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RESEARCH ARTICLE OPEN ACCESS

PERFORMANCE DRIVEN OPTIMIZATION OF CMOS BASED TWO SATGE OPERATINAL AMPLIFIER USING METAHEURISTIC ALGORITHMS

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ABSTRACT

Design of CMOS based analog circuits becomes increasingly complex as transistor sizing plays a crucial role due to the trade-offs among power consumption, silicon area, unity gain bandwidth, slew rate, and open loop gain. This sizing challenge is makes analog circuit design inherently multi objective, and traditional analytical approaches based on simplified transistor level equations often fail to deliver globally optimal results. Metaheuristic optimization techniques have emerged as an effective alternative to explore nonlinear and multi-dimensional design spaces. In this work, the design of a two stage CMOS operational amplifier in the Predictive Technology Model (PTM) 45 nm technology node is optimized using four algorithms: Particle Swarm Optimization (PSO), RAO algorithm, Teaching Learning Based Optimization (TLBO), and the proposed Modified TLBO (MTLBO). The algorithms were implemented in Python and verified through Ngspice-26 simulator on an AMD Ryzen™ processor with 16 GB RAM, 64 bit Ubuntu environment. The proposed MTLBO achieved 86.15 dB voltage gain, 94.05 dB CMRR, and 185 MHz unity gain bandwidth. Comparative analysis shows that the proposed MTLBO algorithm achieves faster convergence with fewer iterations and consistently outperforms PSO, RAO, and TLBO making it a strong candidate for efficient analog VLSI design automation.

I. INTRODUCTION

The scaling of Complementary Metal Oxide Semiconductor (CMOS) technology has made the design of analog and mixed signal circuits design increasingly challenging task. Although digital systems dominate modern integrated circuits, analog blocks such as operational amplifiers (op-amps) remain indispensable because they serve as the critical interface between the physical world and digital processors which is the prime demand of modern mixed signal SoCs. High performance op-amps are widely used in wireless communication, biomedical instrumentation, signal processing, data converters, and control systems [1]. However, analog design in deep submicron nodes is far more complex than digital design due to nonlinear device behavior, process variations, and the simultaneous need to optimize design specifications such as gain, bandwidth, slew rate, power efficiency, and silicon area [2]. Traditional manual device sizing approaches rely on analytical transistor level equations, design heuristics, or rule-based methods often fail to achieve globally optimal results because of simplifying assumptions and their limited ability to explore complex design spaces [3]. To overcome these limitations, optimization driven methodologies have become increasingly popular. Deterministic optimization methods may succeed when the problem is well posed, but they are sensitive to initial conditions and tend to converge to local optima. Metaheuristic algorithm inspired by natural or social processes are more robust, balancing global exploration and local exploitation, making them particularly suitable for high dimensional, multi objective analog circuit design problems [4]. Over the past two decades, a wide range of metaheuristic algorithms have been investigated. Genetic Algorithms (GA) [5] and Particle Swarm Optimization (PSO) [6] are commonly applied but require careful parameter tuning. Artificial Bee Colony (ABC) [7], Differential Evolution (DE) [8], and Whale Optimization Algorithm (WOA) [9] offer improved exploration but remain computationally demanding for highly constrained designs. Teaching Learning Based

Optimization (TLBO) proposed by Rao et al. [10], introduced a parameter less approach inspired by the teacher student learning process which enables faster convergence and simpler to implementation. More recently, Rao [11] developed Rao algorithms, which further reduce parameter dependence and have been successfully applied to a many engineering problems. Multi objective TLBO has been employed for addressing challenging scheduling problems [12], while hybrid PSO-TLBO approaches have reported enhanced convergence characteristics in diverse optimization tasks [13]. Scalable variants such as the parallel subclass TLBO have been proposed for high-dimensional problem spaces [14]. Recent studies have shown that bio-inspired algorithms are also gaining traction in wireless sensor networks, where they have been successfully applied to enhance localization accuracy [15], emphasizing their broad applicability across engineering domains. Motivated by these developments, this work introduces a Modified Teaching Learning Based Optimization (MTLBO) algorithm for analog circuit design automation. The proposed MTLBO integrates the teacher and learner phases into a single update rule, allowing candidate solutions to learn simultaneously from the best solution and peer interactions.

This modification reduces algorithmic overhead, accelerates convergence, and preserves diversity within the search space. The algorithm is implemented in Python and coupled with Ngspice-26 simulator to optimize a two-stage CMOS operational amplifier in PTM 45 nm technology. Its performance is benchmarked against PSO, RAO, and TLBO to validate robustness and efficiency in achieving high gain, wide bandwidth, and low power consumption. The contributions of this paper are as follows: A review and comparative evaluation of metaheuristic algorithms for analog CMOS op-amp design, development of an enhanced MTLBO algorithm with integrated teacher learner update rules, implementation automated framework for two stage CMOS op-amp optimization, comparative results demonstrating that MTLBO achieves faster convergence and superior circuit performance relative to PSO, RAO, and TLBO. This paper is organized as follows: Section II brief over view of TLBO algorithm. Section III presents the proposed MTLBO approach with improved teaching process. Section IV outlines the automated design framework. Section V discusses simulation results. Section VI concludes the work and highlights scope of the future work.

II. THE TEACHING LEARNING BASED OPTIMIZATION

Teaching Learning Based Optimization (TLBO), proposed by Dr. R. V. Rao [10], is a population based meta heuristic algorithm which emulates how students acquire knowledge both from the teacher and the peer interaction. Each generation in TLBO consists of two distinct stages:

II.1 TEACHER PHASE

This phase identifies the most competent learner having best fitness from the population and designated as a teacher. All other learners adjust their solutions by moving closer to the teacher's position, effectively assimilating the teacher's knowledge. In this phase personal best of each candidate is determine, and then appoint the top performing individual as a teacher. All other learners learn from each other and update their own solutions by learning from each other and also from this teacher. Two matrices each for teacher and learner are generated randomly for initial population within the required bound [10]. The two matrix Px and Py generated for the N number of learner in the range Px with x = 1, 2, …, N and Py with y = 1, 2, …, M number of subjects where P is the objective function of the individual candidate.

Matrix Px where x = 1, 2, 3…, N (1)

Matrix Py where y = 1, 2, 3…, M (2)

After generating these two Px and Py random matrices each individual fitness is calculated by the objective function and selecting best indivudal from the population. In the proceeding step mean of each design variable is calculated and learner with best solution is selected as teacher as mentioned in the below equation.

$$Diff_{mean_{x,y,i}} = R_i\left(K_{x,ybest,i} - TFM_{j,i}\right) \tag{3}$$

Where the random number Ri having value in the range of [0,1] and teaching factor TF having value either 1 or 2 and TF is calculated by the formula (4).

$$TF = round[1 + rand(0,1)(2-1)] \tag{4}$$

Hear, TF is randomly selected in the range of 1 or 2 and it is important to note that the teaching factor is not algorithm parameter. After finding the difference mean new solution is obtained by the following equation.

$$K'_{x,y,i} = K_{x,y,i} + Diff\_Mean_{x,i} \tag{5}$$

II.2 LEARNER PHASE

Randomly selected learners are allowed to interact with each other to update their solution based on whether the peer is performing better or worse. This knowledge exchange process further refines the population's solutions. Throughout this process, the learners iteratively improve the performance by incorporating both top-down instruction (from the teacher) and lateral learning (from fellow students), steadily converging toward an optimal solution. The learner updates their knowledge by interacting with the peer who has higher knowledge compared to him. For the minimization process,

$$K''_{x,a,i} = K'_{x,a,i} + R_i\left(K'_{x,a,i} - K'_{x,b,i}\right), \quad if K'_{total-a,i} < K'_{total-b,i} \tag{6}$$

$$K''_{x,a,i} = K'_{x,a,i} + R_i\left(K'_{x,b,i} - K'_{x,a,i}\right), \quad if K'_{total-b,i} < K'_{total-a,i} \tag{7}$$

For the maximization process,

$$K''_{x,a,i} = K'_{x,a,i} + R_i\left(K'_{x,a,i} - K'_{x,b,i}\right), \quad if\, K'_{total-a,i} > K'_{total-b,i} \tag{8}$$
$$K''_{x,a,i} = K'_{x,a,i} + R_i\left(K'_{x,b,i} - K'_{x,a,i}\right), \quad if\, K'_{total-b,i} > K'_{total-a,i} \tag{9}$$

Depending on the type of the process either equation (6), (7) or (8), (9) are applied to find the updated value of the learner phase [10].

III. THE PROPOSED MODIFIED TEACHING LEARNING BASED OPTIMIZATION ALGORITHM

Modified Teaching-Learning-Based Optimization (MTLBO) is an enhanced version of TLBO, designed to improve optimization efficiency by combining the Teacher and Learner phases into a single update rule. This modification allows for a more compact, yet powerful search mechanism, improving both the convergence rate and solution quality. Inspiration Behind MTLBO Just like TLBO, MTLBO is inspired by the learning process for gaining knowledge in a classroom. Students (solutions) improve their knowledge (fitness) either by gaining knowledge from the teacher which is best individual in the population or by the peers within the population. However, MTLBO merges the two separate learning phases of TLBO into a unified learning strategy wich incorporates two random variables r1 and r2 along with the teaching factor TF.

III.1 PSEUDOCODE FOR MTLBO ALGORITHM

Start MTLBO
Initialize the population:
Create a population of solutions (random values within bounds).
Evaluate the cost of each solution.
Save the best solution as Globalbest.
Repeat for each iteration:
a. Calculate the followings:
Obtain population mean as (Popmean).
Obtain the overall individual best as (Popbest).
Obtain the teaching factor (TF = 1 or 2 randomly).
b. For each individual Xi in the population:
Pick a random peer X_k (not equal to X_i).
Set direction A:
If Xi is better than X_k → A = 1
Else → A = -1
Generate random values r_1 and r_2.
Update Xi using:
$X_{new} = X_i + r_1*(Pop_{best} – TF * Pop_{mean}) + A * r_2* (X_i - X_k)$
Keep X_{new} within bounds.
Evaluate X_{new} cost.
If X_{new} is better value than X_i, replace X_i.
If X_{new} is better value than Globalbest, update Globalbest.
c. Record the best cost of this iteration.
Repeat until maximum iterations are reached
Output: Best solution ($Global_{best}$)
End MTLBO

III.2 IMPROVED TEACHING LEARNING PROCESS

This study proposes a Modified Teaching–Learning-Based Optimization (MTLBO) algorithm that enhances the original TLBO framework by incorporating simultaneous dual learning from both the teacher and the student. Each randomly selected participant is initialized within predefined bounds, where every individual is represented by a vector of decision variables. Each solution is then evaluated using a cost function to determine its fitness. In each iteration, the algorithm computes the population mean and identifies the best-performing individual as the teacher. A teaching factor (TF), randomly selected as either 1 or 2, controls the intensity of the teacher's influence. At the same time, each solution is paired with a randomly selected peer. Direction coefficient (A) is then assigned according to their relative performance: if the individual outperforms its peer, $A = 1$ otherwise, $A = -1$. The individual is subsequently updated using a combined learning strategy that incorporates knowledge from both the teacher and the peer. This combine learning strategy enhances knowledge transfer within the population and improves the algorithm's ability to converge efficiently toward high quality solutions is represented in mathematical equation by (10). Given the highly nonlinear, multi objective nature of analog circuit design, the proposed MTLBO framework is particularly well suited for achieving faster convergence while maintaining robustness across complex design spaces.

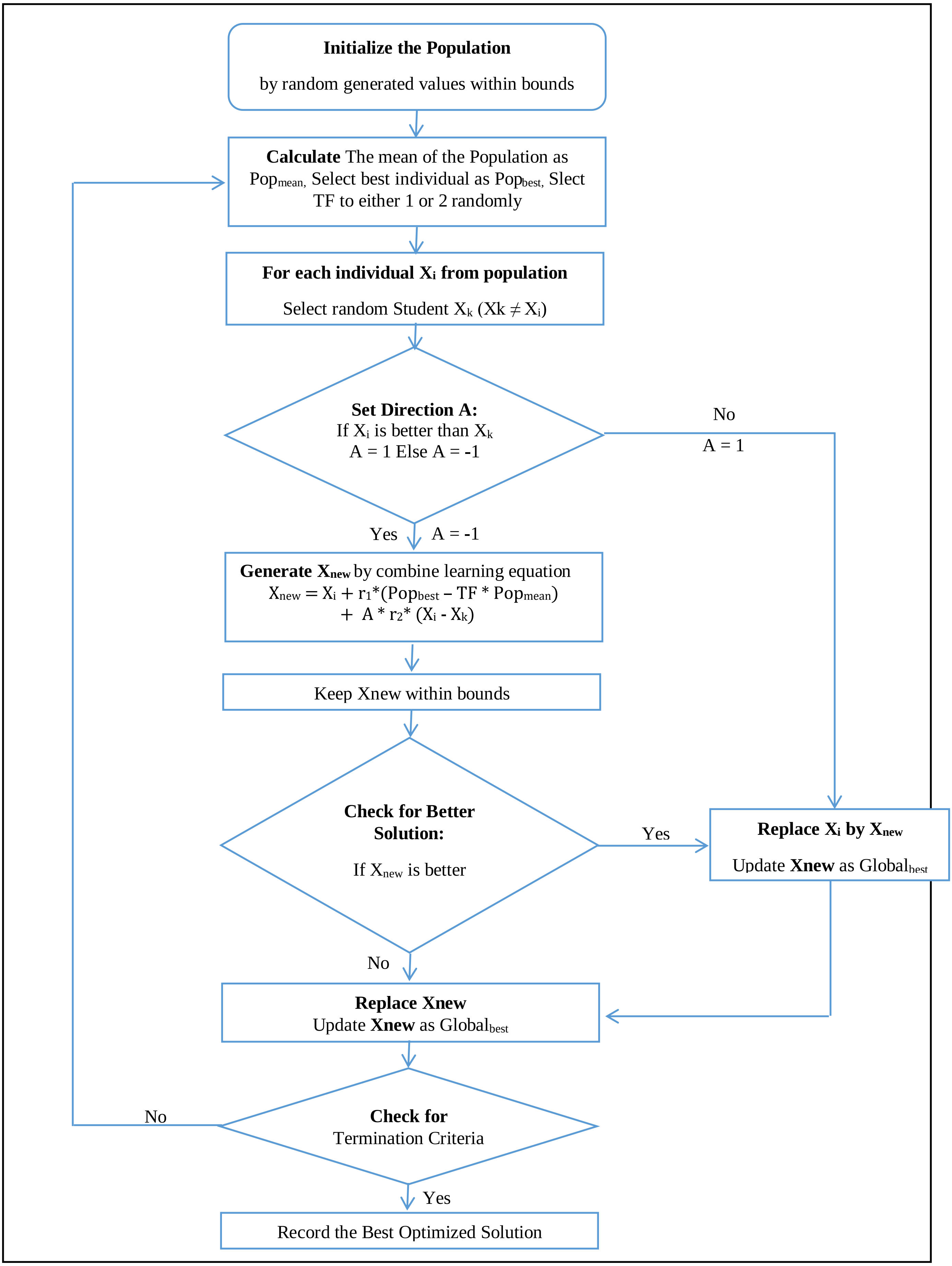

Figure 1: Flow Diagram of proposed MTLBO Algorithm.
Source: Authors, (2026).

$$X_{new} = X_i + r_1 * (Pop_{best} - TF * Pop_{best}) + A * r_2 * (X_i - X_k) \quad (10)$$

Where r_1 and r_2 are randomly generated coefficients. This formulation allows each individual to simultaneously learn from the best solution in the population and adapt based on its relative standing with a peer, thereby promoting a balanced exploration–exploitation trade-off. The updated candidate is bounded within the variable limits and accepted if it yields an improved cost. After all individuals are updated, the global best solution is identified and stored using greedy selection. The algorithm iterates until termination criterion is achieved, either reaching the maximum number of iterations or attaining acceptable convergence. The complete flow diagram of the MTLBO algorithm is shown in Figure 1.

IV. OPTIMIZATION OF TWO STAGE OPERATIONAL AMPLIFIER BY MTBLO ALGORITHM

The MTLBO algorithm is applied to optimize complex multidimensional CMOS analog circuit design problems. It was evaluated on the optimization of a critical CMOS based operational amplifier, which is the fundamental building block of Analog to Digital Converters and Digital to Analog Converters in modern VLSI mixed signal design [16]. Designing a two-stage operational amplifier is itself a multidimensional problem [17], where the sizing of each device parameter must be optimized to achieve required specifications such as gain, bandwidth, power, and area. The MTLBO algorithm automates the design of CMOS analog circuits by optimizing each transistor's width and length as design parameters to meet the desired specifications. The design process combines the MTLBO optimizer with a SPICE simulation environment, where each set of design values is evaluated using Ngspice to ensure that the circuit meets performance targets[18]. A fitness function based on the root mean square (RMS) error is used to measure how closely the simulated results match the desired specifications. The fitness function is calculated as by equation (11), where D is the total number of specifications.

$$Fitness\ Function = \sqrt{\sum_{j=1}^{D} \left(\frac{Specification_{desired} - Specification_{simulated}}{Specification_{desired}}\right)_j^2} \quad (11)$$

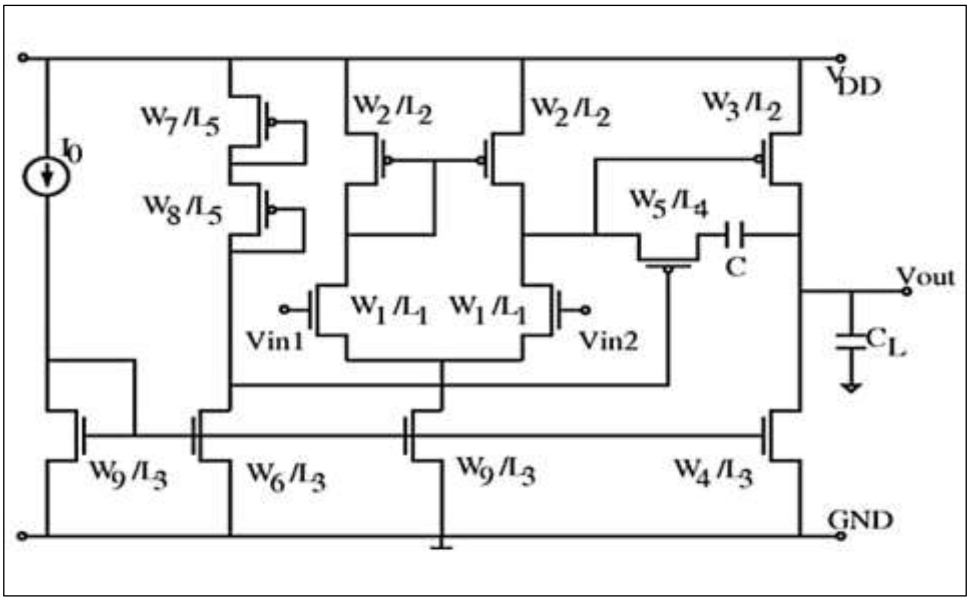

Figure 2: The Two Stage Operational Amplifier.
Source: Authors, (2025).

Table 1: Design Specification of two stage op-amp.

Sr. No.	Required Specifications
1	AC voltage gain AV > 80 dB
2	Phase margin > 60°
3	Unit gain bandwidth (UGB) > 100 MHz
4	Power Supply Rejection Ratio (PSSR) > 80 dB
5	Common Mode Rejection Ration (CMRR) > 80 dB
6	Rise Slew Rate (RSR) > 40 V/us
7	Fall Slew Rate (FSR) > 40 V/us
8	Power Consuption < 0.2µW

Source: Authors, (2026).

This RMS error formula gives equal weight to each specification. The optimizer's main aim is to minimize the fitness function value with each iteration until an acceptable level is reached. The process stops when either the fitness function falls below a set minimum (1e-6) or the maximum number of iterations (1000) is reached [19].

If the stopping criteria are not met, the optimization algorithm generates a new set of design parameters, and the cycle repeats. The two stage op-amp, shown in Figure 2, with design specifications listed in Table 1, represents the multidimensional design problem to be optimized [20]. The MTLBO algorithm is incorporated into the automated design environment, as illustrated in Figure 3, to obtain the desired optimum results.

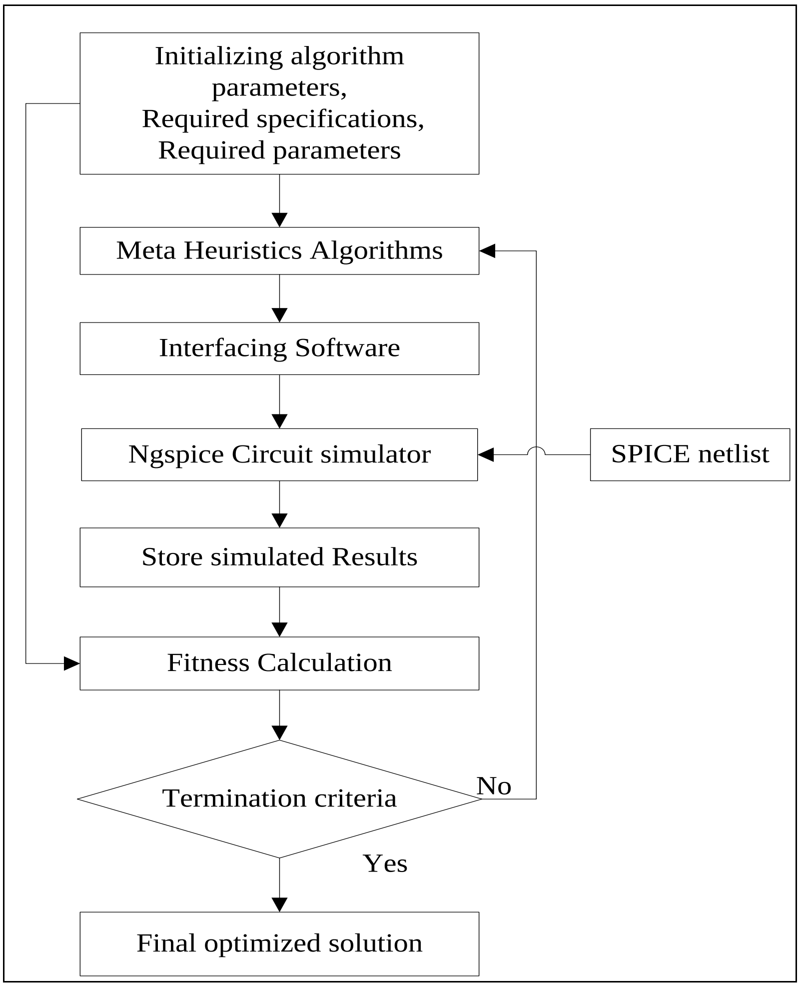

Figure 3: The Automated analog circuit design environment.
Source: Authors, (2026).

Table 2: Optimized parameters of two stage op-amp for the RAO, PSO, TLBO and MTLBO algorithm.

Design Variable	Variable Range	Obtained Parameters RAO	Obtained Parameters PSO	Obtained Parameters TLBO	Obtained Parameters MTLBO
W1 / L1	W: 0.5 to 10 (µm) L: 0.13 to 1 (µm) Transistor dimensions are in µm.	10.0 / 0.37	2.34 / 0.20	1.14 / 0.20	5.82 / 0.34
W2 / L2		0.52 / 0.23	0.50 / 0.20	0.96 / 0.28	2.64 / 0.26
W3 / L2		8.27 / 0.23	2.11 / 0.20	2.19 / 0.28	9.99 / 0.26
W4 / L3		5.24 / 0.20	10.0 / 0.71	1.97 / 0.20	2.93 / 0.35
W5 / L4		1.95 / 0.20	0.50 / 0.20	0.51 / 0.20	0.53 / 0.20
W6 / L3		1.58 / 0.20	9.15 / 0.71	4.86 / 0.20	2.95 / 0.35
W7 / L5		5.75 / 0.20	0.50 / 0.99	1.59 / 0.76	2.00 / 0.20
W8 / L5		10.0 / 0.53	0.50 / 0.99	2.48 / 0.76	5.71 / 0.20
W9 / L3		1.89 / 0.20	10.0 / 0.71	2.57 / 0.20	1.19 / 0.35
Io (µA)	0.01 to 10 µA	2.96	4.87	5.01	2.40
C (pF)	0.1fF to 10 pF	0.045	0.046	0.053	0.040

Source: Authors, (2026).

V. RESULTS AND DISCUSSIONS

The two-stage CMOS operational amplifier was designed using the PTM 45 nm CMOS process. Simulations were performed on an AMD Ryzen™ processor with 16 GB of RAM running a 64 bit Ubuntu operating system. The RAO, PSO, TLBO, and proposed MTLBO algorithms were implemented in Python, while circuit level simulations were carried out using Ngspice-26. For a fair performance comparison, a standardized test setup was used: each algorithm was initialized with a population size of 30, and the design dimension, representing the total number of transistor level variables was set to 16. The maximum number of iterations was fixed at 1000,

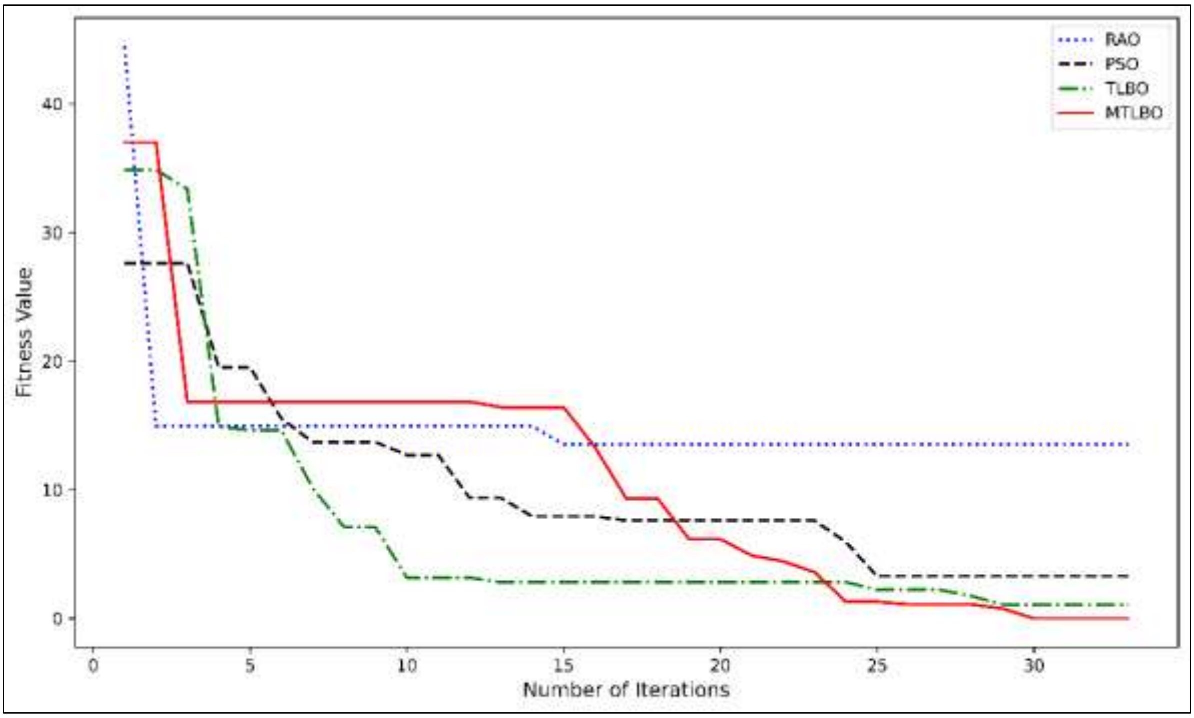

Figure 4: Convergence graph of op-amp for RAO,PSO, TLBO and MTLBO.
Source: Authors, (2026).

With a fitness function threshold of 1×10^{-6}, evaluated over 10 independent runs. The obtained design specifications using these algorithms are shown in Table 3, with the optimized design variables provided in Table 2. These results are compared with previously reported RAO, PSO, and TLBO algorithms. The two-stage operational amplifier optimized using the MTLBO algorithm meets all the design specifications. The convergence graph shown in Figure 4 demonstrates that MTLBO converges more rapidly compared to RAO, PSO, and TLBO algorithms. The performance comparison of the MTLBO algorithm with the other previously reported algorithms is presented in Table 4, which further confirms that MTLBO requires fewer iterations and achieves faster convergence than RAO, PSO, and TLBO.

Table 3: Obtained Specification of two stage op-amp.

Sr. No.	Required Specifications	RAO Algorithm (45 nm)	PSO Algorithm (45 nm)	TLBO Algorithm (45 nm)	MTLBO Algorithm (45 nm)
1	A_V > 80 dB	85.29 dB	84.76 dB	84.85 dB	**86.15 dB**
2	Phase Margin > 60°	71.47°	**73.90°**	66.68°	65.02°
3	UGB > 100 MHz	239 MHz	246 MHz	**268 MHz**	185 MHz
4	PSSR > 75 dB	91.16 dB	83.26 dB	80.75 dB	81.02 dB
5	CMRR > 80 dB	82.11 dB	80.44 dB	80.01 dB	**94.05 dB**
6	Rise Slew rate (RSR) > 40 V/ µs	64.71 V/ µs	**126.57 V/µs**	92.60 V/µs	49.26 V/µs
7	Fall Slew rate (FSR) > 40 V/ µs	**43.72 V/ µs**	40.21 V/ µs	40.37 V/ µs	40.25 V/ µs
8	Power Consumption < 0.2 µW	0.193 µW	**0.179 µW**	0.183 µW	0.196 µW

Source: Authors, (2026).

Table 4: Performance Comparison of Algorithms.

Sr. No.	Performance Parameters	RAO Algorithm	PSO Algorithm	TLBO Algorithm	MTLBO Algorithm
1	Number of Iteration (Max. 1000)	178	105	33	**28**
2	Swarm Size	30	30	30	30
3	Dimension	16	16	16	16
4	Average Time	541.21 s	291.25 s	188.73 s	**87.82 s**

Source: Authors, (2026).

VI. CONCLUSIONS

The two stage CMOS operational amplifier in PTM 45 nm technology has been effectively optimized using the proposed Modified Teaching Learning Based Optimization (MTLBO) algorithm. MTLBO achieves 86.15 dB voltage gain, 94.05 dB CMRR, and 185 MHz unity-gain bandwidth, while meets rest of the all target specifications. Comparative analysis shows that MTLBO converges faster and requires fewer iterations than PSO, RAO, and TLBO, confirming its suitability for analog circuit sizing. The optimized design demonstrates high gain, higher CMRR, and higher bandwidth most suitable for mixed signal applications. Limitations include the focus on transistor level sizing without accounting for process variations and temperature effects. Future work may extend this framework to other analog/mixed signal blocks, such as Operational Transconductance Ampifier (OTA), comparators, filters, oscillators, and ADC front end circuits, highlighting the scalability and adaptability of MTLBO in complex SoC design environments.

VII. AUTHOR'S CONTRIBUTION

Conceptualization: Sureshbhai Bharvad and Pankajkumar Prajapati.
Methodology: Sureshbhai Bharvad.
Investigation: Sureshbhai Bharvad and Pankajkumar Prajapati.
Discussion of results: Sureshbhai Bharvad and Pankajkumar Prajapati.
Writing – Original Draft: Sureshbhai Bharvad.
Writing – Review and Editing: Sureshbhai Bharvad and Pankajkumar Prajapati.
Resources: Sureshbhai Bharvad and Pankajkumar Prajapati.
Supervision: Pankajkumar Prajapati.
Approval of the final text: Sureshbhai Bharvad and Pankajkumar Prajapati.

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