

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## I. Introduction

An analog block that comprises only a small part of the total surface area of modern chips is generally the element that influences their overall performance. Nowadays, one of the challenges to be addressed is the dimensioning of integrated circuits (ICs), which is led by the permanent enhancement of the density of components on the chip. Designers are faced with a challenging task of finding a technique or algorithm that can easily determine the component dimensions while taking into consideration given specifications. Therefore, optimizing the dimensions of the analog circuits automatically using design tools and efficient evolutionary algorithms is of extreme significance for the evolution of the integrated circuit field. Analog circuit optimization is usually a multi-objective issue and is not a simple optimization problem. A wide range of multi-objective techniques, such as Ant Colony Optimization (ACO) [1]–[11], Genetic Algorithms (GA) [12]–[16], and Particle Swarm Optimization (PSO) [17]–[20], have been developed.

To address the multi-objective issue of analog circuit design, an evolutionary algorithm inspired from the artificial intelligence of the ant colony algorithm [1]–[7] was innovated. Circuit designer engineers increasingly use ant colony intelligence methods to optimally design their circuit's parameters [8]–[11].

The operational amplifier (op-amp) is a fundamental building block that is often part of other analog and mixed-signal circuits. Sizing the operational amplifier is a difficult and tedious task due to the numerous variables and functions that the designing engineer must manage [10]–[11]. In this study, we focus on using ACO for the optimal sizing of an operational amplifier. Therefore, we attempt to implement an artificial intelligence (AI) algorithm based on ant colony behavior to design an operational amplifier circuit. The issue dealt with in this manuscript is the optimal dimensioning of CMOS transistors for the best performance of an operational amplifier using an extended version of ACOs.

The principal goal of this study is to capture the optimal design points (optimal dimensions and the main influencing performances) for the CMOS two-stage operational amplifier (op-amp) using a multi-objective 3D ACO algorithm. We have developed simple analog circuit design tool driven by a novel artificial intelligence algorithm based on the three-dimensional concept. The method manages several parameters, is highly fast, and converges to the main optimal performance. The novelty made in this paper is the proposal of a new three-dimensional ant colony algorithm based on artificial intelligence of ants, and this new 3D-ACO algorithm has a several novel features; one is the adoption of new pheromone updating rules, and the other is the exploration of a new three-dimensional search engine.

This paper consists of five main parts: The first section is an introduction to the work, and then a second section explains the 3D ACO approach, followed by the third section describing the proposed ACO algorithm implemented to design the operational amplifier. The fourth section, interprets the obtained results. Finally, the last section includes some conclusions.

### A. Related Works

Many designers and researchers have developed optimization methods using ACO for electronics, using different approaches to improve performance. These methods can be divided into two categories:

Some methods focus on solving electronic problems but do not include analog circuit design. For example, in [8], an ACO algorithm is implemented in CMOS to solve the big TSP problem for adaptive routing in telecommunications networks. In [9], an extended ant colony optimization algorithm is used to optimize the design of a power electronic circuit. In [22], [23],

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S. Barra is with Advanced Electronics Laboratory (L.E.A), the Department of Electronics, University of Batna 2, Batna, Algeria (phone: +213-33-325-410; fax: +213-33-325-411; e-mail: barrasamir@hotmail.com).

genetic algorithm and ACO were used for tuning "Proportional Integral Derivative (PID)" controller parameters, while [11] used ACO to size circuits for an electronic system with different cost functions or objective functions.

Other methods focus on solving analog circuit problems and have shown satisfactory results compared to other evolutionary and classical methods. According to [10], the ACO design approach is based on noise optimization with power consumption for operational transconductance amplifiers. In [11], two metaheuristic techniques, PSO and ACO, were proposed and compared to classical techniques. This work optimized two cost functions for two analog circuits: maximize the open-loop voltage gain and the slew rate of a two-stage CMOS Op-Amp, and minimize noise while maximizing the open-loop voltage gain of an OTA. Consequently, several ACO-based algorithms have been suggested for optimizing various electronic circuits [8]–[11], [22]–[23]; although some of them are dedicated to analog electronic circuits. However, these methods are limited since they use only two cost functions or less and only a few of them are focused on optimizing the operational amplifier circuit [10, 11] due to the difficulty of using non linear multi-objective functions in three dimensions.

To the authors' best knowledge, no articles more recent than <2016> were published on this topic.

## II. 3D ACO APPROACH

The ACO method was first suggested by Dorigo and his colleagues in 1991 [1], [2]. The collective instinctive behavior adopted by the actual ant colony was the source of inspiration for the ACO technique. Ants use a chemical substance (pheromone) to communicate indirectly with each other through dynamic changes in their pheromone paths. The real ants are blind; however, they can discover the shortest path from their home to a feeding source based on the chemical communication phenomenon. The principal idea of the ACO algorithm consists of a number of artificial ants moving virtually on the construction graph [5] to construct solutions for the considered issue. In other words, the optimization problem can be encoded as a multi-layer graph represented in Fig. 1. The number of design variables (set of n variables) is equal to the number of layers (set of n vertices), and the discrete value numbers allowed for each corresponding variable is equal to the number of vertices in each layer. Each design variable value corresponds to each vertex (node), and each arc connects between two nodes [21].

Fig. 1 graphically interprets an example of an optimization problem with six layers (design variables), and each layer has eight vertices (permissible discrete values) for each design variable.

### *A . ACO algorithm*

The ACO is a cyclic algorithm, and at each cycle, N virtual ants are taken into account. Each of them constructs a solution by moving along the edges of the graph from node to node [6], [22], and every ant can choose just a single node in every layer.

At the beginning, the ants start at the home node, and all paths are initialized with the same amount of virtual pheromone. All artificial ants begin by arbitrarily choosing a vertex in each layer, and after the first iteration, every ant locally updates the chemical substance dropped into the paths it pursued after finishing one lap.

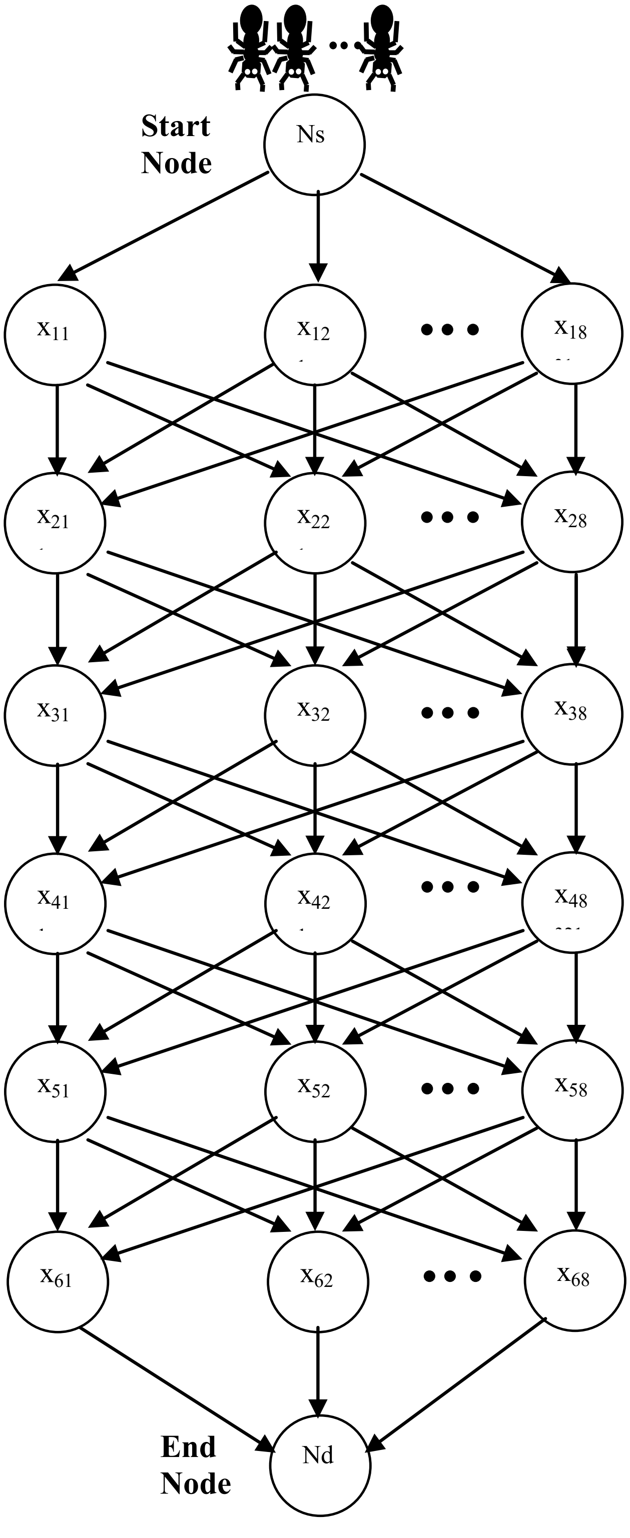

Fig. 1. Graphical Presentation of ACO for Analog Circuit Design

In each iteration, the artificial ants build a solution by walking through the different layers, from the initial to the terminal layer, and finishing at the terminal vertex. The ants run on the different vertices (nodes) in conformity with the probability transition equation. The vertices' trajectory chosen along the way visited by each ant specifies a possible solution of the research. Once the way is finished, the ant lays some chemical substance on the way in accordance with the local updating equation. At the end of an iteration, when all the ants have finished their paths, the chemical substance on the paths is updated using the global updating relations to help the ants build better solutions in their next iterations.

Finally, all artificial ants converge to the same best path (the optimum solution) with the lowest cost function, and the optimization algorithm is terminated if the stopping criteria are reached.

The Ant Colony Optimization iterates over four basic mechanisms [5]:

*A.1. Selecting behavior:*

This behavior is inspired by real ant colonies, where ants explore different paths to escape from local optima. The probability equation calculates the possibility (likelihood) of an artificial ant selecting the next vertex [11].

$$P_{ij}^{(k)} = \begin{cases} \dfrac{\tau_{ij}^{(\alpha)}\eta_{ij}^{(\beta)}}{\sum \tau_{ij}^{(\alpha)}\eta_{ij}^{(\beta)}} \text{ if } J \in N_i^{(k)} \\ 0 \text{ if } j \notin N_i^{(k)} \end{cases} \tag{1}$$

*A.2. Pheromone deposing:*

This instinctive behavior involves ants depositing pheromones on the selected trail to assist other following ants in selecting the best trail. The evaporation of pheromones from each edge is governed by the following formula [5]:

$$\tau_{ij} \leftarrow (1-p)\tau_{ij}; \forall (i,j) \in A \tag{2}$$

*A.3. Searching behavior*:

This behavior is inspired by real ants' cooperative behavior in discovering (which is capable to discover) the shortest path from their home to a food source [22]. Artificial ants construct the best global solution from all possible local solution elements in a finite set [11]. During each search tour, the best solution, which offers the lowest value of the fitness function, increases its pheromone rate, while the worst solution sees its pheromone rate decreasing (fractionally evaporated), according to formula (6).

*A.4. Pheromone evaporation*:

The density of the chemical substance diminishes due to the evaporation phenomenon at the actual ant colony. This phenomenon is reflected in artificial ants by updating pheromones. Pheromone updates are based on solution quality to create explicit memory [5].

The quantity of pheromone value $\tau_{ij}$ on the visited arc $(i,j)$ is locally updated according to Eq. (2) [5]:

$$\tau_{ij} \neg \tau_{ij} + D\tau^{(k)} \tag{3}$$

In the end, the ants come back to the home nest, the pheromone data is globally updated conforming to the formula (4) [3]:

In the end, the ants return to their home nest, and the pheromone information is updated globally according to formula (4) [3]:

$$\tau_{ij} = (1-p)\tau_{ij} + \sum_{k=1}^{N} \Delta\tau_{ij}^{(k)} \tag{4}$$

Where: $\Delta\tau^{(k)}_{ij}$ = The quantity of pheromone dropped by the best ant k on edge ij.

The best ant deposits a certain amount of pheromone on edge ij, as defined by this formula [2]:

$$\Delta\tau_{ij}^{(k)} = \frac{Q}{L_k} \tag{5}$$

To provide a maximum amount of pheromone to the best tour with the best objective function values (solution), Eq. (5) can be implemented as [2]:

$$\Delta\tau_{ij}^{(k)} = \begin{cases} \dfrac{\zeta f_{best}}{f_{worst}} \text{ if } (i,j) \in \textit{ best tour} \\ 0; \textit{otherwise} \end{cases} \tag{6}$$

The proposed approach adopts new pheromone updating rules by enhancing the existing updating rules of [23].

Each ant updates the chemical substance on the paths it visited after completing one cycle. This characteristic is defined as the local pheromone updating relationship, which is as follows:

$$\tau_{ij}(k) = \tau_{ij}(k-1) + \frac{\tau_{pos} \cdot \theta}{f} \tag{7}$$

Where, f is the objective function for the lap walked by the ant, and $\tau_{pos}$ is the positive pheromone constant ($\tau_{neg}$ is the negative pheromone constant).

Global updating enables the ant algorithm to escape from local minimum solutions [23]. All ants update the pheromone levels after completing their tour, according to the following global pheromone updating equations:

$$\tau_{ij} = \tau_{ij}^{\lambda} + [\tau_{ij}^{best} + \tau_{ij}^{worst}] \tag{8}$$

where: $\lambda$ is an evaporation constant

The pheromone levels on the paths corresponding to the best tour (9) and worst tour (10) of the ant colony are updated as follows:

$$\tau_{ij}(k)^{best} = \tau_{ij}(k) + \frac{\theta}{f_{best}} \tag{9}$$

$$\tau_{ij}(k)^{worst} = \tau_{ij}(k) + \frac{\tau_{neg} \cdot \theta}{f_{worst}} \tag{10}$$

### *B. Three dimensions ACO*

The ant intelligence lies at the core of the ACO algorithm, and its searching mechanism is based on the concept of three dimensions.

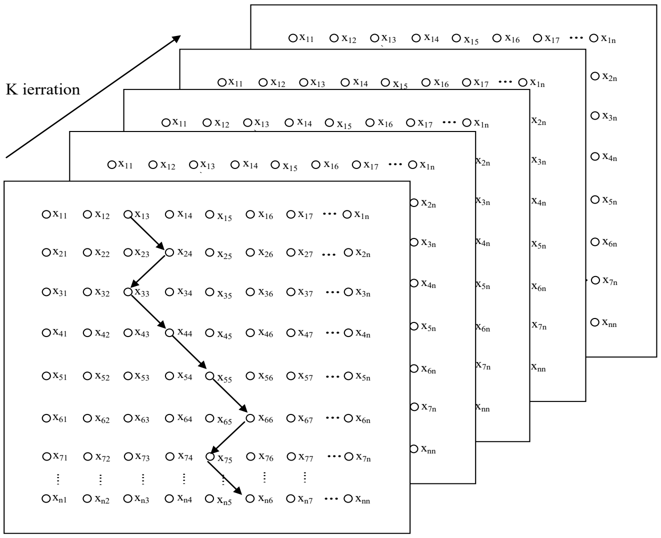

Fig. 2. Graphical Three-Dimension matrix method

The optimization problem can be represented as a three-dimensional array, where each sheet presents a multilayer graph (as shown in Fig. 2), and the dimensions are as follows: the first dimension (*i*) represents the number of layers or variables, the second dimension (*j*) represents the number of nodes or discrete values, and the third dimension (*k*) represents the time or iteration number. Consequently, all possible solution components are stored in the three-dimensional matrix (*i*,*j*,*k*). The three-dimensional method is used to construct the 3D local pheromone matrix, the 3D global pheromone matrix, and the 3D cost function matrix. This means that the algorithm generates matrices to store the pheromones dropped for local updating and for global updating, also creates the cost function matrix holds all excellent solutions. The ACO research engine is implemented mathematically using the 3D dimension matrices method, and the artificial ants move through the 3D possible solution component matrix (as shown in Fig. 2), where the solution component xij is associated with the pheromone value τij. Finally, once the "3D cost matrix" is built, the algorithm works exactly as it does in a real colony case, and the ants select an optimal global path. The proposed three-dimensional matrix method has the advantages of conceptual clarity and computational efficiency.

## III. ANALOG CIRCUIT DESIGN USING ACO

In fact, analog circuit design problems involve more than one objective function. For example, in the CMOS operational amplifier design problem, more than one parameter may be optimized, such as bandwidth, power dissipation, etc. Consequently, an optimization issue can be described by this formula [11]:

Minimize $f(x) : f(x) = (f_1(x), f_2(x),...f_n(x))\&\ x = (x_1, x_2,...x_n)$
Subject to : $g_i(x) \leq 0$, i=1,2,...l and $h_j(x)=0$, j=1,2,...m
where $a_k \leq x_k \leq b_k$, $k$=1,2,...n

### *Two stage Operational Amplifier design*

The configuration considered in this work is for a two-stage operational amplifier (see Fig. 3). This circuit can be characterized by a number of parameters (described by Equations (11)-(16)) given as follows [13]:

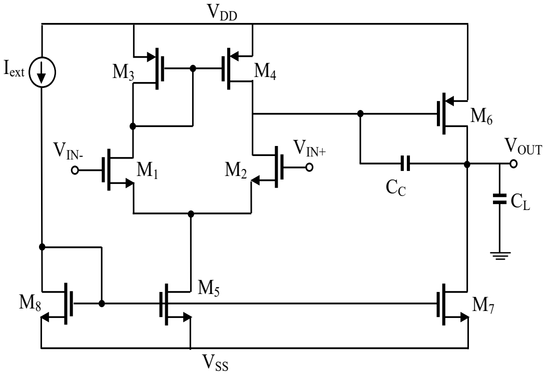

Fig. 3. Two stage Operational Amplifier

- Slew rate (*SR*)
- Power dissipation ($P_{diss}$)
- Gain ($A_v$)
- Phase margin (*PM*)
- Gain Bandwidth product (*GWB*)
- Area of MOS transistor (*A*)

The equations from (11) to (16), defining each characteristic parameter, are used in the fitness function of ACO algorithms based on op-amp circuit design [13] and are considered for obtaining transistor dimensions (Fig. 3).

The expression of DC gain is:

$$A_V = \frac{g_{m1} \cdot g_{m6}}{(g_{ds2} + g_{ds4})(g_{ds7} + g_{ds6})} \tag{11}$$

The gain bandwidth product is given by:

$$GBW = \frac{g_{m1}}{C_c} \tag{12}$$

The phase margin parameter is as follows:

$$PM = 180 - \tan^{-1}\left(\frac{GBW}{p1}\right) - \tan^{-}\left(\frac{GBW}{p2}\right) - \tan\left(\frac{GBW}{z}\right) \tag{13}$$

The slew rate is defined by:

$$SR = \frac{I_5}{C_c} \tag{14}$$

The surface can be easily calculated using this equation:

$$Area = \sum_{i=1}^{k} W_i \cdot L_i \tag{15}$$

The formula for the power dissipation is as follows:

$$P = V_{dd} - V_{ss}(I_5 + I_7) \tag{16}$$

In this work, the issue under consideration is the optimization of transistor dimensions for two-stage op-amp circuits (Fig. 3), with respect to their principal influencing parameters. Optimizing the op-amp circuit is a typical multi-objective problem, meaning it comprises six objective functions. The optimization goal is to decrease the surface and consumed power functions while increasing the other objective functions, which include gain, cutoff frequency, slew rate, and phase margin. Each objective function (or cost function) represents a non-linear, complicated relationship between the design parameters, as given in equations (11)-(16). The design parameters for the circuit under consideration include the dimensions of all transistors, the biasing current, and the value of capacitors.

The input variables and constants used to create the objective functions are specified as follows [18]:

- $K_n$ and $K_p$ are the transconductance parameters for both transistors (NMOS and PMOS, respectively).
- $\mu_n$ and $\mu_p$ :are the electron mobility and hole mobility, respectively.
- $C_{ox}$: is the gate oxide capacitance of the transistor.
- $\lambda_n$ and $\lambda_p$: are the channel length modulation parameters of both transistors.
- $V_{DD}$ and $V_{SS}$: are the positive power supply and the negative power supply, respectively.
- $V_{thn}$ and $V_{thp}$ are the threshold voltages for both transistors.
- $V_{DS}$ is the drain to source voltage of the transistor.
- $V_{GS}$ is the gate to source voltage of the transistor.
- *gm* is the transconductance of the transistor.
- *gds* is the output conductance of the transistor.
- $I_D$ is the drain current of the transistor.
- $C_c$ is the compensation capacitor of the considered operational amplifier.

We focus on a popular two-stage op-amp topology shown in Fig. 3, which serves as a case study to verify the effectiveness of the proposed algorithm. In fact, designing a CMOS operational amplifier remains a challenging task as the transistor dimensions shrink in each successive CMOS technology generation.

*Proposed ACO algorithm*

The considered optimization problem is tackled using an ant colony optimization (ACO) algorithm, which simulates a number of ants moving on a three-dimensional graph that encodes the problem itself (as shown in Fig. 1). To create a graphical representation of the problem, the number of layers corresponds to the number of design variables, and the number of vertices in each layer represents the discrete values allowed for that variable. Each vertex represents a specific value for the corresponding design variable, and each arc represents a connection between two values. An artificial ant constructs a solution by traversing the entire graph, moving from node to node along the arcs, and progressively building a fractional solution.

For solving an op-amp design problem using ACO, a construction graph is implemented as a step-by-step 3D ACO algorithm, as shown in Fig. 4.

The three-dimensional graph encodes the problem itself. The new 3D ACO algorithm is the heart of the developed optimization tool, which has been implemented in Matlab.

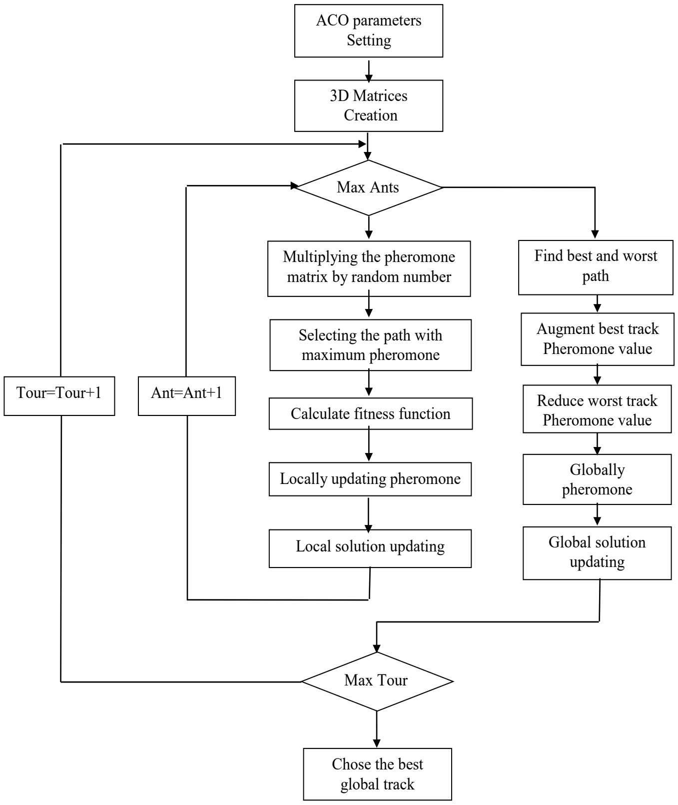

Fig. 4. 3D ACO Algorithm used for Operational Amplifier Design

The ACO algorithm can be summarized as follows:

First, all parameters of the ant colony are set, and an equal amount of chemical substance is initially assigned to each path that a virtual ant can pass. This value is kept in the pheromone matrix. When the first ant leaves the starting node, it randomly chooses a path to follow (based on the amount of chemical substance on each path) since there is the same quantity of chemical substance at paths that has been previously explored and finished the search tour by passing through n nodes. To ensure that the next virtual ant (ant = ant + 1) doesn't follow the same path as the previous ant in the search trajectory, the pheromone matrix is also updated with random numbers. Additionally, the ant attempts to pass through the given reference trajectory by varying the value of each design variable in each tour.

At the end of the ant tour, the local solution was evaluated by calculating objective functions with selected variable values, and the values of the tracks visited by the virtual ant in the pheromone matrix were locally updated (using local pheromone updating rules).

If the resulting objective function value was good with the chosen design variable values, the next ants attempted to complete their tasks by retracing these design variable values.

Once all ants finished their round or iteration, a new iteration number began as tour=tour+1, and then all the ants returned to the nest to begin new research and globally update the pheromones on different arcs. In other words, the pheromone amount at the track of the virtual ant that had the best objective function value was augmented, and the pheromone quantity of the virtual ant that had the worst objective function value was reduced compared to the quantity of the best ant. Also, the pheromone quantity on the tracks that all virtual ants visited was evaporated.

If the stopping criteria were reached, the best tour that had the greatest value in the chemical substance table with the better objective function values (all the ants selecting the identical best road) was selected as the result of optimization.

## IV. Simulation Results

The evolutionary algorithm has been implemented in Matlab. The optimal parameters obtained from the ACO algorithm were used to physically implement the operational amplifier circuit in the Spectre simulator and evaluate its parameters. The optimum dimensions of the operational amplifier circuit corresponding to this optimum performance conforming to the specifications. The optimization tool allows to search for the optimal dimensions and to estimate the performances of the target circuit. The cadence platform allows the validation by the implementation of the target circuit using these dimensions obtained in the optimization, and the extraction of their actual performances. The proposed algorithm consists of a feedback mechanism. If the simulation results under cadence are matched with those obtained from the optimization, these results will be validated. Otherwise, a feedback loop will trigger a new search cycle under the optimization tool to get new dimensions that will match to the results under the cadence simulator.

Several testbenches were utilized to obtain the performance of the target analog circuit. This section will present the simulation results of an op-amp circuit design problem using ACO tools and Spectre. The new 3D ACO algorithm is written in Matlab and runs in a Matlab software environment suitable for optimization. When applied to the issue under consideration, the 3D ACO algorithm is initialized by the parameter values shown in Table 1. The number of tours is 100, the number of ants is 75, and the design variables were coded by 35 nodes (the permissible discrete values). Augmenting the number of ants in the colony will increase the possibility of discovering the most suitable values [1].

Table I
ACO Parameters

| Parameter | Value |
|---|---|
| Iterations | 100 |
| Ants | 75 |
| Nodes | 35 |
| Evaporation Rate λ | 0.95 |
| Positive Pheromone constant (τpos) | 0.2 |
| Negative Pheromone constant (τneg) | 0.3 |
| General Pheromone coefficient | 0.06 |

In this study, a 3D ACO algorithm was used to optimize the main performance parameters of an operational amplifier circuit. The CMOS operational amplifier was then implemented in Cadence Virtuoso using the optimal device sizes obtained from the ACO algorithm (see Table II). The circuit was redesigned in Spectre using 0.18μm TSMC technology, with a voltage power supply of $V_{DD}/V_{SS}$=+1.8V/-1.8V.

Table II
Parameters Obtained with ACO

| Parameter | Value |
|---|---|
| *Ibia(μA)* | 91 |
| *W1/ L1 , W2/ L2* (μm/ μm) | 5/5 |
| *W3/ L3 , W4/ L4* (μm/ μm) | 5/5 |
| *W5/ L5* (μm) | 5/5 |
| *W6/ L6* (μm) | 45/5 |
| *W7/ L7* (μm) | 7/5 |
| *W8/ L8* (μm) | 10/5 |

The ACO-based design methodology was utilized to size the considered circuit, and the computer-aided design platform was used to implement the optimal circuits. Figure 3 illustrates the structure of an operational amplifier, with specifications of $SR \geq 1$V/μs, $GWB \geq 1$MHz, $AV \geq 1000$V/V, $PM \geq 60°$, $P_{diss} \leq 3$mW, and $Area \leq 300\mu m^2$.

The design parameters of the target circuit are constrained by its essential components, such as $C_C \geq 1$pF, and $5\mu m \leq$W/$L \geq 200$μm. To decrease the channel modulation effect, all length values of transistors were selected as 5μm.

The 3D ACO algorithm was initialized with the parameter values shown in Table II, and the evolutionary algorithm was used for intelligent searching to find the optimal parameter designs for the target circuit. Table III provides these parameter designs and their corresponding performances. The numerical results obtained by our ACO tool were compared with the results of Spectre, and are summarized in Table III.

Table III
The summary of the ACO results by means of design specifications

| Design criteria | Specification | ACO | Spectre |
|---|---|---|---|
| SR (V/μs) | ≥1 | 5 | 5,11 |
| $P_{diss}$ (μW) | ≤300 | 300 | 300 |
| PM (°) | ≥45° | 90 | 74 |
| GWB (MHz) | ≥1 | 2.3 | 2 |
| AV Gain (dB) | >40 | 77 | 90 |
| Total area (μm2) | ≤500 | 429 | 429 |

The operational amplifier was resized using the obtained parameters in Spectre in order to demonstrate that the ACO design technique conforms to the specifications. The results from Spectre (see Fig. 5) demonstrate that 3D ACO not only meets all specifications, but also reduces the transistor surface, as shown in Table III.

The objective of the cost function in this study was to satisfy the specification, particularly by achieving a surface area lower than 500μm2. The 3D ACO-based design method produced a surface area of 429μm2, which is lower than the specified value. Additionally, the computation time was 59 seconds using an

Intel CPU G6200 @2.60 GHz.

The plots of DC gain and a phase margin of a two stage op-amp are illustrated in Fig. 5.

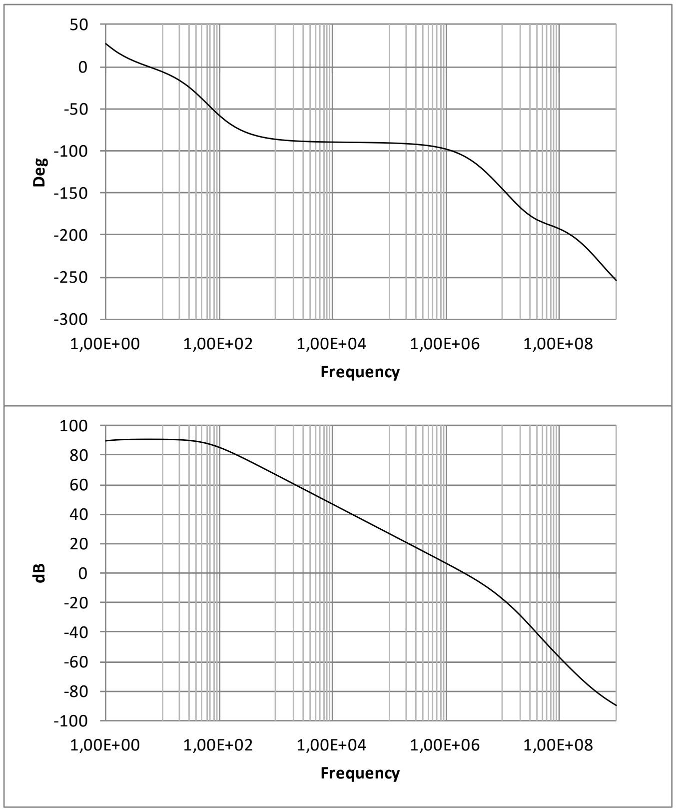

Fig. 5. Gain and phase margin of Operational Amplifier circuit

The proposed hybrid design method combines the Matlab algorithm and the Cadence platform for 3D ACO implementation and Spectre simulations, respectively. In addition to sizing the circuit dimensions, it completes all simulations in a short time, minimizes power consumption, and reduces the circuit's area.

To validate the method, the obtained optimal components from the evolutionary approach are utilized to redesign the considered analog circuit in the Cadence platform. As a result, the design method based on 3D ACO enables to redesign the target operational amplifier circuit utilizing the obtained parameters from the Spectre simulator.

This method not only satisfies all specifications but also decreases the surface area compared to previous methods, as shown in Table 3. The evaluated design parameters using 3D ACO closely match the simulated Spectre results of the operational amplifier circuit, demonstrating the accuracy of the implemented ACO algorithm in Matlab. For example, the Spectre simulations in figure 5 illustrate that both parameters, gain and phase margin of the operational amplifier closely match the specifications. However, there is a slight difference between the ACO and Spectre results due to the error in extraction of parameters value from transistor models using 0.18μm TSMC technology. The transistor model parameters, such as *gm*, *gds*, $C_{ox}$, $\lambda_n$, $\lambda_p$, $K_n$, $K_p$, and $V_{Th}$, used in the proposed 3D ACO algorithm, which was implemented in Matlab, were extracted directly from transistor model or by simulation in Spectre Cadence and complex hand calculation.

## V. Conclusion

Optimization of analog circuits is a challenging and time-consuming task as some parameters conflict with each other and the dominance of one objective affects others and vice versa.

In this study, a novel 3D-ACO algorithm was used to design a CMOS operational amplifier circuit. The optimal dimensions (size of all transistors) obtained from the proposed evolutionary algorithm were used to implement the circuit in Cadence Spectre. The proposed technique is distinct in its ability to efficiently size operational amplifier circuits and find both local and global cost functions in three dimensions.

During the implementation of the ACO algorithm in Matlab, some difficulties were encountered due to a non-linear and complicated relationship, which required manual settings and the extraction of technological transistor parameters through simulation in Spectre Cadence to achieve better results.

In the presented application, 3D ACO demonstrated its effectiveness in analog circuit design, showing extreme ability in a short time. The operational amplifier circuit design problem was successfully tackled by the efficient 3D ACO algorithm, providing promising results and making it appealing for more challenging circuit design applications. In future work, 3D ACO will be utilized to solve more complex problems in analog circuits.

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