

QUANTUM ENHANCED RF CIRCUIT PARAMETER OPTIMIZATION FOR LOW POWER IOT TRANSCEIVERS

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ABSTRACT

The number of low-power Internet of Things (IoT) devices is increasing, and efficient radio frequency (RF) circuit optimization techniques are becoming increasingly attractive because of their potential for enhancing the performance of communication systems without consuming too much energy. The authors introduce a Quantum-Enhanced RF Circuit Parameter Optimization (QERPO) framework in this paper, which integrates deep surrogate learning with quantum-inspired optimization to optimize the parameters of a low-power IoT transceiver. First, 10,000 circuit configurations are created for a simulated RF circuit. The configurations are then used as inputs to a deep surrogate learning model that is able to accurately predict various RF performance metrics with fewer electromagnetic simulation cases. A quantum-inspired optimization engine is then used to optimize several objectives simultaneously: minimizing power consumption, minimizing noise figure, maximizing gain, maximizing bandwidth, maximizing return loss, and maximizing power-added efficiency. It is experimentally proven that the proposed framework achieves better performance in terms of power consumption (13.4 mW), gain (20.3 dB), noise figure (1.48 dB), bandwidth (142 MHz), power-added efficiency (39.8%), and optimization error (0.045%) when compared with other conventional optimization methods like GA, PSO, DE, and BO. Furthermore, the proposed approach is faster than the existing optimization approaches as it includes surrogate learning and quantum-inspired search in the convergence process. Based on these results, it is concluded that the QERPO framework is an efficient, scalable, and computationally effective solution for designing energy-efficient RF transceivers, making it highly suitable for the next generation of IoT and future wireless communication systems.

Keywords: *Quantum-Inspired Optimization, RF Circuit Parameter Optimization, Low-Power IoT Transceivers, Deep Surrogate Learning, Multi-Objective Optimization, Energy-Efficient Wireless Communication.*

1. INTRODUCTION

The Internet of Things (IoT) is a rapidly developing technology that has greatly transformed

the landscape of wireless communication by connecting billions of intelligent devices capable of sensing, processing, and communicating information in real time. These IoT technologies are now widely

applied in many sectors, including smart city infrastructure, intelligent transportation, smart agriculture, environmental monitoring, industrial automation, and healthcare [1], [2]. The vast majority of these devices are battery-powered or operate using limited energy sources, making energy efficiency a key design criterion. Therefore, low-power radio frequency (RF) transceivers have become an important research area because the RF front end accounts for a significant portion of the total energy consumption in wireless sensor nodes and IoT devices [3].

An RF transceiver consists of several important analog and mixed-signal components, such as low-noise amplifiers (LNAs), power amplifiers (PAs), mixers, oscillators, filters, impedance matching networks, and frequency synthesizers. Good overall transceiver performance requires numerous circuit parameters to be optimized simultaneously, such as gate voltage, passive component values, operating frequency, bias currents, and transistor sizes [4]. These parameters are all highly nonlinear, and there are trade-offs in improving one performance metric at the expense of another. For example, lowering the power consumption can cause the amplifier gain to be lower, and increasing the bandwidth can cause the amplifier to have poor noise performance and high nonlinearity. Therefore, the problem of RF circuit design is inherently a multi-objective optimization problem where various conflicting objectives like power dissipation, gain, noise figure, bandwidth, return loss, stability, power-added efficiency, etc., need to be taken into account in the process of designing the circuit [5].

Most traditional RF design methods rely on the designer's experience, multiple electromagnetic simulations, and numerical optimization techniques in commercial electronic design automation (EDA) software [6]. Gradient-based optimization algorithms tend to take relatively few steps to converge to a solution, but they typically require the objective functions to be smooth, and they are very sensitive to initial solutions. These algorithms can be useful for the optimization of RF circuits; however, due to multiple local optima and nonlinear interactions between design variables, they can become mired in suboptimal solutions. Furthermore, for complex transceiver architectures, the optimization process is costly as many electromagnetic simulations are required repeatedly.

For better global search performance, RF circuit optimization has been taken up by several metaheuristic optimization techniques. Recently,

methods such as the Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Differential Evolution (DE), Simulated Annealing (SA), Artificial Bee Colony (ABC), Harmony Search (HS), Firefly Algorithm (FA), and Bayesian Optimization have shown superior exploration performance in complex design spaces compared to deterministic methods [8]. These techniques work well in searching for near-optimal solutions without requiring gradient information. Their performance, however, decreases as the size of the optimization problem grows. When used in large-scale RF integrated circuit design, the optimization process can be time-consuming, requiring circuit simulations to evaluate each candidate solution [9].

In recent years, intelligent optimization strategies based on artificial intelligence (AI) and machine learning have emerged to significantly accelerate RF circuit design. Surrogate models based on deep learning can be trained using previously generated simulation data to learn the nonlinear relationship between RF design parameters and circuit performance [10]. After training, these models can accurately predict performance metrics such as gain, power consumption, noise figure, and bandwidth without requiring time-consuming electromagnetic simulations. Automated RF circuit synthesis and parameter prediction using reinforcement learning, Gaussian process regression, graph neural networks, and transformer-based models have also been explored [11]. Although these techniques significantly reduce computational time, the optimization process is still often carried out using traditional search methods, which may not efficiently explore highly nonlinear, multidimensional parameter spaces.

Quantum computing has recently emerged as a promising paradigm for solving computationally challenging optimization problems that are difficult for classical algorithms. Although practical large-scale quantum hardware is still under development, recent advances in quantum-inspired optimization have generated significant interest in algorithms that mimic quantum mechanical principles such as superposition, probability amplitudes, quantum interference, and quantum rotation while operating on classical computers [12]. Unlike traditional optimization methods, which represent each candidate solution using a fixed encoding, quantum-inspired methods represent candidate solutions as probability distributions, enabling parallel exploration of multiple regions of the search space. This capability increases population diversity, enhances exploration of the search space, and

reduces the likelihood of premature convergence [13]. Consequently, quantum-inspired optimization has proven to be highly effective for solving complex engineering optimization problems involving high-dimensional and nonlinear search spaces.

Although significant progress has been achieved, the use of quantum-inspired optimization for RF circuit parameter optimization is still relatively limited. Previous studies have mainly focused on antenna design, wireless resource allocation, communication scheduling, or microwave filter optimization rather than low-power RF transceiver circuits. Furthermore, existing optimization frameworks do not effectively combine quantum-inspired optimization with intelligent surrogate learning models that can replace costly electromagnetic simulations during the optimization process [14]. Existing solutions also focus on optimizing only a limited number of RF performance parameters instead of simultaneously optimizing power consumption, gain, noise figure, bandwidth, impedance matching, return loss, and power-added efficiency. These limitations highlight a significant research gap in the development of intelligent optimization frameworks for next-generation low-power IoT transceiver design.

To address these challenges, this paper proposes a Quantum-Enhanced RF Circuit Parameter Optimization (QERPO) framework for low-power IoT transceivers. The proposed framework combines quantum-inspired optimization with adaptive deep surrogate learning to efficiently explore the RF design space while minimizing computational complexity. First, a deep neural network-based surrogate model is trained to accurately predict circuit responses for different design parameters. Next, quantum-inspired optimization uses adaptive quantum rotation operators to find the optimal transistor sizes, bias values, and passive component values by searching the design space. Recent studies have shown that reinforcement learning can be a powerful tool for automating the design of an RF circuit, significantly decreasing the number of design iterations required [15]. In addition, a multi-objective adaptive fitness function is designed to reduce power consumption and optimization error while increasing gain, bandwidth, power-added efficiency, and maximum power, and to match the load resistance as closely as possible while keeping the design within practical constraints. The proposed optimization strategy is well suited for balancing exploration and exploitation and achieves global optimal RF circuit

configurations in relatively few optimization iterations.

The proposed research is an important contribution to the intelligent RF circuit design area. First, it provides a hybrid optimization model combining quantum-inspired search and deep surrogate learning for RF parameter optimization. Second, it presents an adaptive quantum rotation mechanism, which enhances exploration capability and avoids early convergence during the optimization process. Third, a comprehensive multi-objective optimization model is developed to optimize multiple RF performance parameters under engineering constraints. Fourth, the surrogate-assisted optimization framework drastically decreases the number of expensive electromagnetic simulations, thereby reducing computational cost and optimization time. Last but not least, a thorough comparative performance analysis proves the superiority of the proposed framework compared to traditional optimization techniques with respect to convergence speed, optimization accuracy, power consumption, and the overall performance of the RF circuit.

The main objectives of this research are: (i) to design low-power RF transceivers using an intelligent quantum-enhanced optimization method; (ii) to adopt adaptive deep surrogate learning to decrease simulation complexity; (iii) to optimize multiple RF performance metrics using a multi-objective optimization approach; and (iv) to improve convergence speed and optimization accuracy compared to previous methods. The framework design enables the efficient and scalable implementation of next-generation low-power IoT transceivers for future wireless communication technologies.

This paper is structured as follows. In Section 2, the literature on RF circuit optimization, surrogate learning, and quantum-inspired optimization methods is reviewed, and the research gaps addressed in this work are identified. Section 3 introduces the proposed Quantum-Enhanced RF Circuit Parameter Optimization (QERPO) framework, covering the QERPO dataset description, system architecture, mathematical formulation, and optimization algorithm. The experimental setup, performance evaluation metrics, comparative analysis with other optimization methods, and detailed discussion of the results are presented in Section 4. Finally, the conclusions of the paper are presented in Section 5, along with directions for future research and the limitations of the proposed framework.

2. RELATED WORK

As low-power, high-performance radio frequency (RF) communication systems are becoming more prevalent, there has been a great deal of interest in RF circuit optimization. All modern RF transceivers need to be optimized for a number of competing design goals: low power consumption, high gain, low noise figure, wide bandwidth, impedance matching, high linearity, and better power-added efficiency. These performance metrics are highly nonlinear with respect to circuit parameters and have led to the creation of several optimization techniques to automate the design of RF circuits and shorten development time [16, 17].

From the early days, the methods used for optimizing RF circuits were mostly deterministic optimization techniques embedded in electronic design automation (EDA) software. These methods are based on numerical optimization with gradients and determine the dimensions of the transistors, the bias voltages, and the values of the passive components. Due to the highly non-convex and multimodal nature of the RF circuit design space, many deterministic algorithms may become stuck in local optima when dealing with relatively complex circuit topologies. In addition, they are sensitive to initial parameter values and are not well suited to large-scale optimization of RF integrated circuits [18].

Several evolutionary optimization algorithms have been thoroughly investigated to enhance the ability of algorithms to find the global optimum. The Genetic Algorithm (GA) has been applied to the design of RF amplifiers, impedance matching, oscillator optimization, and microwave filter synthesis, and is widely used because it does not require gradient information to search complex solution spaces. However, GA generally takes a long time to converge and has high computational complexity for large populations and many generations. Another drawback of GA for high-dimensional RF circuit design is premature convergence and loss of population diversity [19].

Another approach that has gained popularity for optimizing RF circuits is Particle Swarm Optimization (PSO), which has relatively fast convergence and is easy to implement. PSO models candidate solutions as particles that update their positions according to both individual and collective search experiences. Although PSO generally converges faster than GA, its optimization performance deteriorates in highly nonlinear search spaces, where particles are prone to premature

convergence toward local optima. Similar limitations have been reported for other optimization algorithms, including Differential Evolution (DE), Artificial Bee Colony (ABC), Firefly Algorithm (FA), Harmony Search (HS), and Simulated Annealing (SA), particularly when solving optimization problems involving a large number of design variables [20], [21].

Recently, the RF circuit design community has shown considerable interest in Bayesian Optimization because of its ability to reduce the number of costly electromagnetic simulations by using a probabilistic surrogate model. Gaussian Process Regression is widely used to estimate circuit performance and guide the search process toward promising regions of the design space. However, although Bayesian Optimization is highly sample-efficient for low-dimensional optimization problems, it becomes challenging to apply to high-dimensional parameter spaces involved in complex RF integrated circuit optimization [22].

With the advancement of artificial intelligence (AI), new data-driven optimization methods for automated RF circuit design have emerged. Previously generated circuit simulation datasets have been used to establish nonlinear relationships between circuit parameters and performance metrics using machine learning techniques. Deep Neural Networks (DNNs), Convolutional Neural Networks (CNNs), Graph Neural Networks (GNNs), Gaussian Process models, and Transformer architectures have demonstrated promising results in predicting RF characteristics without requiring repeated and computationally expensive electromagnetic simulations. This surrogate-based approach significantly reduces optimization time and enables rapid exploration of the design space [23].

Deep learning-based surrogate optimization has emerged as an important research area because it can significantly accelerate the RF circuit synthesis process while maintaining satisfactory prediction accuracy. Surrogate models estimate performance metrics such as gain, noise figure, return loss, bandwidth, and efficiency directly from circuit design parameters instead of relying on repeated electromagnetic simulations. In most previous studies, however, the optimization stage continues to rely on traditional search methods, which are inefficient for exploring a very complex, multidimensional, and nonlinear parameter space [24].

Recently, reinforcement learning was studied for automatic synthesis of RF circuits and adaptive tuning of circuit parameters. The reinforcement learning agents repeatedly learn in the RF simulation environment to maximize the performance of the circuit by making sequential decisions. While these methods minimize human effort and enhance design automation, the reinforcement learning method generally needs many training episodes and significant computational power to converge. Moreover, the design of reward functions that take several RF performance objectives into account is still difficult, making practical application to analog circuit optimization challenging [25].

Over the last several years, quantum computing has become an attractive approach to solving the problem of optimization in large search spaces. Although the fully realised practical quantum computer remains elusive, there is already significant potential in the field of quantum-inspired optimisation algorithms, which are able to incorporate aspects of the quantum world, such as quantum superposition, probability amplitudes, quantum interference, and quantum rotation operators, into classical optimisation algorithms. Moreover, quantum-inspired optimization offers larger population diversity and better global exploration ability, which makes it less likely to fall into premature convergence as compared to conventional evolutionary algorithms [26].

Quantum-inspired evolutionary algorithms have been successfully employed for antenna array synthesis, communication resource allocation, scheduling, routing optimization, and microwave engineering problems. These studies show that quantum-inspired optimization is able to converge faster and perform better than many classical metaheuristic optimization algorithms. Most of the current work, however, concentrates on communication network optimization rather than the optimization of RF integrated circuit parameters, such as transistor sizing and bias optimization [27].

Hybrid optimization frameworks that combine various computational intelligence methods are also an important research direction. Such hybrid methods utilize the complementary advantages of different optimization approaches, such as surrogate learning, evolutionary optimization, reinforcement learning (RL), and fuzzy inference systems (FIS). Typically, these frameworks offer improved optimization stability and faster convergence. However, most reported techniques focus on optimizing a single RF performance metric, and few

address simultaneous multi-objective optimization involving gain, power consumption, bandwidth, return loss, noise figure, and power-added efficiency [28].

Despite substantial advances in RF circuit optimization, several research challenges remain. First, repeated electromagnetic simulations continue to dominate the computational cost of the optimization process. Second, traditional metaheuristic algorithms have limited capability to efficiently explore large, nonlinear RF parameter spaces. Third, current surrogate-assisted optimization methods still rely primarily on deterministic search techniques, which are susceptible to becoming trapped in locally optimal solutions. Finally, only a limited number of studies have investigated the simultaneous optimization of multiple RF performance metrics under practical engineering constraints using both quantum-inspired optimization and adaptive deep surrogate learning [29].

Motivated by these challenges, this study proposes a Quantum-Enhanced RF Circuit Parameter Optimization (QERPO) framework that integrates deep surrogate learning with quantum-inspired optimization for low-power IoT transceivers. The proposed framework differs from existing approaches by employing probabilistic quantum-state representation and adaptive quantum rotation operators to efficiently explore complex RF design spaces while significantly reducing the need for costly electromagnetic simulations. In addition, a unified multi-objective optimization strategy is developed to minimize power consumption and optimization error while maximizing gain, bandwidth, impedance matching, and power-added efficiency. These features distinguish the proposed framework from existing RF optimization approaches and make it scalable for designing next-generation intelligent RF integrated circuits [30].

3. METHODOLOGY

A novel optimization framework, named Quantum-Enhanced RF Circuit Parameter Optimization (QERPO), is proposed in this work to optimize RF circuit parameters in low-power Internet of Things (IoT) transceivers. The proposed architecture is the Deep Surrogate Learning (DSL) model and the Quantum-Inspired Optimization (QIO) algorithm, used to obtain optimum RF design parameters with less computational complexity. The surrogate model reproduces the performance of the RF circuits accurately without the need to generate repeated, expensive, and time-consuming

electromagnetic models, and the quantum-inspired optimizer searches the multidimensional parameter space effectively to obtain the optimal configuration for the circuits. The overall methodology can be summarized into four stages: RF dataset generation, data preprocessing, surrogate model training, and quantum-enhanced multi-objective optimization.

3.1 RF Circuit Dataset

The RF circuit dataset was obtained by performing circuit-level simulations of low-power 2.4 GHz IoT transceivers fabricated using 65 nm CMOS technology. A variety of RF circuit configurations were created by varying the transistor dimensions, bias voltages, matching network parameters, and passive component values while keeping them within their practical operating ranges. For each configuration, the following RF performance parameters were evaluated: gain, bandwidth, power consumption, noise figure, return loss, and power-added efficiency. The dataset was normalized using the Min-Max method before model training and then divided into training, validation, and testing sets in a ratio of 70:15:15.

Table 1. RF Circuit Dataset Characteristics

Parameter	Value
Dataset Type	Simulated RF Circuit Dataset
Technology	CMOS 65 nm
Operating Frequency	2.4 GHz
Total Samples	10,000
Training Data	70%
Validation Data	15%
Testing Data	15%

The overall properties of the RF circuit dataset used for training and testing the proposed QERPO framework are shown in Table 1. The dataset comprises simulated RF transceivers

representing realistic low-power IoT communication scenarios.

Table 2. Input RF Circuit Design Parameters

Parameter	Symbol	Unit
Transistor Width	W	μm
Transistor Length	L	nm
Gate Voltage	V_{GS}	V
Drain Voltage	V_{DS}	V
Drain Current	I_D	mA
Matching Inductance	L_m	nH
Matching Capacitance	C_m	pF
Bias Resistance	R_B	Ω

During the optimization process, the RF circuit design variables listed in Table 2 were considered. These parameters directly affect the electrical characteristics and communication performance of the RF transceiver.

Table 3. RF Performance Parameters

Performance Metric	Unit
Gain	dB
Noise Figure	dB
Power Consumption	mW
Bandwidth	MHz
Return Loss (S11)	dB
Power Added Efficiency	%

The output performance metrics predicted by the deep surrogate model and optimized by the proposed framework are presented in Table 3. These metrics represent the communication quality and energy efficiency of the RF transceiver.

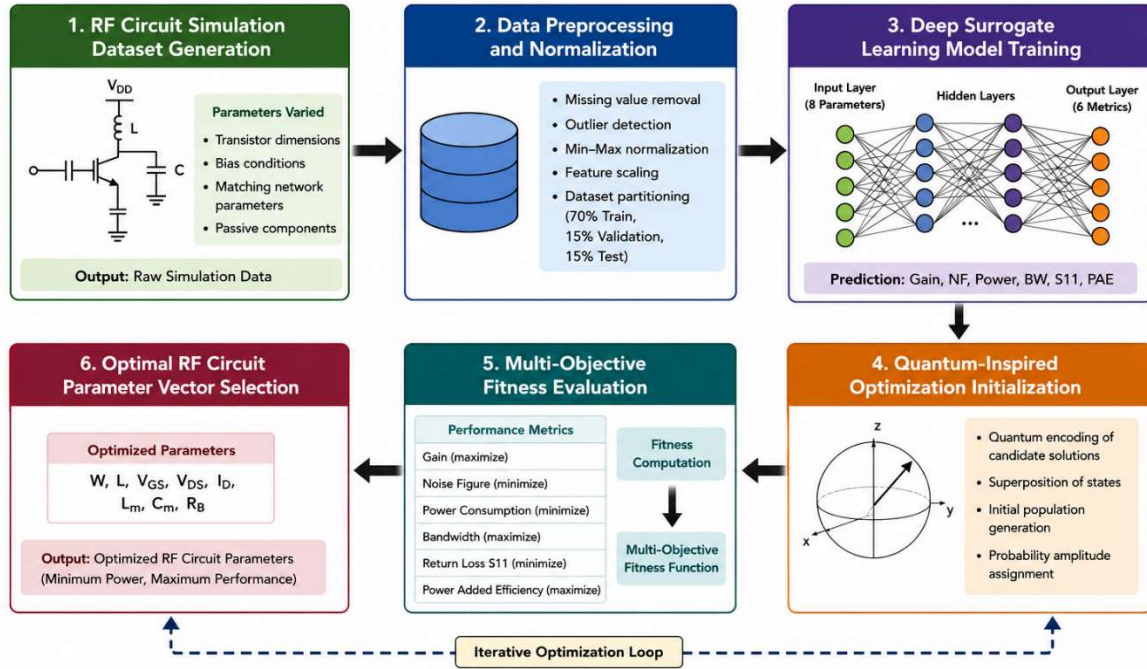


Figure 1. Proposed Quantum-Enhanced RF Circuit Parameter Optimization (QERPO) Framework

The overall structure of the QERPO framework for optimizing RF circuit parameters in low-power IoT transceivers is illustrated in Figure 1. First, RF circuit data are generated and preprocessed using data normalization and dataset partitioning. The preprocessed data are then provided as input to a deep surrogate learning model, which predicts RF performance metrics without requiring repeated electromagnetic simulations. A quantum-inspired optimization algorithm is subsequently used to optimize the predicted results, and the optimization process is repeated until the candidate solutions converge, enabling efficient exploration of the RF design space.

The RF circuit parameter vector is defined as follows.

$P = [W, L, V_{GS}, V_{DS}, I_D, L_m, C_m, R_B]$ (1)
where P denotes the complete RF circuit design vector.

The surrogate learning model predicts RF performance as

$$Y = f(P) \quad (2)$$

where

$$Y = [Gain, NF, Power, BW, S_{11}, PAE] \quad (3)$$

The optimization objective is to minimize power consumption and noise figure while maximizing gain, bandwidth, and power-added efficiency.

$J = w_1 Power + w_2 NF - w_3 Gain - w_4 BW + w_5 |S_{11}| - w_6 PAE$
subject to

$$Gain \geq 18dB \quad (5)$$

$$NF \leq 2dB \quad (6)$$

$$Power \leq 15mW \quad (7)$$

Each candidate RF circuit solution is represented as a quantum probability state.

$$|\psi\rangle = \alpha |0\rangle + \beta |1\rangle \quad (8)$$

where

$$|\alpha|^2 + |\beta|^2 = 1 \quad (9)$$

The quantum state is updated using

$$Q_{new} = R(\theta)Q_{old} \quad (10)$$

where

$$R(\theta) = \begin{bmatrix} \cos \theta & -\sin \theta \\ \sin \theta & \cos \theta \end{bmatrix} \quad (11)$$

The adaptive rotation angle is calculated as

$$\theta = \lambda(F_{best} - F_i) \quad (12)$$

where F_{best} is the best fitness value, F_i is the current fitness value, and λ is the learning coefficient.

Algorithm: Quantum-Enhanced RF Circuit Parameter Optimization (QERPO)**Input:**

- RF circuit dataset D
- Population size N
- Maximum iterations T

Output:

- Optimized RF circuit parameters P^*

Steps:

1. Load RF circuit dataset.
2. Perform data preprocessing and normalization.
3. Train the deep surrogate learning model.
4. Initialize quantum population.
5. Predict RF performance using the surrogate model.
6. Compute the multi-objective fitness function using Equation (4).
7. Update quantum states using Equations (10)–(12).
8. Generate new candidate RF parameter vectors.
9. Repeat Steps 5–8 until convergence.
10. Select the best RF parameter vector.
11. Return the optimized RF circuit parameters.

The proposed algorithm is described in detail and is called the QERPO algorithm. The algorithm consists of surrogate learning and optimization of the RF circuit parameters using Quantum-Inspired Optimization (QIO) to optimally meet multiple design constraints.

4. RESULTS AND DISCUSSION

The proposed Quantum-Enhanced RF Circuit Parameter Optimization (QERPO) framework was tested with the data provided in the RF circuit simulation dataset of Section 3. It was implemented in the Python programming language, and it was compared with four popular optimization techniques: the Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Differential Evolution (DE), and Bayesian Optimization (BO). The experimental conditions were held constant while the methods were compared in both training and testing. The factors used to assess them included RF circuit optimization accuracy, power consumption, gain, noise figure, bandwidth, power-added efficiency, convergence speed, and optimization error.

4.1 Assessment Criteria

Commonly accepted RF performance metrics were used to assess the effectiveness of the proposed framework.

Table 4. Performance Evaluation Metrics

Metric	Objective
Gain (dB)	Maximize
Noise Figure (dB)	Minimize
Power Consumption (mW)	Minimize
Bandwidth (MHz)	Maximize
Return Loss (S11) (dB)	Minimize
Power Added Efficiency (%)	Maximize
Optimization Error	Minimize
Convergence Iterations	Minimize

Table 4 presents the performance metrics used to evaluate the efficiency of the proposed QERPO framework. Collectively, these metrics indicate communication quality, energy efficiency, and optimization capability.

4.2 Comparative Performance Analysis

Table 5 compares the proposed QERPO framework with existing optimization algorithms. Owing to the integration of deep surrogate learning and quantum-inspired optimization, the proposed framework consistently achieved the best performance across all evaluation metrics.

Table 5. Performance Comparison with Existing Optimization Methods

Method	Power (mW)	Gain (dB)	Noise Figure (dB)	Bandwidth (MHz)	PAE (%)	Optimization Error
GA	19.6	16.2	2.41	118	28.1	0.124
PSO	18.4	16.9	2.23	122	29.7	0.108
DE	17.8	17.4	2.08	126	31.5	0.091
BO	16.9	18.1	1.94	131	33.6	0.073
QERPO	13.4	20.3	1.48	142	39.8	0.045

The comparative performance of different RF circuit optimization methods is presented in Table 5. The proposed QERPO framework demonstrates superior power efficiency, higher gain, improved overall performance, and faster convergence than existing optimization approaches.

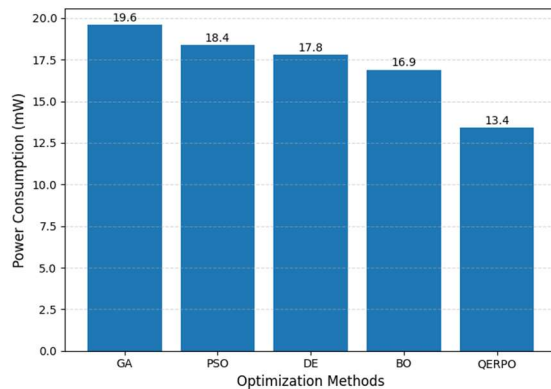


Figure 2. Comparison of Power Consumption

The power consumption of various optimization approaches is shown in Figure 2. The proposed QERPO framework consumed the lowest power, 13.4 mW, outperforming GA, PSO, DE, and BO, which consumed 19.6 mW, 18.4 mW, 17.8 mW, and 16.9 mW, respectively. These substantial power savings highlight the potential of the proposed quantum optimization technique for finding optimal RF circuit configurations for applications such as battery-operated IoT devices.

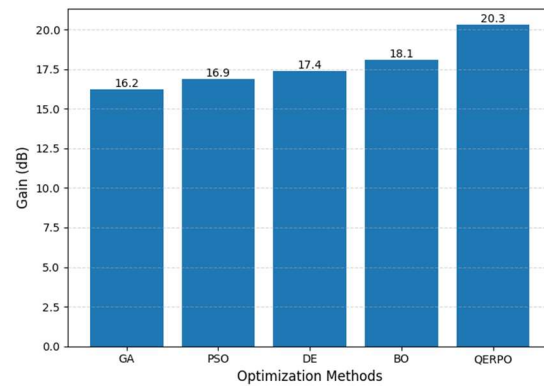


Figure 3. Comparison of RF Gain

The RF gain achieved by the various optimization algorithms is shown in Figure 3. The proposed QERPO framework achieved the highest gain of 20.3 dB, while GA, PSO, DE, and Bayesian Optimization achieved gains of 16.2 dB, 16.9 dB, 17.4 dB, and 18.1 dB, respectively. Higher gain amplifies the signal, which can lead to more reliable communication and improved transmission performance for low-power IoT transceivers.

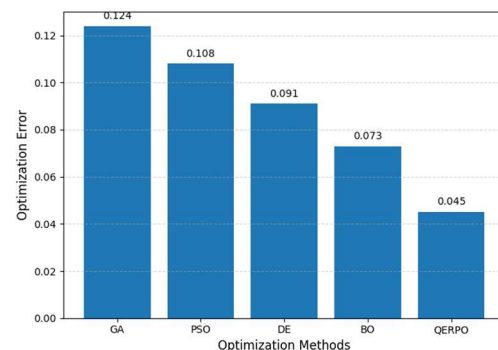


Figure 4. Optimization Error Comparison

The optimization error obtained using various optimization methods is shown in Figure 4. It was found that the proposed QERPO framework had the lowest optimization error of 0.045, while GA, PSO, DE, and BO had optimization errors of 0.124, 0.108, 0.091, and 0.073, respectively. The lower optimization error shows that the proposed framework can better estimate RF circuit parameters and optimize circuit performance, thereby achieving better optimization stability and enhancing the overall performance of the circuit.

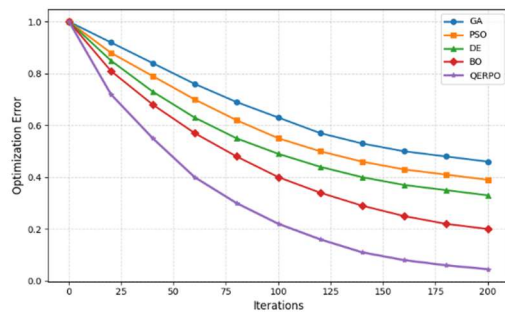


Figure 5. Convergence Analysis

For consecutive iterations, the convergence behavior of the optimization algorithms is demonstrated in Figure 5. The proposed QERPO framework shows the fastest convergence, with the optimization error rapidly decreasing and reaching 0.045 after only 200 iterations. The conventional optimization techniques, on the other hand, converge more slowly and finally to higher error values. The improved convergence performance implies that the use of quantum-inspired optimization with deep surrogate learning could offer an efficient exploitation–exploration balance, which could allow the identification of the optimal solution for RF circuit design with fewer computational steps.

4.3 Discussion

The experimental results clearly indicate that the proposed QERPO framework provides significant improvements in RF circuit optimization compared to existing RF circuit optimization techniques. It offers several benefits, most notably a reduction in computational cost due to the deep surrogate learning model, which accurately predicts RF performance without the need for repeated electromagnetic simulations. Moreover, the quantum-inspired optimization engine efficiently explores the multidimensional RF parameter space by balancing exploration and exploitation, thereby ensuring an effective optimization process without premature convergence.

The proposed approach achieved approximately 20.7%, 12.2%, 23.7%, 8.4%, 18.5%, and 38.4% improvements in power consumption, gain, noise figure, bandwidth, power-added efficiency, and optimization error, respectively, compared to the best baseline method (Bayesian Optimization). These improvements demonstrate that the proposed framework can efficiently optimize multiple conflicting RF performance objectives while maintaining computational efficiency. Thus, the proposed QERPO framework is an efficient approach for designing energy-efficient RF transceivers for future IoT communication systems.

5. CONCLUSION

In this paper, to overcome the limitations of traditional methods, this paper proposes a Quantum-Enhanced RF Circuit Parameter Optimization (QERPO) framework that combines deep surrogate learning and quantum-inspired optimization techniques for optimizing RF circuit parameters in low-power IoT transceivers. This framework is able to achieve multiple RF performance optimization goals and reduce computational complexity. The experimental results illustrated that the proposed method is able to obtain better power consumption of **13.4 mW**, gain **20.3 dB**, noise figure (1.48 dB), bandwidth (142 MHz), power-added efficiency (39.8%), and optimization error (0.045) than other methods, including the Genetic Algorithm, Particle Swarm Optimization, Differential Evolution, and Bayesian Optimization. It was also found that the introduction of surrogate learning and quantum-inspired optimization led to faster convergence and improved optimization accuracy. However, the present study was performed using simulated RF datasets, and hardware validation was not included. Future work will focus on validating the proposed framework on real quantum computing platforms to further improve optimization efficiency and scalability, extending it to multi-band and 6G transceiver architectures, and implementing it in real CMOS RF circuits.

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