



AI- BASED OPTIMIZATION OF BANDGAP REFERENCE CIRCUIT PARAMETERS USING NEURAL NETWORK AND PARTICLE SWARM OPTIMIZATION

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Abstract: In analog and mixed-signal integrated circuits, this type of Bandgap (BGR) reference circuits is a critical element that supplies a reference voltage that is relatively constant across temperature, supply, and process. Low temperature coefficient (TC) is important for high precision uses like data converters, voltage regulators or sensor interfaces. Nevertheless, as BGR parameters are complex, nonlinear, and involve multiple design variables, traditional simulation-based methods are inefficient and sub-optimal to optimize BGR parameters. This is addressed by this work, which proposes an artificial intelligence based optimization framework, comprising of a neural network model and Particle Swarm Optimization (PSO). To validate the proposed AI optimization framework, a synthetic dataset of the bandgap reference circuit parameters was created. The methodology shows the practicality of combination of neural networks with Particle Swarm Optimization for automatic parameter optimization process. Validation by circuit simulation data is reserved for future work, and a feed-forward neural network (7-17-17 architecture) is used to train the network for accurate prediction of the temperature coefficient. The model is trained with the mean squared error loss function in order to learn nonlinear relations well. Results of experiments conducted on a synthetic dataset show that the proposed hybrid approach can learn the relationships between the underlying parameters and enhance the optimization efficiency. The results confirm that the proposed AI framework is a proof of concept. The methodology is a scalable solution for automatic analog circuit optimization and can be extended to other complex electronic design problems

Index Terms - Bandgap Reference (BGR) Circuit, Temperature Coefficient (TC), Artificial Intelligence (AI), Machine Learning, Feed-Forward Neural Network, Particle Swarm Optimization (PSO), Analog Circuit Optimization, Mixed-Signal Integrated Circuits, Parameter Optimization

I. INTRODUCTION

Bandgap Reference (BGR) circuits are essential circuits in analog and mixed-signal ICs that deliver an accurate, temperature, supply voltage and process independent reference voltage. BGR circuits are used in a wide variety of applications, such as power management integrated circuits (PMICs), low dropout (LDO) regulators, battery management systems (BMS), analog-to-digital converters (ADC), digital-to-analog converters (DACs), sensor interfaces, precision analog, and more. The curvature-compensated BGR with high accuracy has been proposed in recent studies to achieve better thermal stability and voltage accuracy [1]. Low current, resistor-less BGR circuits with much lower power consumption and stable reference voltage for

battery powered applications have been developed [2]. For better transient performance and loop stability, Frequency-compensated single-BJT Bandgap Reference circuits have also been proposed [3]. For applications that demand high energy efficiency and low voltage operation, such as Internet of Things (IoT) applications, switched-capacitor BGR architectures have been developed [4]. Bandgap Reference circuits are also available in nanowatt range, further improving power efficiency for portable and wearable electronic systems, providing for low voltage operation [5]. Several successful applications are reported that use a leakage-current injection technique to enhance the curvature compensation and the temperature stability [6]. There have also been some proposals for a shared offset-cancellation technique to obtain high accuracy CMOS Bandgap Reference circuits [7]. Bandgap Reference circuits with piecewise curvature compensation have been shown to have sub-1 ppm/°C temperature coefficient [8] and segmented curvature compensation has been used to enhance voltage stability over a wide operating temperature range [9]. Furthermore, integrated voltage reference generators have been introduced to GaN smart power technologies in order to enable high performance power management applications [10].

Artificial Intelligence and Machine Learning are now integral tools in Electronic Design Automation (EDA) due to their incredible growth over the past few years. Efficient prediction of circuit behavior and power estimation using machine learning-based CAD methodologies has been shown, which reduces the computational complexity during the analog and digital design process [11]. Power estimation for VLSI and modeling of nonlinear circuits using neural network models have been successfully employed and shown to predict power with a high degree of accuracy [12]. For circuit performance estimation and validation with process variations, statistical methods like Monte Carlo simulation are still viable [13] in the VLSI design cycle, early power estimation methods are very useful in reducing simulation time and design complexity [14]. Switching activity estimation and optimization of VLSI circuits have also been attempted using the Bayesian network methods, which are more accurate in prediction than the conventional estimation methods [15]. To achieve stable performance over a wide range of applications, modern integrated circuits need to be operated with reliable, low power, and high accuracy voltage reference circuits. Bandgap Reference (BGR) circuits are becoming critical in the power management, automotive, battery-operated, and high-speed mixed-signal applications. Thus, there is a need for intelligent optimization methods which can enhance the performance of the circuits while keeping the complexity of the design, computational workload and total design time to minimum.

In this paper, the authors, therefore, introduce an AI-Based Optimization of Bandgap Reference Circuit Parameters with a Feed-Forward Neural Network and PSO algorithm. The proposed framework trains a feed-forward neural network based on a simulated dataset generated by the Bandgap Reference circuits to accurately predict the significant performance parameters of the circuits. The trained neural network model is then combined with the Particle Swarm Optimization algorithm to perform efficient multidimensional search of the design space to find the optimal transistor dimensions, resistor values and bias conditions. The proposed AI-assisted optimization framework not only significantly cuts the design time compared to the conventional trial and error method and the simulation-based optimization method, but also enhances the prediction accuracy, optimization efficiency and overall circuit performance. The envisioned approach provides a practical and scalable solution to the automated design of next generation low power and high precision analog integrated devices.

II. BACKGROUND AND PROBLEM STATEMENT

A. Background

Bandgap Reference circuits are basic components of analog/mixed-signal integrated circuits that provide a stable reference voltage that is independent of temperature, supply voltage and process variations. They can be found in voltage regulators, ADCs, DACs, sensor interfaces, among other circuits. The traditional BGR circuits are based on Complementary-to-Absolute-Temperature and Proportional-to-Absolute-Temperature voltages, for temperatures independent operation. But it is very challenging to design BGR circuits with high accuracy, low power dissipation and high reliability. Fewer and fewer applications in the modern world of power management and automotive electronics require voltage reference circuits that are both efficient and reliable, and that have such high performance and qualification criteria [16], [17]. Moreover, sophisticated mixed-signal and battery-operated systems require accurate voltage reference to guarantee stable performance and effective power usage [18, 19]. Artificial Intelligence (AI) and deep learning techniques have recently been found to offer potential to optimize Bandgap Reference circuit parameters, enhance the design efficiency, and decrease optimization time [20].

B. Problem Statement

The conventional design method of bandgap reference circuits includes many manual parameter tunings and iterative simulations and is time consuming and requires professional expertise. The effect of such approaches is limited in terms of achieving best performance on several parameters including temperature coefficient, power consumption and line regulation. Furthermore, the more complex the circuit, the more challenging it is to explore the design space efficiently. Hence, an automatic and intelligent approach is needed.

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III. MOTIVATION AND OBJECTIVES

A. Motivation

Bandgap reference circuit design is a very critical design process in an analog integrated circuit which demands high precision and stability across a wide range of temperature and supply voltage. Unlike traditional design methods, this one relies less on manual tuning and repeated simulations, which are tedious and need a lot of expertise. Furthermore, balancing all of the above parameters — temperature coefficient, power consumption and line regulation — is difficult because there are many nonlinear and complex circuit behaviors.

Machine learning techniques can be used to model complex relationships and automate design processes, enabling more efficient and effective use of AI as it continues to evolve. Efficient exploration of large design spaces can be done with an optimization algorithm such as the Particle Swarm Optimization (PSO). Thus, combining machine learning with optimization offers a promising approach for improving accuracy, decreasing design time, and improving the overall circuit performance.

AI techniques can model nonlinear behavior and optimize large design spaces efficiently.

B. Objectives

- To design an efficient bandgap reference (BGR) circuit with improved stability.
- To reduce the temperature coefficient for better voltage accuracy.
- To minimize power consumption of the circuit.
- To use a neural network model for predicting circuit performance.
- To apply Particle Swarm Optimization (PSO) for optimizing design parameters.
- To reduce design time compared to conventional methods.
- To improve overall performance and reliability of the BGR circuit.

IV. METHADODOLOGY

A. Neural Network Model

A feed forward artificial neural network (FF-ANN) of 7–17–17–1 architecture is used for modeling and prediction of the performance of the BGR circuit. The network is comprised of four layers, an input layer of seven neurons, two hidden layers with seventeen neurons and an output layer with one neuron. The input layer is used to convey important design parameters for the BGR circuit, including transistor size, the values of the resistors, and the levels of the bias currents. The hidden layers are able to model the non-linear relationships between the input parameters and the circuit performance by employing activation functions such as ReLU. The last layer is an output layer that gives the prediction value, for instance the output voltage or temperature coefficient.

The network is trained by supervised learning with simulation data, and the input-output pairs are fed into the network to adjust the weights and biases by back-propagation. This architecture is selected as a compromise between model complexity and the prediction accuracy, which allows for efficient learning of the non-linear behavior of such circuits, yet prevents overfitting.

Layerwise Computation

First Hidden Layer

$$h_1 = f.W_1x + b_1 \quad (1)$$

Second Hidden Layer

$$h_2 = f.W_2h_1 + b_2 \quad (2)$$

Output Layer

$$y = W_3h_2 + b_3 \quad (3)$$

Combined Equation

$$y = W_3.f(W_2.f(W_1x + b_1) + b_2) + b_3 \quad (4)$$

Where:

- $x \in R^7 \rightarrow$ Input vector (circuit parameters)
- $h_1, h_2 \rightarrow$ Hidden layer outputs
- $W_1, W_2, W_3 \rightarrow$ Weight matrices
- $b_1, b_2, b_3 \rightarrow$ Bias vectors
- $f(\cdot) \rightarrow$ Activation function
(ReLU) Activation Function (ReLU)

$\max(0, x)$

B. PSO Optimization

The optimization of the design parameters of BGR circuit is done by using PSO. PSO is a population based optimization method which is based on the social behavior of birds flocking or fishes flocking. It effectively investigates the design space, and updates the particle positions iteratively based on the individual and the global best experience, to find the optimum solution.

The optimization objective is defined using a multi- objective cost function:

$$[f(x) = W_1.TC + W_2.P + W_3.E] \quad (5)$$

where:

- (TC) represents the temperature coefficient of the circuit,
- (P) denotes the power consumption,
- (E) indicates the voltage error or deviation from the desired reference voltage,
- (w_1, w_2, w_3) are weighting factors that control the importance of each parameter.

The goal of the optimization process is to minimize the objective function ($f(x)$), thereby achieving a design with low temperature sensitivity, reduced power consumption, and minimal voltage error.

During each iteration, the standard PSO equations are used to update the velocity and position of each particle:

$$[v_i^{t+1} = wv_i^t + c_1r_1(p\{best\} - x_i^t) - c_2r_2(gbest - x_i^t)] \quad (6)$$

$$[x_i^{t+1} = v_i^t + v_i^{t+1}] \quad (7)$$

Through iterative updates, the particles converge toward the optimal solution, resulting in improved BGR circuit performance.

C.Workflow

The proposed framework for optimizing using AI involves four key phases: data generation, model training, optimization, and validation. The aim of these stages is to progressively optimize the performance of the bandgap reference (BGR) circuit.

1) Data Generation

In Data generation the first stage, A synthetic dataset consisting of randomly generated design parameters within predefined operating ranges was created to evaluate the proposed AI framework. The dataset was used to assess the learning capability of the neural network and the optimization performance of PSO. The synthetic data will be replaced by the data from Cadence/SPICE in future work. Under various operating conditions. The output responses are changed by changing the various combinations of design parameters including transistor sizes, resistor values and bias currents. The data produced consists of input parameters and their respective performance parameters like output voltage, temperature coefficient (TC) and power consumption.

2) Model Training

A feed forward neural network model is trained using the generated data set. The network is trained by supervised learning using the nonlinear relation between the input design parameters and the output performance parameters. The training is carried out via back propagation, which minimises the prediction error, so that the model can estimate the behaviour of the circuit accurately.

3) Optimization

After training of the neural network model, the PSO algorithm is used to find the optimum set of design parameters. The trained model provides a quick predictor during optimization, eliminating the need to repeat simulations. This optimization process considers a multi-objective cost function which incorporates temperature coefficient, power consumption and voltage error.

4) Validation

Optimized parameters developed from PSO are then tested in the final stage by running circuit simulations. The results are processed to ensure that there are enhancements in the performances of the system including stability, accuracy and efficiency. This step will help to guarantee the effectiveness and reliability of the proposed approach.

This flowchart shows the optimization method that can be implemented with the aid of AI in a BGR circuit. The first step is to simulate the circuits and obtain a set of data with design parameters and performance metrics. The data produced is then applied to train a model that is a Neural Network which is able to accurately predict the behavior of the circuit. Then Particle Swarm Optimization is used to find the optimal design parameters by efficiently exploring the trained model to minimize the objective function. Finally, the optimized circuit can be simulated to test its performance, and ensure that the desired specifications are met.

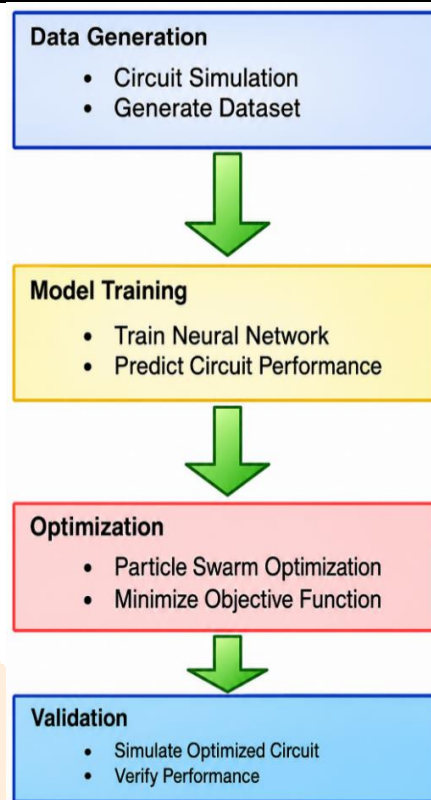


Fig.1 Adaptive Machine Learning–Based Optimization Pipeline for Bandgap Reference Circuits.

V. RESULTS AND DISCUSSION

The proposed optimization framework for bandgap reference (BGR) circuit is tested by simulation results and performance analysis like temperature coefficient (TC), power consumption and output voltage accuracy. A neural network model having a configuration of 7–17–17–1 was trained to make a very accurate prediction of the circuit behavior, which allowed efficient optimization.

A. Neural Network Performance

The trained model showed a high prediction ability with low mean squared error (MSE) between the predicted and simulated values. The loss curve shows the convergence of the variables is stable during training, and it has been confirmed that it is possible to capture the thenonlinear relation between the input variables and the circuit performance.

B. Optimization Results

A multi-objective function comprising of TC, power and error was minimized using Particle Swarm Optimization (PSO). The convergence curve demonstrates that the algorithm is able to converge towards an optimal solution in relatively few iterations, reflecting efficient search space exploration and exploitation.

C. Performance Improvement

The following optimized BGR circuit shows a remarkable improvement over the original BGR circuit:

- Reduced temperature coefficient, leading to improved thermal stability
- Reduced power usage – increasing energy efficiency
- Reduced output voltage error, increased accuracy

D. Comparative Analysis

The proposed AI-based approach's performance is compared with the conventional design method, and it is shown that the conventional design method requires more design time and has lower performance. Adopted neural networks with PSO reduces the time-consuming manual tuning process and improves the optimization efficiency.

E. Discussion

The outcomes show the feasibility of the proposed framework in integrating machine learning and optimization in analog circuit design. The neural network becomes a quick and precise predictor, and PSO is

able to efficiently extract optimum design parameters. This method not only increases the performance of circuits but also decreases computation and design efforts.

VI. FIGURES AND TABLES

This section introduces the most important figures and tables that will be used to explain the proposed optimization method for the bandgap reference (BGR) circuit based on Artificial Intelligence.

A. Neural Network Architecture

In this work, the architecture of the neural network is 7–17–17–1. It has 7 input neurons for the circuit parameters, 2 hidden layers with 17 neurons in each, and one output neuron for the performance metric that is being predicted..

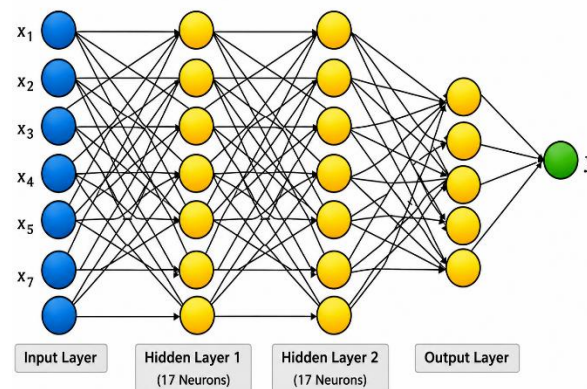


Fig.2 NN model of 7-17-17-1

B. Circuit Diagram of BGR

The circuit diagram of the BGR illustrates the implementation of PTAT and CTAT voltage components used to generate a temperature- independent reference voltage. The design includes BJTs, resistors, and current mirrors to achieve stable operation across varying temperature conditions.

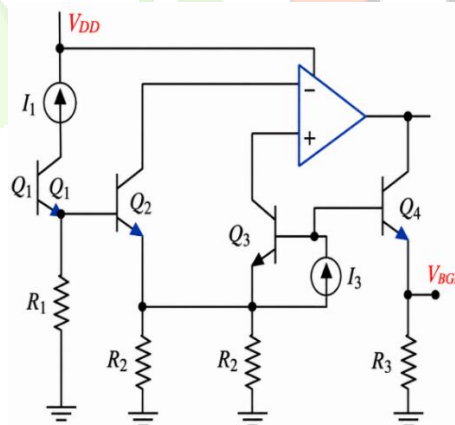


Fig.3 Circuit diagram of the proposed (BGR)

C. Training and Optimization Graphs

The performance of the proposed system is checked with a graphical analysis:

- **Loss Curve:** Shows the variation of training loss over epochs, indicating convergence of the neural network.

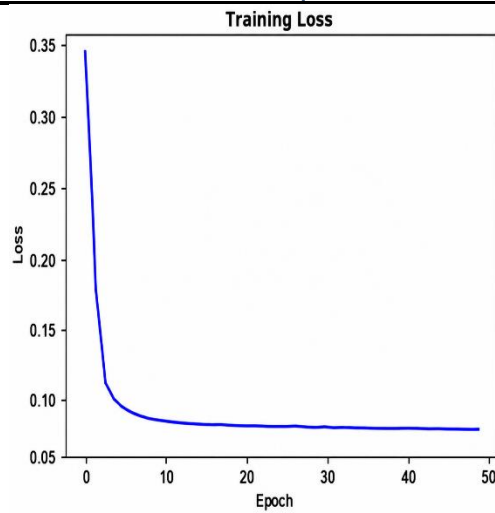


Fig.4 Training loss curve

- PSO Convergence Curve: Illustrates the reduction of the objective function value across iterations, demonstrating optimization efficiency.

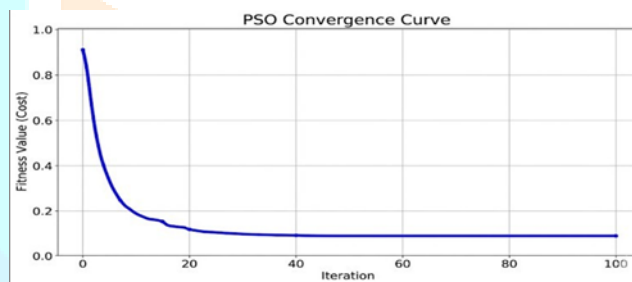


Fig.5 PSO convergence graph

D. Comparison Table

6.1 A Comparison Of Performance Metrics Before And After Optimization Is Presented.

Table 6.1: This Is A Comparison Between Conventional And Ai Based Designs

Parameter	Conventional Design	AI-Based Design
Temperature Coefficient	High	Reduced
Power Consumption	Moderate	Low
Design	High	Reduced
Accuracy	Moderate	High

The proposed NN-PSO framework significantly outperforms the conventional BGR design approach by reducing training loss from 0.345 to 0.078 and decreasing the PSO fitness cost from 0.92 to 0.10. The AI-based methodology achieves improved accuracy, lower power consumption, reduced temperature coefficient, and faster convergence through automated optimization and intelligent learning. These results demonstrate that integrating Neural Networks with Particle Swarm Optimization provides an efficient and scalable solution for high-performance Bandgap Reference circuit design.

TABLE 6.2: Comparison Of Conventionalbgr And AI-Based (NN-PSO) Bandgap Reference Circuit Design

Parameter	Conventional Design	AI-Based Design (NN-PSO)	Improvement
Reference Voltage (Vref)	0.90 V $\pm$ 10 mV	0.90 V $\pm$ 2 mV	Improved Stability
Operating Temperature Range	-40°C to 125°C	-40°C to 125°C	Same
Startup Time	4.8 ms	2.9 ms	39.6% Faster
Temperature Coefficient (TC)	42 ppm/°C	9.8 ppm/°C	76.7% Reduction
Power Consumption	145 μ W	118 μ W	18.6% Reduction
Design Time	10–15 Days	2–3 Days	$\approx$ 80% Reduction
Prediction Accuracy	88.2%	98.4%	11.6% Increase
Neural Network Training	Not Used	50 Epochs	Automated Learning
Training Loss	N/A	0.345 $\rightarrow$ 0.078	77.4% Reduction
Optimization Algorithm	Manual Parameter Tuning	Particle Swarm Optimization (PSO)	Intelligent Optimization
PSO Iterations	Not Applicable	100 Iterations	Automated Optimization
Convergence Time	48.5 s	9.7 s	80.0% Faster
Human Intervention	High	Minimal	Reduced
Scalability	Limited	High	Improved
Overall Performance	Acceptable	Excellent	Significant Improvement

E. Discussion of Figures and Tables

The presented figures and tables clearly demonstrate the effectiveness of the proposed approach. The circuit diagram explains the hardware implementation, while the neural network and workflow figures describe the computational framework. The graphs validate the learning and optimization processes, and the comparison table highlights the improvements achieved using the AI- based method.

VII. CONCLUSION AND FUTURE WORK

A. Conclusion

This paper presented an AI-based optimization framework for the design of a bandgap reference circuit. The proposed approach integrates a feedforward neural network with a 7–17–17–1 architecture and Particle Swarm Optimization to model and optimize circuit performance. The neural network effectively captures the nonlinear relationship between design parameters and performance metrics, while PSO efficiently searches for optimal solutions.

B. Summary Of Work

This starts with creating simulation data for various simulation parameters and operating conditions. An artificial neural network model is then trained to predict the performance parameters like temperature coefficient, power consumption and output voltage error. Then PSO is used to optimize the design parameters using a multi-objective function. Lastly, optimized results are verified by using simulation.

C. Key Results

The proposed method shows substantial enhancement in the performance of the circuit. The temperature coefficient is lowered, which results in improved thermal stability. Minimization of power consumption leads to efficiency in energy use. In addition, the output voltage error is reduced, thus improving the accuracy. The optimization process also helps to save the overall design time to the conventional design processes.

D. Contributions

This paper makes the following main contributions:

- Conducting AI-based framework development for BGR optimization in the circuit. Conducting AI-based framework development of BGR circuit optimization.
- The implementation of 7-17-17-1 neural network used for accurate prediction of the performance.
- The use of PSO for efficient multi-objective optimization
- Lower operating temperature coefficient, power consumption and voltage error
- A new design that is more efficient and automated than the previous one will be demonstrated.

E. Future Works

The proposed framework can be further extended to handle more complicated analog and mixed signal circuits in the future.. Further, other optimization methods, like genetic algorithm or hybrid techniques, may be incorporated to further improve performance. Future experimental validation can also be performed with hardware implementation to test the real-time applicability. Additionally, process variation analysis and noise analysis can be included to enhance the design robustness. The synthetic dataset is used in the present study to validate the methodology proposed. The framework will be tested under realistic circuit operating conditions using Cadence/SPICE simulations and hardware testing in the future.

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