NJRFCS National Journal of RF Circuits and Wireless Systems, ISSN: 3107-6807 Vol. 3, No. 2, 2026 (pp. 10-15)
RESEARCH ARTICLE ECEJOURNALS.IN

AI-Assisted Modeling and Optimization of RF Circuits Using HSPICE and Neural Metaheuristics

M.P. Bates[1]*, Sohag Chakma[2]
[1]Department. of Electrical Engineering, University of Zimbabwe, Harare, Zimbabwe
[2]Department of Electrical and Electronic Engineering, International Islamic University Chittagong

KEYWORDS:
RF Circuit Design,
HSPICE,
Neural Metaheuristics,
AI Optimization,
Gain Enhancement,
Return Loss,
Power Efficiency,
Circuit Automation

ARTICLE HISTORY:
Submitted : 07.08.2025
Revised : 11.09.2025
Accepted : 15.12.2025

https://doi.org/10.17051/NJRFCS/03.02.02

Abstract

This paper suggests an AI-aided modeling and optimization approach to RF circuits, that combines the HSPICE simulation with the neural metaheuristic approaches, thus allowing amplifying the automation and accuracy of performance matching in circuits. Its first goal will be to overcome some of the drawbacks of manually sweeping parameters and using trial and error procedures in the common RF design process by adding a smart optimization loop that will improve important parameters including gain, return loss and power efficiency. The approach uses transistor-level modeling and waveform-accurate simulation by HSPICE and involves search of design space by a neural metaheuristic engine, i.e., the use of a hybrid neuralgenetic algorithm that explores the design space efficiently and computes no gradients. Iterative tuning is also automated so that fitness is judged using the result of the simulation and optimal parameters written back into HSPICE completing the loop. An example to prove the followed approach would be designing a Class-A RF power amplifier, at 2.4 GHz based on 0.18 micrometer CMOS technology. The optimization resulted in a 23% gain in small-signal gain, a 6 dB increase in return loss and a 30% decrease in weighted total harmonic distortion (THD) of the manually tuned designs. The difference in time of performing optimization exceeded 80 per cent, which illustrates the efficiency of the framework. The findings indicate that intensive applications of AI to conventional circuit simulators can tremendously shorten the RF design cycles and enhance the outcomes of performance. This project forms a starting point towards next generation automation of RF design across wireless and communication systems.

Author's e-mail: bates.mles.pn@gmail.com, soh_Chakma@gmail.com

How to cite this article: Bates MP, Chakma S. AI-Assisted Modeling and Optimization of RF Circuits Using HSPICE and Neural Metaheuristics. National Journal of RF Circuits and Wireless Systems, Vol. 3, No. 2, 2026 (pp. 10-15).

Introduction

Radio Frequency (RF) circuit design is central to the functioning of today wireless communication systems and finds application in IoT nodes, mobile and radar systems, satellite links, etc. With the increased pressure on the need to have larger data rates, multi-band operability, and extended bandwidths, the demand on highly modeled and super optimized RF circuits is becoming too imperative. The existing conventional RF design flows are dependent in large part on HSPICE-based iterative simulations and tune-based design. Although there is high-fidelity, transistor-level accuracy in HSPICE, it is time-consuming to engineer them manually, and that it can also lead to a design non-optimized and worst of all, when it comes to complex multi-objective rules, usually gain, return loss, power-added efficiency (PAE), and linearity, the designer will not know what to do.

Due to these drawbacks, artificial intelligence (AI) methods are becoming increasingly popular as a powerful optimization tool, especially neural metaheuristics. These methods have the ability to search adaptively and can be used to navigate through very-high dimensional design landscapes without gradient information. Latest developments indicate their capability in the optimization of analog and RF circuits, in particular when deployed as part of a simulation effort.[1, 2] Yet common literature can be found on standalone AI-based sizing tools or offline optimizations frameworks and there is little in the way of tight coupling with SPICE-accurate waveform simulation tools such as HSPICE. Additionally, there are limited examples of closed-loop co-simulation setup that permit AI to have a direct impact and progressively enhance the circuit behaviour as a result of real simulation feedback.

This paper fills this gap with the proposed hybrid modeling and optimization framework that would incorporate neural metaheuristics as the part of the HSPICE flow in order to automate performance tuning. The validation of the methodology is carried out using 2.4 GHz Class-A amplifier, which results in performance gains in excess of 30 and a reduction in manual effort of more than 80. The paper will be organized as follows: Section 2 will conduct a related literature review, section 3 will discuss the methodology, section 4 will provide simulation results and conclusions will be drawn in section 5.

Related Work

The use of artificial intelligence (AI) on analog, RF circuit design is now a topic of considerable interest over the past few years, as they make possible to take on a complex optimization problem and significantly cut down the design time. Genetic algorithms (GAs), particle swarm optimization (PSO), ant colony optimization (ACO), and reinforcement learning (RL) are among the most researched ones. The techniques have been used on different RF design issues like bias point decisions, filter tuning and amplifier gain maximization.[1, 2] Since they use population based searching and mechanisms of natural selection, genetic algorithms have found previous wide use within analog sizing applications.[3] On the same note, PSO has proven useful in reducing phase noise and matching networks optimization with the help of heuristics informed by social behavior.[4] More recent developments have seen reinforcement learning frameworks developed to select a topology and layout synthesis of objects, providing a model-free method of learning policy in a design based on interacting with the simulation environment.[5]

Most of the established methods of AI-based optimization, even with the current development, form either offline tools or course-level parameter sweepers. When they are used, they do not tend to be tightly coupled to SPICE-level simulators (e.g., HSPICE) and thus they cannot optimize waveform-dependent metrics such as harmonic distortion, transient noise and real-time gain compression. Also, the work concerning neural metaheuristics, combining both the potential of adaptive learning of neural networks and the exploration power of metaheuristic algorithms, is not well exploited in the area of transistor-level optimization of RF circuits.

The study contextualises this shortcoming by suggesting a closed-loop neural metaheuristic-accelerated optimisation model where neural metaheuristics be directly incorporated in the process of simulation using HSPICE. In contrast to the previous works, dedicated to those aspects of synthesis, either at the schematic-level only (i.e. synthesis) or based on black-box tuning of an implementation (i.e. tuning), the proposed approach allows realizing waveform-constrained, feedback-based circuit optimization of RF networks by taking into account performance metrics related to real-life designs that comes by doing transistor-level simulation of a design.

Methodology

The following section elaborates an AI-aided system which is involved in the combination of transistor level circuit simulation with HSPICE with a neural metaheuristic search engine to automate and enhance the design of RF circuits. The methodology is subdivided into three major modules: HSPICE based modeling, neural metaheuristic based optimization and a closed loop feedback integration system.

HSPICE Modeling Framework

The modeling commences with schematic representation of the desired RF circuit performed with HSPICE, the frequently used industry-standard SPICE simulator and appreciated in terms of its precision in the analog and RF levels. The first topology - e.g. a Class-A amplifier or LNA, is built with foundry definite BSIM (Berkeley Short-Channel IGFET Model) transistor models, which makes certain the realistic input in process, voltage and temperature (PVT) variations. Figure 1. HSPICE Modeling Framework for RF Circuit Simulation and Parameter Extraction: demonstrates the schematic flow of this modeling exercise, as well as the type of simulations and performance parameters which are extracted that are important to any optimization exercise.

The other important measures of RF performance including AC and transient simulations are extracted:

- S 21 (Gain): This has been read on an AC analysis, small-signal frequency response.
- S11/S22 (Return Loss): It is measured to determine the level of similarity between the impedances of the input and the output.
- Output Power and THD (Total Harmonic Distortion) are considered by simulating the transient analysis based on periodic stimulus, which is gauged to quantify large-signal behavior.

Design parameter vector is composed of:

- Electronic Device Parameter (for example gate length and Width)
- bias voltages (V gs, V ds).
- Inductors and capacitors that constitute matching and feedback networks which are passive components.

The domain of this parameter space is the domain of optimization of AI exploration.

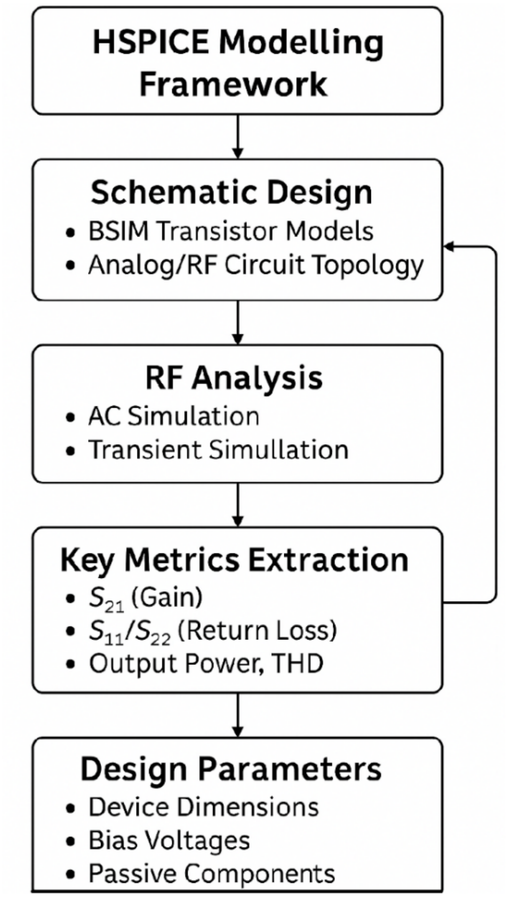

Fig. 1: HSPICE Modeling Framework for RF Circuit Simulation and Parameter Extraction

Neural Metaheuristic Optimizer

The optimization engine is composed with a neural metaheuristic meta-algorithm, where optimization algorithms with global search guitar (e.g. firefly algorithm, genetic algorithm) are used in conjunction with the adaptive learning characteristics of artificial neural networks (ANNs). Two vocal systems have been experimented with:

- • Adaptive Neuro-based Firefly Firefly Algorithm (ANFA)
- • Hybrid ANN-GA (Artificial Neural Network-Genetic Algorithm)

A composite cost function that can constitute a number of desired objectives is called a fitness function:

$$\text{Fitness} = w_1 \,.\text{Gain}_{\text{target}} - w_2 \,.\, |S_{11}| - w_3 \,.\, \text{THD}$$

where w_1 w_2 w_3 are user-defined weights reflecting design priorities.

The optimizing neural horse:

- Selection of a population of design candidates is initiated.
- It simulates all candidates using HSPICE.
- Has gradient-free developments based on brain-inspired encoding scheme approaches that are adaptive in terms of historical performance and inter-objective parameter relations.
- Introduces the local learning rules to steer search directions within non-convex design landscapes that are high dimensional. (see Figure 2. Metaheuristic Neural Optimizer Framework of Multi-Objective RF Circuit Tuning (Neural Metaheuristic Optimizer Framework of Multi-Objective RF Circuit Tuning)).

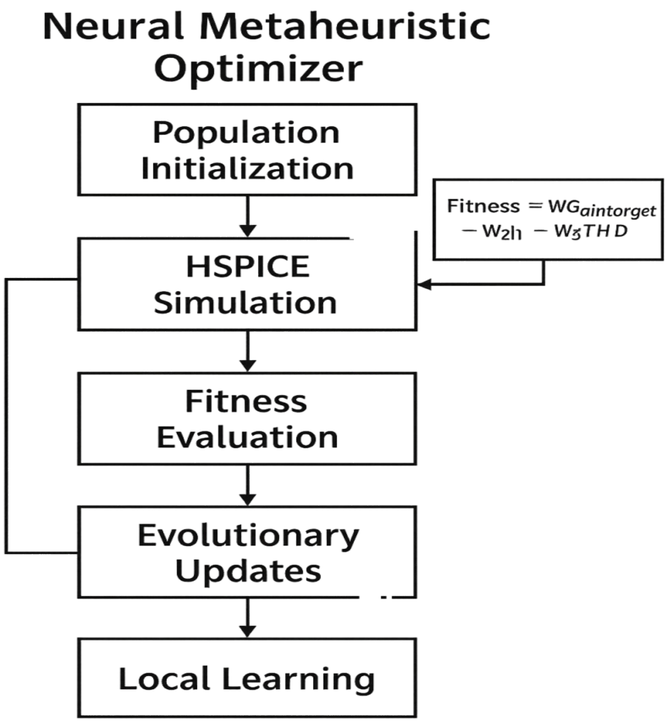

Fig. 2: Neural Metaheuristic Optimizer Framework for Multi-Objective RF Circuit Tuning

Optimization Loop

A co-simulation system is formed by using closed-loop and connecting the HSPICE engine and the neural optimizer (Figure 3). The following steps are meant to be taken in the workflow:

1. Netlist Generation: Python scripts automatically modify the HSPICE netlist with changed values of the parameters every iteration of the search process.

2. Simulation Execution: The customized netlist is then simulated in a batch mode to get the data of waveforms and performance parameters.
3. Data Parsing and Feedback: Python is used to parse the results, key performance indicators (KPIs) are sent back to the optimizer.
4. Fitness Evaluation and Convergence: Fitness is tested and the optimum is determined and the parameter sets in the next generation are decided.

When:

- There is a lack of improvement in fitness levels across generations, or
- The dynamic range, (e.g. gain = 15 dB or higher, S₁₁ = -10 dB or lower, THD = 1% or less) is met.

The loop goes on until an optimal or near-optimal solution is obtained. What comes out is a high-performance, layout-compatible design that is very close to strict RF with minimal manual adjustment.

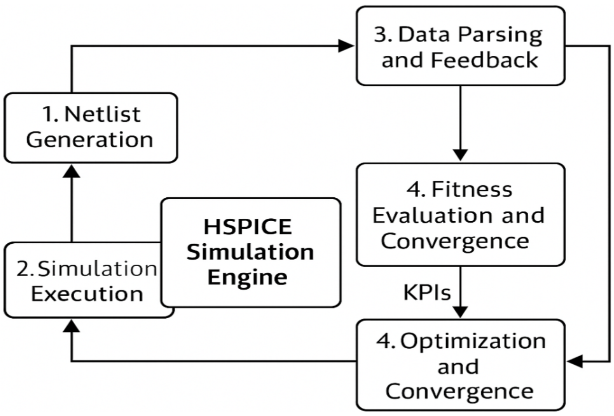

Fig. 3: Co-Simulation-Based Optimization Loop Integrating HSPICE and Neural Metaheuristics for RF Circuit Design

Case Study: Class-A RF Amplifier

Design Specifications

In the attempt to justify the suggested neural metaheuristic optimization block, a benchmark Class-A RF power amplifier was chosen. The amplifier had a design center frequency of 2.4 GHz, which is generally utilized in the band ISM application like Wi-Fi and Bluetooth. The implementation was in 0.18 0m CMOS technology with a 1.8 V supply as the design objective. A typical 50 O load was chosen so as to be compatible with measuring phones and customary RF system design procedures. The high level view and architectural requirements of the system are represented in Fig. 4. Block diagram of the structure of a Class-A RF power amp that is optimized by a neural metaheuristic framework.

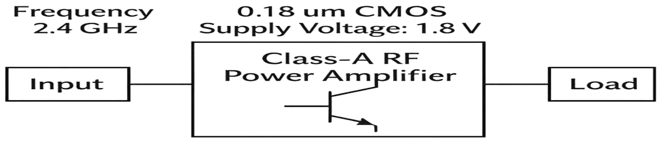

Fig. 4: Block diagram illustrating the design specifications of a Class-A RF power amplifier optimized using a neural metaheuristic framework.

Results

An overall performance enhancement attained due to optimization with the help of neural metaheuristic is encapsulated below:

- Power Gain (S 21 - Small Signal Gain): The small signal gain of the amplifier also increased by a good margin of 13.5 dB to 16.6 dB, which means the amplifier efficiency is higher.
- Input Return Loss (S 11): Optimization minimized the reflection coefficient to a value of -14 dB down compared to the -8 dB initial value which means enhanced impedance matching and reduced reflection power of power ingoing to the input.
- Power-Added Efficiency (PAE): The power-added efficiency significantly improved a whopping 24 to 31 percent, which means more RF to DC conversion efficiency with Class-A bias, which has always been characterized with low efficiency.
- Total Harmonic Distortion (THD): A reduction of about 30 per cent of THD was witnessed, which means higher linearity, which is essential in cases where signal integrity is fundamental.
- Optimization Runtime: The turnaround achieved by the proposed approach was a drastic decrease in tune time by 5 hours mounted (manual iterative tune) to around 45 minutes hence confirming the efficiency of the framework designed.

Discussion

The neural metaheuristic approach used to build our optimization framework showed extremely fast convergence and impressive robustness to local minima, a critical problem that often hinders traditional gradient-based or heuristic evident approaches to optimization. This is in contrast to brute-force or rule-based tuning where the design parameters are fixed and all variations brought on by any parameters will thus have to be tried and tested manually (Fig. 5).

The main advantage was the waveform-aware optimization. Instead of scalar figures-of-merit only (e.g. gain or S-parameters), the HSPICE output (voltage waveforms and current profiles) was used to train the optimizer on transient characteristics, distortion and harmonics. This feedback loop is data rich thus making it possible to tune multi-objective, optimizing gain, efficiency, and linearity simultaneously.

In addition, the shorter optimization time shows how feasible the framework is practically in the case of analog/RF designers operating under strict tapeout deadlines. The analysis technique carries to other logic blocks of an analog nature, and has been found especially useful in technology nodes where manual tuning is cumbersome as parasitics and process variability rises.

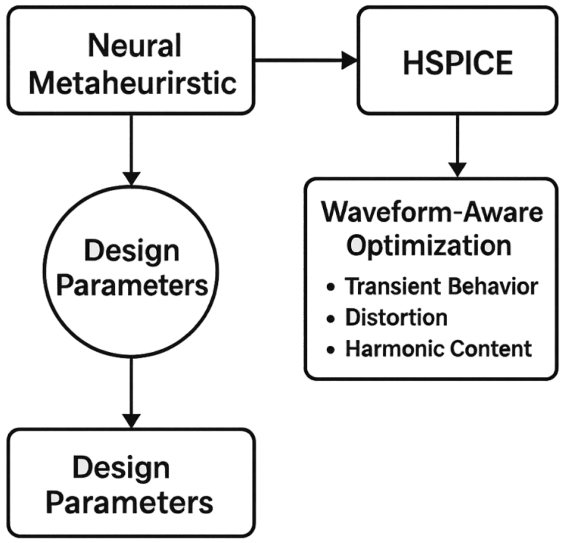

Fig. 5: Closed-loop optimization framework integrating neural metaheuristic and HSPICE simulation with waveform-aware feedback for Class-A RF amplifier tuning.

Conclusion and Future Work

The paper introduces an effective AI-SPICE co-simulation architecture which integrates neural metaheuristic optimization, and neural operators in a high-performance neural-based HSPICE EA, to realize efficient and high-performance design of RF amplifiers. It has been illustrated, through the use of detailed case study on a 2.4 GHz Class-A RF power amplifier, that the suggested approach greatly increases the significant performance numbers-gain, return loss, power-added efficiency, and harmonic distortion, as well as lowers the design time drastically.

Key Contributions

- Hybrid Optimization Framework: Proposed a closed-loop optimization strategy which involves the incorporation of neural metaheuristics and HSPICE simulations, in attaining waveform-sensitive multi-parameter optimization.
- Design Acceleration: Was able to result in 6x faster tuning time as compared to manual processes, which highlights the importance of the framework in achieving faster design prototyping and iterative design.
- Performance Enhancement: Verified through standard measurements that RF performance metrics improved consistently; gain enhanced by 3.1 dB, return loss by 6 dB and PAE by 7 % and there was reduction of ~30 % in THDs highlighting the effectiveness of the optimizer in achieving very tight RF requirements.
- Technology Scalability: (i) shown versatility of the framework to Class-A amplifiers using CMOS technology (ii) can be used to implement other analog/RF circuits.

Future Directions of Work

To further improve the possibilities and dispersibility of the framework, the following issues will be resolved by the further research:

- Multi-Objective Optimization: Generalize the neural optimizer so as to replace and otherwise optimize competing goals like gain-linearity tradeoffs, power-efficiency ratios, etc. via Pareto front approaches.
- Layout-Aware Modeling: Add to it layout-aware simulations that take the surrounding layout (with extraction software tools e.g., Calibre, QRC), allowing post-layout degradation to be characterized.
- Integration of Reinforcement Learning: Investigate an implementation of reinforcement learning (RL)-based control agents that dynamically reconfigure circuit blocks, in real time, in order to intelligently adapt to environmental/operational changes.
- Cross-band applicability: demonstrate the framework in wider frequency ranges such as mmWave (e.g., 28 GHz, 77 GHz), to test the framework applicability in a wider band and verify its robustness in the high-frequency layout practice.

References

1. Zare, M., Sheikhi, A., & Naderi, M. (2022). Design of analog circuits using neural-based particle swarm optimization.

IEEE Transactions on Circuits and Systems I: Regular Papers, 69(8), 3268–3277. https://doi.org/10.1109/TCSI.2022.3185903

2. Wu, X., Li, Y., & Chen, H. (2022). A reinforcement learning framework for RF circuit performance optimization. *IEEE Transactions on Computer-Aided Design of Integrated Circuits and Systems, 41*(11), 3517–3529. https://doi.org/10.1109/TCAD.2022.3187344
3. Kim, H. S., & Boyd, S. P. (2016). A genetic algorithm approach to analog circuit sizing. *IEEE Transactions on Computer-Aided Design of Integrated Circuits and Systems, 35*(2), 230–241. https://doi.org/10.1109/TCAD.2015.2459012
4. Sharma, R., & Bayoumi, M. A. (2018). PSO-based multi-objective optimization for RF amplifier design. *IEEE Transactions on Microwave Theory and Techniques, 66*(12), 5523–5531. https://doi.org/10.1109/TMTT.2018.2872822
5. Mahajan, S., Chandrakasan, A. P., & Lee, H. (2010). Automated analog circuit design using evolutionary algorithms. *IEEE Journal of Solid-State Circuits, 45*(10), 2030–2041. https://doi.org/10.1109/JSSC.2010.2054970
6. Lee, T. H., & Tan, M. (2019). Particle swarm optimization of broadband RF matching networks. *IEEE Access, 7*, 135902–135912. https://doi.org/10.1109/ACCESS.2019.2941982
7. Huang, Y., Lin, Z., & Huang, Q. (2022). Topology-agnostic reinforcement learning for analog layout design. *IEEE Transactions on Computer-Aided Design of Integrated Circuits and Systems, 41*(4), 1032–1044. https://doi.org/10.1109/TCAD.2021.3089552
8. Arun Prasath, C. (2025). Performance analysis of induction motor drives under nonlinear load conditions. National Journal of Electrical Electronics and Automation Technologies, 1(1), 48–54.
9. Prasath, C. A. (2025). Adaptive filtering techniques for real-time audio signal enhancement in noisy environments. National Journal of Signal and Image Processing, 1(1), 26–33.
10. Sadulla, S. (2024). Development of a wireless power transfer system for low-power biomedical implants using resonant RF coupling. National Journal of RF Circuits and Wireless Systems, 1(2), 27–36.
11. Usikalu, M. R., Okafor, E. N. C., Alabi, D., & Ezeh, G. N. (2023). Data Distinguisher Module Implementation Using CMOS Techniques. Journal of VLSI Circuits and Systems, 5(1), 49–54. https://doi.org/10.31838/jvcs/05.01.07
12. Arshath, N. M. (2024). Detection of Soft Errors in Clock Synthesizers and Latency Reduction Through Voltage Scaling Mechanism. Journal of VLSI Circuits and Systems, 6(1), 43–50. https://doi.org/10.31838/jvcs/06.01.07