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# Performance Optimization of Two Stage OTA Using Novel Modified Teaching Learning Based Optimization Algorithm

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***Abstract***
The Evolutionary algorithms have become an essential tool in computer-aided design for addressing complex optimization problems. However, their application in analog VLSI design is often constrained by high computational cost, large memory demand, and the necessity for fine tuning of parameters. To address these limitations, this work presents the design optimization of a two-stage operational transconductance amplifier (OTA) using PTM 45 nm CMOS technology. The Modified Teaching Learning Based Optimization (MTLBO) algorithm is employed, which eliminates the need for additional control parameters by mimicking the natural learning interaction between teachers and learners. The algorithm was implemented in Python and executed on an AMD Ryzen™ processor with 16 GB RAM under Ubuntu OS. Simulation results show that the optimized two stage OTA achieves the of 83.17 dB, higher unity gain bandwidth of 1.71 MHz with least power consumption of 3.24 μW. Comparative analysis demonstrates that MTLBO provides faster convergence with fewer iterations and outperforms other metaheuristic approaches, establishing it as a strong candidate for efficient, low power, and high performance analog CMOS circuit design automation. Future work may include extending the methodology to more complex analog and mixed-signal circuits, exploring multi-objective optimization.
***Keywords***: *RAO Algorithm, PSO Algorithm, TLBO Algorithm, MTLBO Algorithm, Optimization,* Operational Transconductance Amplifier (OTA).

## 1. INTRODUCTION

Analog and mixed-signal design continues to face increasing complexity due to shrinking CMOS nodes, nonlinear device behavior, and conflicting design objectives such as gain, bandwidth, power, and area. Conventional analytical sizing methods struggle to capture high-dimensional interactions, which has motivated the adoption of metaheuristic algorithms for analog VLSI design automation [1], [2]. Among these, Teaching Learning-Based Optimization (TLBO) stands out for its parameter less structure, inspired by teacher learner knowledge transfer. Unlike Genetic Algorithms or Particle Swarm Optimization, TLBO eliminates the need for algorithm specific tuning such as mutation rates, inertia weights, thereby simplifying deployment while retaining robustness in complex search spaces [3].
Recent studies have refined TLBO for engineering problems: adaptive TLBO with dynamic teaching strategies [4], self-adaptive and reinforcement learning TLBO [5], multi-objective TLBO with Pareto-based ranking [6], hybrid TLBO integrating PSO or Levy flights [7], and parallel/distributed TLBO for large-scale design problems [8], [9]. These advances consistently report faster convergence, reduced iteration count, and stronger global search capability, making TLBO increasingly suitable for time critical applications like analog circuit optimization.
Building on this, the present work applies a Modified TLBO (MTLBO) for the automated design of a bulk-driven two-stage CMOS OTA in PTM-45 nm technology. By fusing and streamlining teacher and learner phases, the proposed MTLBO reduces computational overhead while preserving diversity in the solution space. Implemented in Python and coupled with SPICE simulations, MTLBO is benchmarked against recent metaheuristic baselines to demonstrate its effectiveness in achieving high gain, wide bandwidth, and efficient power utilization.
Section 2 discuss about the teaching learning based optimization algorithm proposed by Rao et al. [13] with teacher and learner phase in brief. In section 3 Modified Teaching Learning Based Optimization (MTLBO) algorithm with enhanced teaching learning process is discussed. In the section 4 Proposed Automated Analog Circuit Design Environment using MTLBO Algorithm framework is discussed and applied this automated design frame work to two stage OTA design. In the section 5 results obtained from this automated design frame work by applying MTLBO algorithm is discussed. In the section 6 conclude this work and future scope of the work is discussed.

## 2. Teaching Learning Based Optimization

Optimization plays a crucial role in solving real world engineering and scientific problems, particularly those involving large scale, nonlinear, and complex systems. Traditional mathematical optimization techniques often face difficulties when dealing with non-convex, discontinuous, or high dimensional problems, thereby motivating the development of robust population based metaheuristic algorithms. The Teaching Learning Based Optimization (TLBO) originally proposed by Rao et al. [13] population based algorithm. Conventional algorithms such as Genetic Algorithms (GA), Particle Swarm Optimization (PSO), and Differential Evolution (DE), TLBO not require algorithm dependent parameters like crossover rate, mutation probability, or inertia weight. This parameter independent nature makes algorithm easy to implement and overcome the parameters fine tuning. The TLBO algorithm replicate the teaching learning process in two phases.

**Teacher Phase:** In this phase learners gain knowledge from the teacher which is the best solution in the population. Teacher guides the overall progress toward optimal results.

**Learner Phase:** In this phase learners enhance gain knowledge from interacting with peers, facilitating exploration and diversity in the search space.

By incorporating this dual mechanism, TLBO effectively balances exploration (searching new regions) and exploitation (refining search areas). The algorithm has demonstrated strong performance on multi-dimensional benchmark functions and real world applications, including structural design, mechanical engineering, scheduling, and optimization problem solving [14].

### 2.1 Teacher Phase

In this phase, the most competent learner in the population which is the best fitness candidate, is designated as the teacher. All other learners adjust their solutions by moving closer to the teacher's position, thereby assimilating knowledge from the teacher. During this process, the personal best of each candidate is determined, and the top-performing individual is appointed as the teacher. For initialization, two matrices each for teacher and learner are generated randomly for initial population within the required bound. 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 individual 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).

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

Here, 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.

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

### 2.2 Learner Phase

In this phase, learner gain the knowledge by interacting with peers within the population. This interaction is based on a comparative learning mechanism, where a learner updates its solution by learning from another randomly selected peer. If the peer exhibits superior performance (i.e., lower fitness value in the case of minimization problems), the learner modifies its position toward the peer; otherwise, the update is directed away from the peer.

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.

## 3. The Modified Teaching Learning Based Optimization (MTLBO) Algorithm

The Modified Teaching Learning Based Optimization (MTLBO) algorithm is a refined extension of the standard TLBO framework, specifically designed to improve optimization efficiency by integrating the Teacher and Learner phases into a single, unified update mechanism. In contrast to the conventional TLBO, where these phases are executed sequentially, MTLBO streamlines the process into a more compact yet effective learning strategy, thereby accelerating convergence and enhancing solution quality. Drawing its inspiration from the classroom learning environment, MTLBO models students (candidate solutions) who continuously improve their knowledge (fitness) either through guidance from the teacher (the best-performing solution) or through interaction with peers. The MTLBO algorithm merge the knowledge transfer mechanism into unified update equation which incorporates two random variables $r_1$, $r_2$ and the teaching factor (TF), to simultaneously balance exploration and exploitation.

The MTLBO algorithm reduces algorithmic redundancy by consolidating the two phases within the population. Which results in the algorithm is capable of achieving faster convergence without compromising solution quality, making it more effective for tackling high dimensional, nonlinear, and optimization of engineering manufacturing process [15].

### 3.1 Enhanced Teaching Learning Process

This study demonstrates the Modified Teaching Learning Based Optimization (MTLBO) algorithm, updated from the original TLBO framework by enabling simultaneous dual learning from both the teacher and peer learners within a single update step to improve optimization. This modification allows efficient knowledge transfer and reduces algorithmic redundancy while improving convergence speed. The algorithm begins with candidate solutions within the population, where each solution is represented by a vector of decision variables and bounded within the search space. Every candidate is evaluated using the problem's cost function which determines the fitness value. At each iteration the best performing candidate is identified as teacher and the population mean is computed. The influence of the teacher on the learners is moderated by the teaching factor (TF), which is randomly assigned a value of either 1 or 2. This factor essentially reflects the variability in teaching effectiveness, ensuring diversity in the learning process. In parallel, peer to peer learning is introduced. For each learner, a random peer is selected from the population, and a direction coefficient (A) is determined based on their relative performance:

If the learner outperforms the peer, A = +1, reinforcing the current trajectory. If the peer performs better, A = −1, encouraging the learner to move toward the peer's knowledge. Finally, the learner's solution is updated using a combined strategy that integrates both the teacher's influence and the peer interaction. In this way, each candidate simultaneously benefits from top down knowledge transfer (teacher guided exploitation) and lateral exploration (peer guided diversity). This dual mechanism strikes a balance between intensifying the search around promising regions and maintaining sufficient exploration of the search space, enabling MTLBO to converge efficiently toward optimal solutions. The combine strategy is demonstrated by the following equation (10).

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

In the MTLBO algorithm two random coefficients $r_1$ and $r_2$ are generated within the interval [0,1]. These coefficients regulate the relative contribution of teacher guided learning and peer interaction, ensuring stochasticity and diversity in the search space. Through this formulation, each learner simultaneously benefits from guidance by the best performing individual (teacher) and adaptive adjustment relative to a peer, which balance between exploitation (refinement around promising regions) and exploration (discovery of new areas in the search space).

Once the updated candidate solution is generated, it is projected back within the predefined variable bounds to maintain feasibility. The new solution is then evaluated against the objective function. If the updated solution demonstrates an improved cost compared to its previous state it is accepted otherwise, the original solution is retained. This greedy selection mechanism ensures that the population does not deteriorate across iterations within search space.

After all individuals in the population have been updated, the global best solution is identified and stored for reference in subsequent iterations. The algorithm continues this cycle of teaching learning updates until a termination criterion is satisfied, which may be either maximum number of iterations or achieving a satisfactory convergence threshold defined by the problem.

## 4. Optimization of High Gain Low Voltage Two Stage OTA using MTLBO Algorithm

### 4.1 Automated Analog Circuit Design Environment using MTLBO Algorithm

The Modified Teaching Learning Based Optimization (MTLBO) algorithm further applied to optimize the design of a two stage CMOS Operational Transconductance Amplifier (OTA), which is widely used in analog and mixed signal integrated circuits such as filters, oscillators, and ADC front ends. The OTA plays a significant role in signal amplification and conditioning, making its optimum design essential for overall system performance.

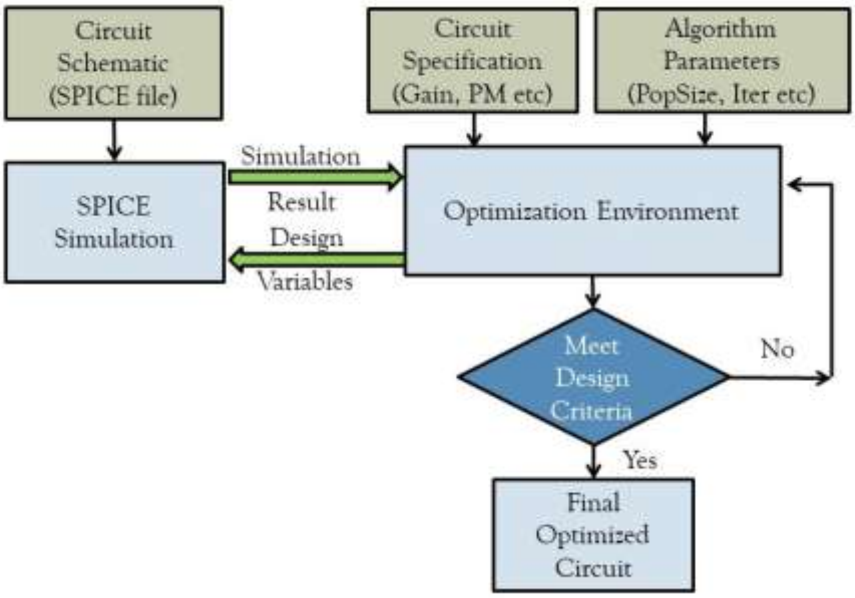


Figure 1: Automated analog circuit design environment.

The two stage OTA design is a multidimensional optimization problem, which requires the careful adjustment of transistor level parameters, primarily the width (W) and length (L) of MOS transistors to meet multiple design objectives simultaneously. These include high gain, sufficient bandwidth, low power consumption, improved slew rate, and minimal silicon area. Manual design makes it more challenging as it becomes multidimensional design problem motivates to automated intelligent design environment with the help of metaheuristic algorithm.

In this study demonstrates the MTLBO algorithm applied to automate transistor sizing in the two stage OTA design. Each candidate solution corresponds to a vector of transistor dimensions, which is simulated using a SPICE-based environment (Ngspice). This automated simulation framework as shown in Figure 1 provides accurate circuit level performance evaluations. To drive the optimization process, a fitness function is defined using the root mean square (RMS) error [16], which measures the deviation between simulated results and target specifications. The fitness function is calculated by equation (11).

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

Where, D represents the total number of design specifications considered in the optimization. The root mean square (RMS) error formulation ensures that all specifications are treated with equal importance, without bias toward any individual parameter. The main objective of the optimizer is to iteratively minimize the fitness function value, steering the design closer to the desired specifications. The optimization process continues until one of the stopping criteria is satisfied: either the fitness value drops below a predefined tolerance (1e-6) or the algorithm reaches the maximum number of iterations (1000). This iterative process repeats and gradually refining the design toward optimal results [17].

### 4.2 High Gain, Low Voltage OTA Design

The two stage Operational Transconductance Amplifier (OTA) is one of the most widely used building blocks in analog circuit design [18]. It plays a crucial role in many applications such as active resistors, active inductors, voltage controlled oscillators (VCOs), ADCs, DACs, and $g_m$-C filters. With the growing demand for low power and low voltage circuits the design of OTA become more critical.

Traditional MOSFET circuits face limitations in low voltage operation due to the threshold voltage barrier of the transistor. When the supply voltage is close to or below the threshold voltage, MOSFETs cannot operate effectively. To overcome this limitations, the bulk driven technique has emerged as a promising alternative [19]. In this method, the input is applied to the bulk (substrate) terminal of the MOSFET in place of the gate which bypasses the threshold voltage limitation and allow the MOSFETs to function properly even under very low supply voltages. A key advantage of this approach is that it does not require any modification to the MOSFET structure, making it compatible with standard CMOS fabrication technologies [20].
The bulk driven technique also have its own drawback: the transconductance $g_m$ of bulk driven MOSFETs is significantly lower which reduces the achievable gain of bulk driven OTAs, which can limit their performance of analog systems. To overcome this issue, the design presented in this work focuses on a high gain, low voltage bulk driven OTA. The schematic of the two stage OTA is shown in Figure 2. The design incorporates two key strategies: Cross coupled connection of input transistors M1A, M2B and M1B, M2A.
This configuration introduces a negative impedance effect, which effectively enhances the overall transconductance of the differential pair which enhance the small signal gain of the OTA [21]. Regulated current mirrors M12, M14, Ic and M11, M15, Ic stabilize the biasing currents and significantly improve the output resistance, which directly translates into a higher voltage gain for the OTA [22]. Through this combination of bulk-driven input stage, cross-coupling for transconductance boosting, and regulated current mirrors for gain enhancement, the two stage OTA achieves high performance suitable for low voltage applications.

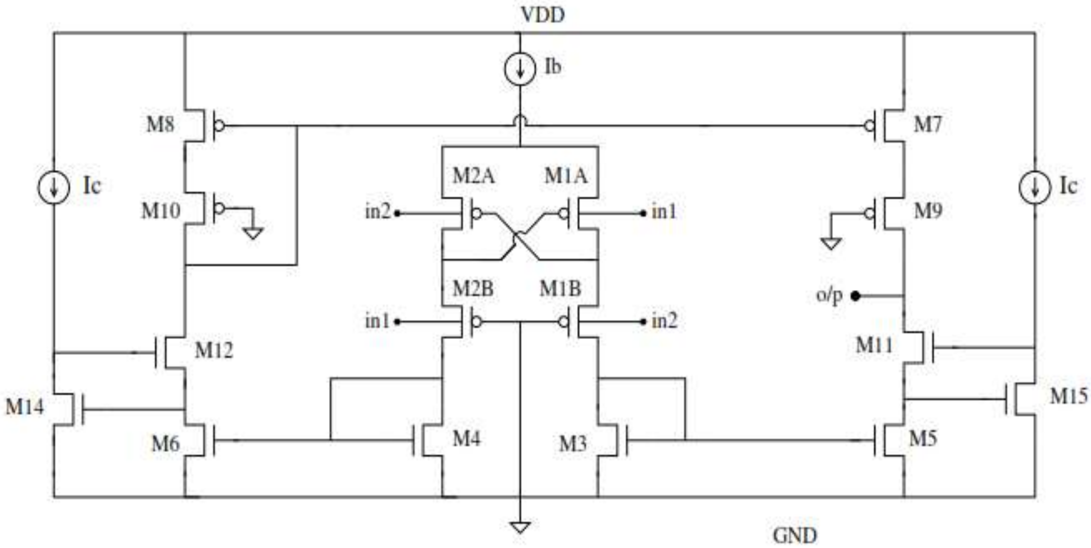


Figure 2: The Two Stage Operational Transconductance Amplifier.

## 5. RESULTS AND DISCUSSIONS

The two stage CMOS based Operational Transconductance Amplifier (OTA) was designed using automated analog circuit design environment in the PTM 45 nm CMOS process compared manual analog circuit design proposed in [23]. Simulations were performed on an AMD Ryzen™ processor with 16 GB RAM, running a 64-bit Ubuntu operating system. For optimization, four metaheuristic algorithms: RAO, PSO, TLBO, and the proposed MTLBO were implemented in Python and circuit level simulation carried out in the Ngspice-26 circuit simulator. To ensure a fair comparison across all algorithms, a common test setup was established. Each algorithm was initialized with, Population size: 30, Design dimensions: 11 (representing the total number of OTA design variables), Maximum iterations: 1000, Fitness value: 1e-6, Runs per algorithm: 10 (to capture robustness and consistency) to meet the design specifications listed in the Table 1. Within this automated optimization environment, each algorithm generated candidate OTA designs, which were then verified in Ngspice. After completing all runs, the best performing results from RAO, PSO, TLBO, and MTLBO were compared. The optimized transistor level parameters obtained from each algorithm are summarized in Table 2. While the achieved OTA design specifications are reported in Table 3 and compared with the previously reported work in [24] for same experimental setup, these experimental data show that MTLBO achieves higher gain of 83.17 dB, higher unity gain bandwidth of 1.71 MHz with least power consumption of 3.24 μW while achieving all design specifications within the range.

| Sr. No. | Required Specifications |
|---|---|
| 1 | Voltage Gain AV > 80 dB |
| 2 | Phase margin > 60° |
| 3 | Unit gain bandwidth (UGB) > 1.5 MHz |
| 4 | Rise Slew Rate (RSR) > 0.1 μV/us |
| 5 | Fall Slew Rate (FSR) > 0.1 μV/us |
| 6 | Power Consumption < 5 μW |

**Table 1:** Design Specification of two stage OTA.

| Design Variable | Variable Range | Obtained Parameters RAO (45 nm) | Obtained Parameters PSO (45 nm) | Obtained Parameters TLBO (45 nm) | Obtained Parameters MTLBO (45 nm) |
|---|---|---|---|---|---|
| M1A, M2A (W / L) | W: 1 to 100 (μm) L: 0.2 to 2 (μm) | 31.5 / 0.28 | 70.9 / 0.2 | 4.38 / 0.34 | 17.5 / 0.2 |
| M1B, M2B (W / L) | | 29 / 0.53 | 27.3 / 0.2 | 10.2 / 0.22 | 3.6 / 0.4 |
| M3, M4 (W / L) | | 27.6 / 0.2 | 33.2 / 0.2 | 1.52 / 0.2 | 6.01 / 0.2 |
| M5, M6, M11,M12 (W / L) | | 100 / 0.2 | 94.9 / 0.2 | 16.3 / 0.2 | 44.9 / 0.2 |
| M7, M8, M9, M10 (W / L) | | 96.3 / 0.2 | 46.8 / 0.2 | 3.90 / 0.2 | 4.14 / 0.2 |
| M13, M14 (W / L) | | 92 / 0.2 | 54.5 / 0.2 | 50.8 / 0.2 | 69.3 / 0.2 |
| $I_b$ (μA) | 0.1 to 2 μA | 1.93 | 1.43 | 0.66 | 0.95 |
| $I_c$ (μA) | 0.1 to 1 μA | 0.57 | 0.1 | 0.10 | 0.1 |

**Table 2:** Optimized parameters of two stage OTA for the RAO, PSO, TLBO and MTLBO algorithm.

| Sr. No. | Required Specifications | MPSO Algorithm (90 nm) [24] | RAO Algorithm (45 nm) | PSO Algorithm (45 nm) | TLBO Algorithm (45 nm) | MTLBO Algorithm (45 nm) |
|---|---|---|---|---|---|---|
| 1 | $A_V$ > 80 dB | 80.6 dB | 82.82 dB | 82.81 dB | 80.01 dB | **83.17 dB** |
| 2 | Phase Margin > 60° | 61.20° | **66.79°** | 62.55° | 61.29° | 61.97° |
| 3 | UGB > 1.5 MHz | 1.63 MHz | 1.51 MHz | 1.43 MHz | 1.60 MHz | **1.71 MHz** |
| 4 | Rise Slew Rate (RSR) > 0.1 μV/us | 0.24 μV/us | 0.30 μV/us | 0.25 μV/us | 0.32 μV/us | **0.33 μV/us** |
| 5 | Fall Slew Rate (FSR) > 0.1 μV/us | 0.24 μV/us | **0.27 μV/us** | 0.23 μV/us | 0.27 μV/us | 0.25 μV/us |
| 6 | Power Consumption < 5 μW | 4.16 μW | 4.82 μW | 4.21 μW | 3.53 μW | **3.24 μW** |

**Table 3:** Obtained Specification for two stage OTA.

| Sr. No. | Performance Parameters | RAO Algorithm | PSO Algorithm | TLBO Algorithm | MTLBO Algorithm |
|---|---|---|---|---|---|
| 1 | Number of Iteration (Max. 1000) | 31 | 57 | 46 | **23** |
| 2 | Swarm Size | 30 | 30 | 30 | 30 |
| 3 | Dimension | 11 | 11 | 11 | 11 |
| 4 | Average Time | 229.35 s | 1936.58 | 358.35 s | **203.78 s** |
| 5 | Successful Run (Out of 10) | 10 | 8 | 10 | **10** |

**Table 4:** Performance Comparison of Algorithms

A detailed performance comparison of the algorithms is presented in Table 4. The results demonstrate that MTLBO not only accelerates convergence but also consistently delivers stable, high-quality solutions, making it particularly well suited for multidimensional OTA optimization problems where both speed and precision are critical. Analysis shows that the proposed MTLBO algorithm reliably achieves all target specifications for the two-stage OTA. The convergence behavior of the algorithms is illustrated in Figure 3, where it is evident that MTLBO converges faster and requires fewer iterations compared to RAO, PSO, and standard TLBO.

The superior performance of MTLBO in OTA design can be attributed to its enhanced ability to manage conflicting design trade-offs. In a two-stage OTA, parameters such as gain, bandwidth, phase margin, and power consumption are tightly interdependent, where improving one metric often adversely affects others. Traditional algorithms like PSO or TLBO frequently become trapped in local optima when navigating these trade-offs, resulting in slower convergence or suboptimal solutions. In contrast, MTLBO's modified learning mechanism enables each candidate solution to simultaneously learn from both the global best design and peer solutions, achieving a more effective balance between exploration and exploitation. This mechanism facilitates rapid convergence toward configurations that satisfy high gain, low power, and wide bandwidth requirements, while maintaining strict adherence to design constraints.

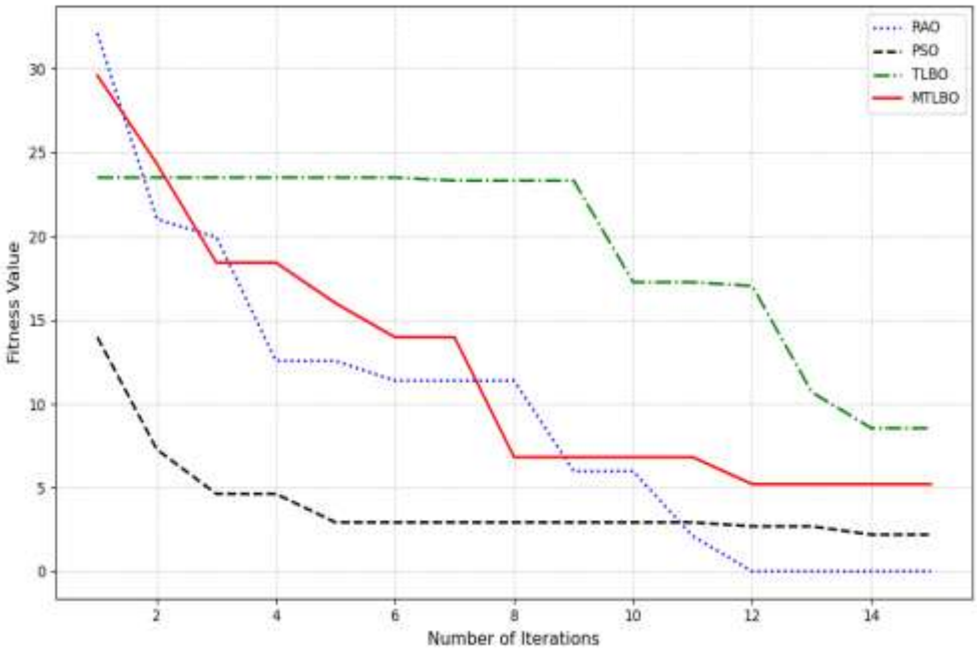


Figure 3: The Convergence graph of MTLBO algorithm with PSO, RAO and TLBO algorithms.

## 6. CONCLUSION

An automated optimization framework for CMOS-based two-stage OTA design using the MTLBO algorithm in PTM 45 nm technology is presented. The proposed approach effectively optimizes key performance metrics, achieving a gain of 83.17 dB, unity-gain bandwidth of 1.71 MHz, and power consumption of 3.24 µW. Simulation results confirm that the optimized OTA satisfies all target specifications. Compared to conventional algorithms, MTLBO demonstrates faster convergence and a more balanced trade-off among speed, power, and overall performance. These results highlight the effectiveness of MTLBO for analog circuit sizing, enabling compact, energy-efficient, and high-performance OTA designs suitable for modern mixed-signal and low-power VLSI applications. Future work will focus on extending this framework to other critical analog/mixed-signal blocks, including comparators, filters, oscillators, and ADC front-end circuits, further validating the scalability and adaptability of MTLBO in complex SoC design environments.

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