Computational Optimization Techniques to Design RF Circuits

Computational Optimization Techniques to Design Radio Frequency Circuits

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Abstract: This paper presents a comprehensive review of computational optimization techniques to design radio frequency (RF) circuits. The most important design techniques of machine learning and global optimization used to optimize RF circuits such as Genetic algorithm (GA), particle swarm optimization (PSO), reinforcement learning (RL), Surrogate modelling (SM) etc have been discussed in paper. Basics of the techniques their merits, demerits with examples have also been covered in this article so that new researchers can understand the theory of the techniques. Furthermore, this paper provides the guidelines to select the techniques according to a specific circuit. A comparative analysis of the design techniques has been made in this paper so that designers select the techniques according to their requirements.

I. INTRODUCTION

Radio frequency (RF) circuits are critical components in modern communication systems, such as wireless communication, radar, and satellite systems. Designing RF circuits poses several challenges due to their inherent nonlinearity, high-frequency operation, and sensitivity to parasitic effects. As a result, RF circuit design is a highly complex and time-consuming process, demanding significant expertise. Traditionally, RF circuit design relies on heuristic methods, manual tuning, or physics-based modeling. However, these methods are increasingly becoming inadequate due to the growing complexity of modern RF systems, which often integrate multiple functionalities in a single compact device. Global optimization techniques and machine learning (ML) algorithms have become promising solutions to these challenges in recent years. Global optimization methods, such as genetic algorithms (GA) and particle swarm optimization (PSO), have been employed to explore the vast design space of RF circuits, ensuring a comprehensive search for optimal solutions. These methods are well-suited to handle RF design's complex, nonlinear, and multi-objective Nature. ML has become a disruptive technology in several fields. It provides strong predictive modeling, pattern identification, and data analysis tools. ML techniques can predict and identify possible problems, automate and optimize the design process, and enhance overall system performance by utilizing vast datasets. It can potentially improve the effectiveness and performance of RF circuits/systems design. ML algorithms/techniques are becoming a valuable tool in RF circuit design. Design engineers are revolutionizing RF circuitry through ML, such as reinforcement learning (RL), Surrogate modelling, and parametric yield optimization (PYO). ML-based techniques have helped to create efficient and compact circuits for microwave applications. A flow graph to design ML-based RF circuits is given in Fig.1. Here, we present a comprehensive review of computational optimization techniques used for RF circuit design. However, a review article on NN-based

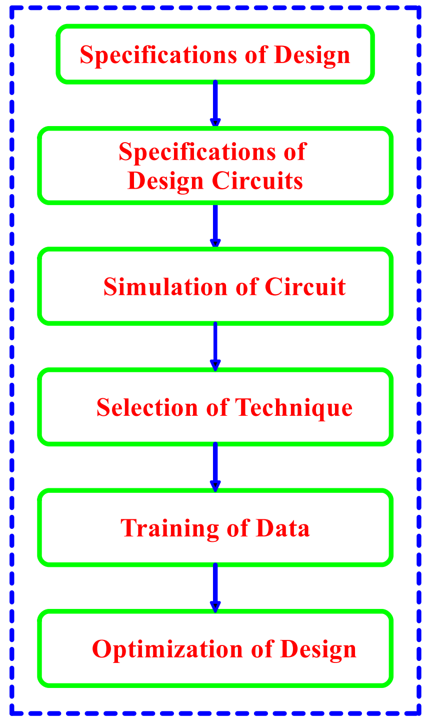

Fig.1 Design flow graph for Computing optimization.

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techniques and design optimization has been discussed in [1]. Other computational computational optimization-based design techniques have not been addressed, so it has a limited scope [1]. The article fills that gap by discussing classical ML and global optimization design techniques used for RF circuits. In addition, guidelines for selecting a technique for the design requirement by comparing different methods to design are presented in this paper. The authors hope that the present article will be valuable to new researchers and design engineers working in this field.

II. GENETIC ALGORITHM

Optimization using GA was introduced by Holland in 1975 and has been widely used for solving synthesis problems in the area of Science and engineering, including in the area of electromagnetics. Genetic Algorithms (GAs) are based on a unique principle derived from natural selection and genetic evolution [1]-[2]. In this method, initial potential solutions, chromosomes, are generated randomly. The individuals with higher fitness are then chosen for reproduction, mimicking the natural selection process. This leads to the ongoing improvement of a population through the selection process, crossover, and mutation of genes. The effectiveness of this approach lies in its ability to leverage genetic variation and natural selection, enabling it to iteratively move towards optimal solutions in optimization and problem-solving tasks within a framework [3]-[4]. GA optimization starts with modeling any arbitrary circuit as a set of data structures, as shown in Figs. 2 (a)-(b). Each data structure comprises three parts, describing the topology of the two-port network with the corresponding connection method to the previous element and its electrical parameters. In GA, a basic structure is defined as a gene, and the set of structures is a chromosome, as shown in Fig. 2(c). An empty special gene describes a circuit with an arbitrary number of basic two-port circuit elements and the order. Following this, the optimization process employs conventional GA to investigate suitable circuit topologies and their respective electrical parameters simultaneously. The design problem can be formulated as in (1).

$$g^{*} = \arg(\min U(S(g))) \tag{1}$$

where g denotes the chromosome, U is the objective function, which needs to be minimized, S(g) is simulated S-parameters, and g* is the appropriate chromosome.

This technique can be used to design dual-band circuits by employing hybrid-coded GA [5]. This optimization scheme used the one-point crossover method and a step and topology mutation to create new chromosomes for the next generation [6]. The crossover is an important operator and plays a major role in the GA's convergence. However, the mutation is a reproduction operator that plays a critical role in getting out of the trap of local optimum solutions by randomly selecting the gene values. The step mutation changes the electrical parameters of the circuit without changing the circuit topology in the chromosomes [7]. As a result, this optimization method can predict circuit topology and its corresponding electrical parameter values to achieve dual-band characteristics. A dual-band passband filter with a sharp cut-off in the passband and good rejection in the stopband is designed using GA. The desired scattering parameters of the bandpass filter are given in Fig. 2(d). These parameters are realized using transmission line sand stub and their physical parameters.

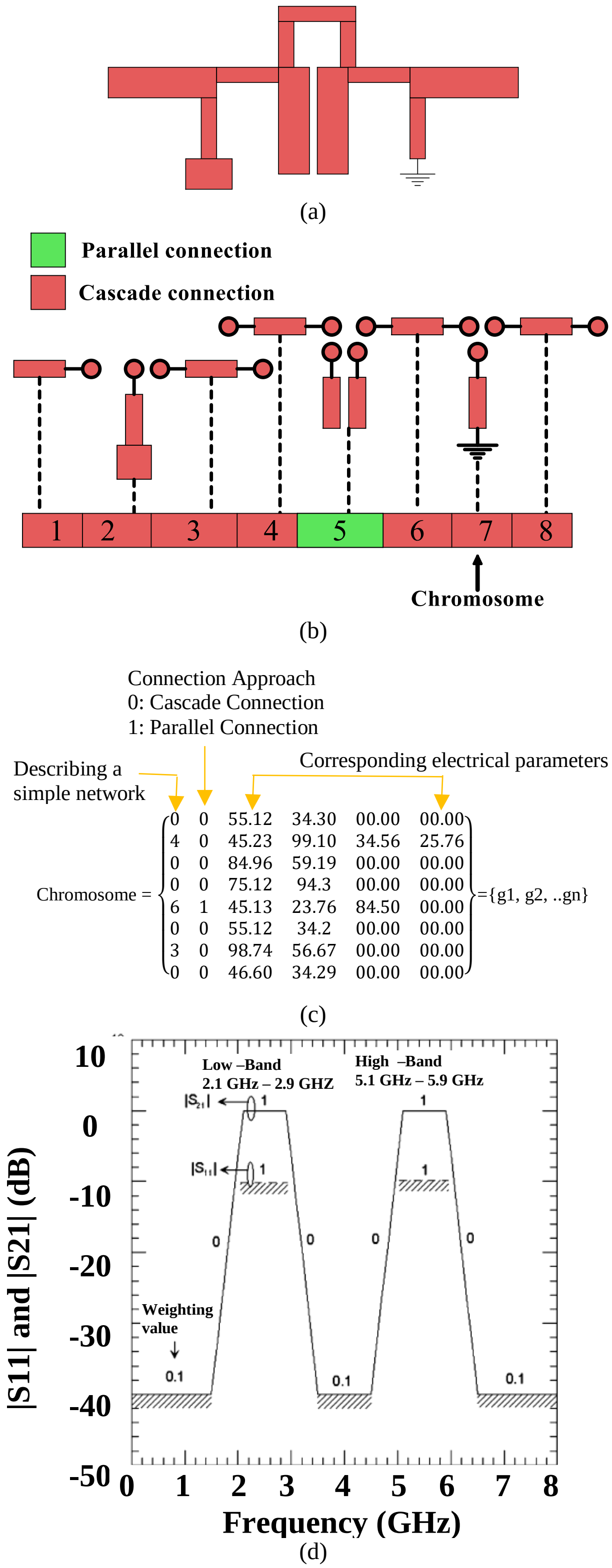


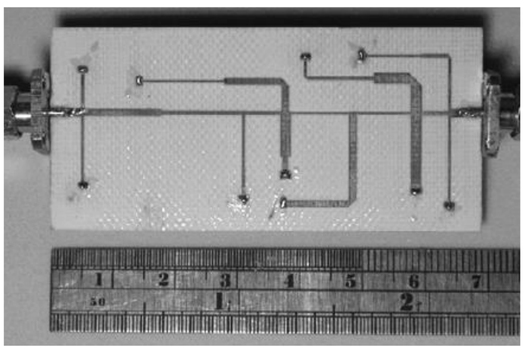
Fig.2. Representation scheme in the proposed algorithm. (a) A typical passive microstrip circuit. (b) Decomposition of the circuit; (c) Chromosome of the circuit; (d) Desired frequency responses [5].

The process is summarized as follows:

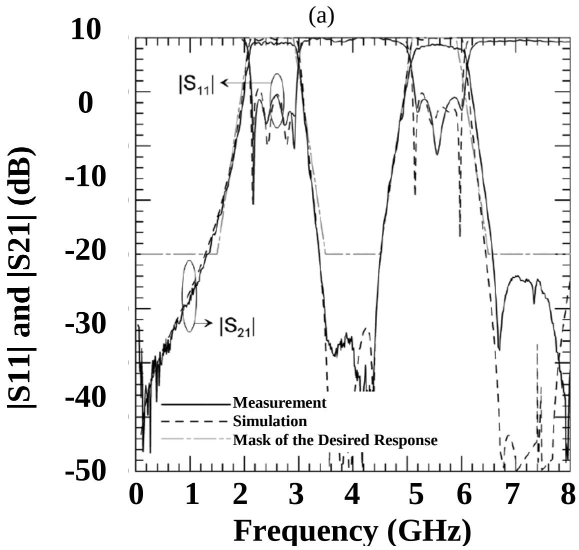
i. Convert the chain of ABCD matrices associated with the chromosome into the scattering matrix.
ii. Determine the optimal solution by optimizing the topology and relevant electrical parameters following the provided design specifications.
iii. Translate the attained electrical parameters back into their original physical parameters based on the corresponding relationship. After that, the filter can be constructed in any microwave simulator, such as ADS and HFSS, based on the physical parameters.

The layout, prototype, and S-parameters of the dual-band filter proposed in [5] are shown in Fig. 3(a)-(c). It achieves a -3.2 dB coupling coefficient and 20dB return loss. Several RF circuits, including filters [5], power amplifiers [8]-[9], matching circuits [10], couplers [11], and LNA [12], were designed using GA.

GAs' excel in data mining and efficiently solve complex optimization problems. However, their implementation requires careful parameter tuning, which can be computationally expensive in high-dimensional scenarios.



(a)



(b)

Fig. 3(a) Photograph; (b) Comparison between the simulated and measured scattering parameters [5].

III. Particle Swarm Optimization:

Particle Swarm Optimization (PSO) is a resilient stochastic evolutionary computation method that leverages the collective movement and intelligence observed in swarms, first introduced in 1995 [13]. In PSO, a population of potential solutions, represented as particles, collaboratively explores the solution space to find optimal solutions to an optimization problem [14]. Each particle in the swarm represents a potential solution to the problem, and its position in the solution space corresponds to a particular set of parameter values. The position of the particles is updated throughout the iteration. The following equations provide the update about the position of the particle as [15]:

$$V_i^{s+1}= V_i^s+a_1b_1(q_h^s-y_i^s)+a_2b_2(q_i^s-y_i^s) \qquad 2(a)$$

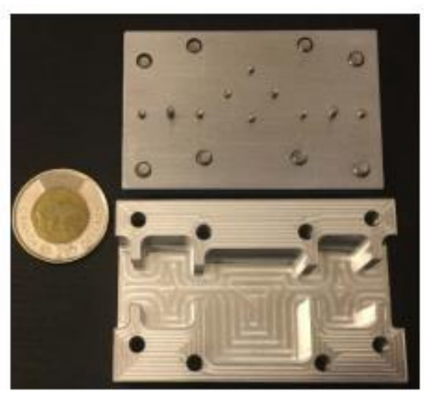
$$y_i^{s+1}= y_i^s+V_i^{s+1} \qquad 2(b)$$

There are two important types of PSO available in the literature, namely gray wolf optimizers (GWO) [16] and whale optimization algorithms (WOA) [17]. The GWO and WOA are based on bubble net hunting of humpback whales and gray wolves, respectively. Mathematically, GWO and WOA can be represented as in (3).

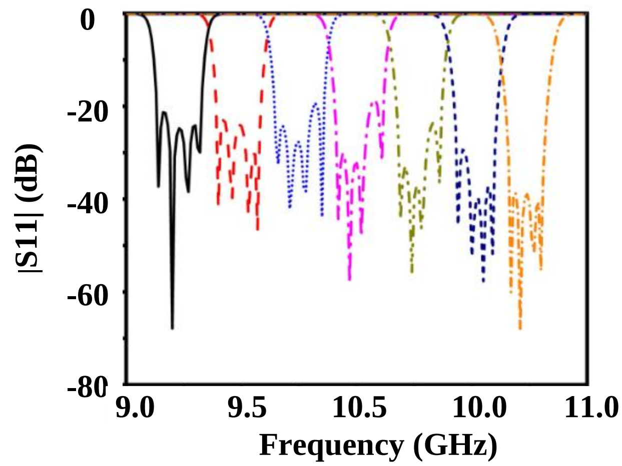
$$\vec{Q} = |\vec{P}.\vec{Y}(t) - \vec{Y}\,(s)| \qquad 3(a)$$
$$\vec{Y}\,(s+1) = \vec{Y}\,(s) - \vec{B}.\vec{Q} \qquad 3(b)$$

This technique is used to solve many electromagnetic design problems and to achieve fine-tuned circuits, including microwave filters [18]-[20], microstrip couplers [21], bandpass filters [22], microwave cavity filters [23], broadband microwave filters [24], reconfigurable mixer [25], low noise amplifier [26], microwave microfluidic sensors [27].

It is worth noting that tunable circuits can be designed by employing hybrid optimization of metaheuristic optimization algorithms and homotopy optimization methods. The reflection and transmission responses of fine-tuned bandpass filters are shown in Fig.4. Its prototype and S-parameters are shown in Fig.4(c)-(c). It achieves a -3.2 dB coupling coefficient and 20 dB return loss.



(a)



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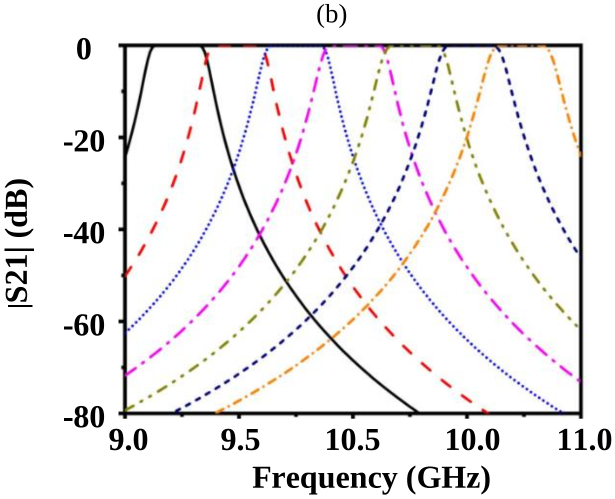


(c)

Fig.4 The tunable bandpass filter (a) prototype (b) reflection responses. (c) transmission responses [22].

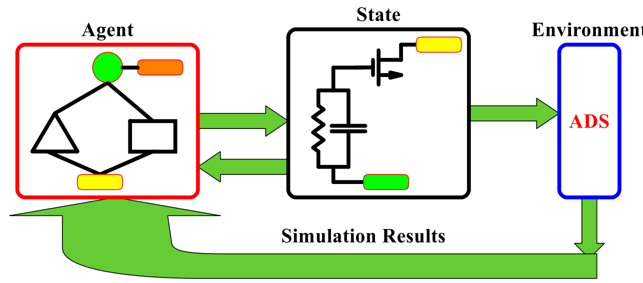
The goal of the swarm is to converge toward the optimal solution or a high-quality solution in the optimization landscape [28]. Swarm Optimization algorithms excel in determining optimal values for complex functions and adapting to changes. However, it may face challenges like local optima in high-dimensional datasets, low convergence rates, and performance instability tied to swarm size.

IV. REINFORCEMENT LEARNING

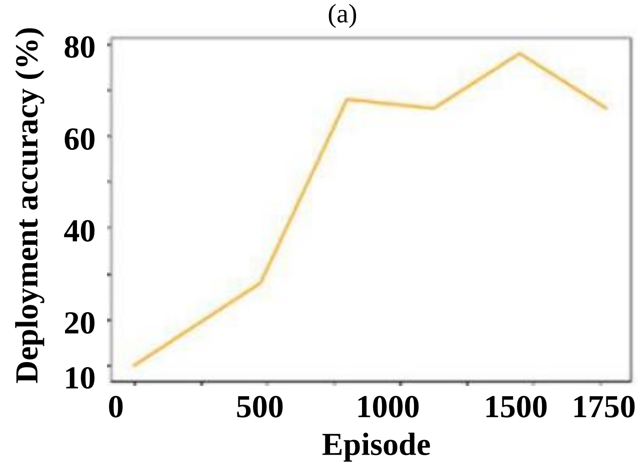
Reinforcement learning (RL) constitutes a dynamic paradigm where an agent actively engages with an environment, learning optimal strategies through trial and error [29]. In the RL framework, the agent observes the current state of the environment, takes an action based on a predefined policy, and receives a subsequent reward or reinforcement. The agent's overarching objective is maximizing cumulative rewards obtained over time. A critical challenge in RL is the exploration-exploitation trade-off, where the agent must balance trying new actions (exploration) against choosing actions with known rewards (exploitation) [30]. Value functions, such as Q-values, are crucial in estimating the expected rewards associated with different states and actions, guiding the agent's strategic choices [31].

The RL excels in handling sequential decision-making tasks, making it a powerful paradigm for training agents to adapt and make informed decisions in complex and dynamic environments [32]-[33]. RL boasts distinctive advantages, starting with the autonomy of RL agents in mastering complex tasks through trial and error, circumventing the need for human-labeled data. Their adaptability shines as RL agents continuously explore and update policies, enabling them to navigate dynamic environments effectively.

An RL agent is formulated as a Markov decision process (MDP), defined by a tuple (S, A, R, γ) [34], where S and R represent the state space and action space, respectively. And R(s, a) is a reward function. A few RF circuits, including power amplifiers [34]-[36] and filters [37], were designed using the RL technique. The RL is useful for designing linear and non



(a)



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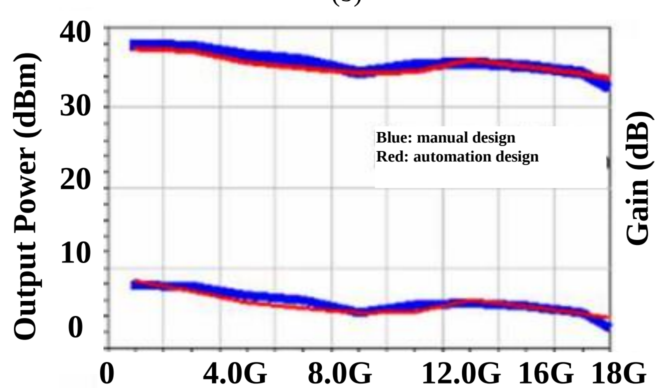

(c)

Fig.5 (a) RL interaction with high fidelity simulator; (b) and (c).

linear circuits and has global optimization capability. But it suffers from computational complexity.

V. ARTIFICIAL NEURAL NETWORK

An ANN is a computational model inspired by the human brain's neural structure. An ANN consists of a collection of neurons, with connecting weights linking neurons from neighboring layers and bias values assigned to each neuron. ANNs offer solutions to common challenging problems in microwave CAD. They effectively tackle the computational burden of forward modeling and the absence of analytical equations for inverse design [38]-[42]. An ANN can model a microwave circuit. The model's accuracy depends on data generation methods and sampling. Several sampling methods for the ANN model include uniform/nonuniform grid distribution and star distribution. The research encompassed diverse microwave applications in the initial stages of utilizing ANNs for microwave CAD. These included microstrip circuit design [43]-[44], antennas [45]-[46], spiral inductor construction [40], impedance matching [48] techniques, and the analysis of MESFET devices and circuits [49]-[50]. Various types of neurons and different methods of interconnecting them lead to diverse ANN architectures including dynamic neural networks (DNNs) [51]- [52], recurrent neural networks (RNNs) [53]-[57], and time-delay neural networks (TDNNs) [57]-[60], are commonly employed to analyze the dynamic performance of nonlinear devices or circuits in the time domain. Various types of neurons and different methods of interconnecting them lead to diverse ANN architectures.

A. *Deep Neural Network*

A deep neural network (DNN) comprises numerous hidden layers [61]-[67]. The DNN can be categorized as deep multilayer perceptron (MLP), convolutional neural network (CNN), and deep belief network (DBN). The first is an MLP, where the choice of activation functions for hidden neurons significantly influences the training accuracy [63], [67]. The rectified linear unit (ReLU) is particularly popular in deep MLP due to its effectiveness in mitigating the vanishing gradient problem. The second is the CNN [69]-[70], which typically consists of convolutional, nonlinearity, and pooling layers structured in stages, making it adept at learning from image-like representations, as applicable in electromagnetic (EM) problems [70]. Thirdly, DBN represents a hybrid class of DNN where both directed and undirected layers are incorporated [71], and it can tackle the challenges of inverse modeling in microwave CAD [72]. A comparative analysis of DNN techniques is provided in Table I.

Several RF circuits, including power amplifiers [63]-[67] and filters [68], [72] were designed using RL. A detuned filter is designed in [73]. A comparison between the desired S-parameters and those calculated from the extracted coupling matrix (i.e., outputs of the hybrid deep MLP model) for the detuned filter is presented in Fig.6. A comparison of MLP, CNN, and DBN is given in Table I.

Complex modeling issues characterized by intricate relationships are addressed by deep neural networks (DNNs).

Table I
Comparison of DNN techniques

	MLP	CNN	DBN
Structure	Fully Connected	Partially connected	Stack of Restricted Boltzmann Machines (RBMs)
Training complexity	Simple	Medium	Complex
Time domain modeling with memory effects	No	No	No
Activation function	ReLU, Sigmoid, Tanh	ReLU, Sigmoid, Softmax	Sigmoid (typically used in RBMs)
Handling Sequential Data	Ineffective	Ineffective	Primarily used for feature extraction, it requires other mechanisms to handle sequential data

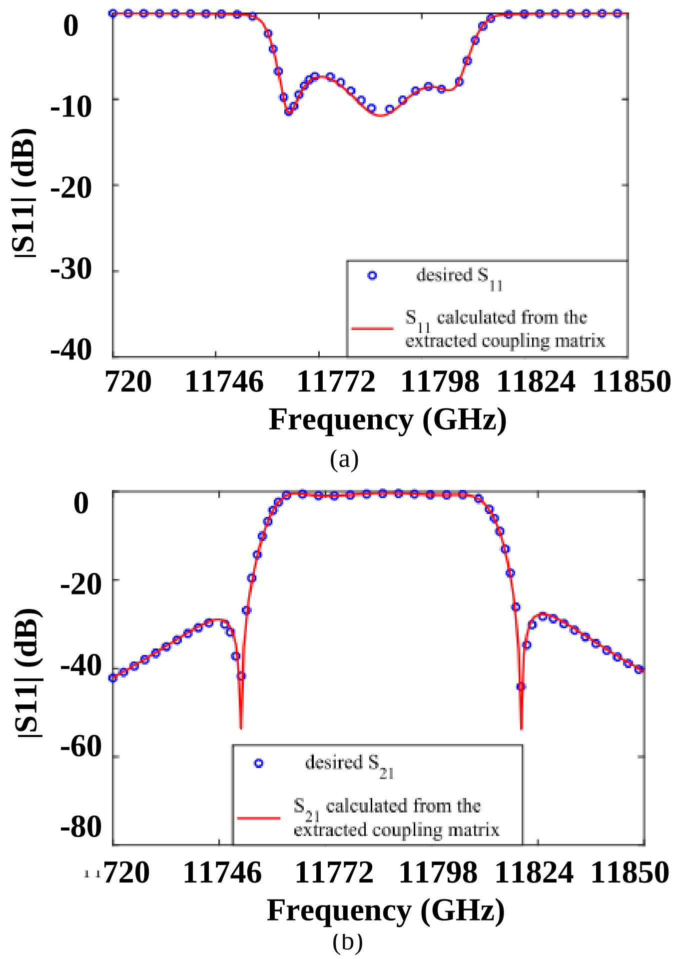

Fig.6 Comparison between the desired S-parameters and the S-parameters (a) Return loss S11. (b) Insertion loss S21 [73].

B. *Knowledge-Based Neural Network*

Knowledge-based neural networks (KBNNs) have become instrumental in microwave CAD, leveraging established equivalent circuit models and empirical data for components [74]-[79]. In this type of NN, domain-specific knowledge is incorporated into it. Thus, the need for extensive training data is reduced by integrating this knowledge into NNs, enhancing the model's ability to extrapolate. The Basic KBNN embeds pre-existing knowledge, such as rules or heuristics, directly into the network, enhancing its learning efficiency and accuracy. A model for basic KBNN is shown in Fig.7, where x and y represent the input and output of the KBNN model, respectively, and d represents the values of y in the training or validation data generated from EM simulation.

Knowledge-based models with Adjoint Neural Networks extend this concept by pairing the neural network with an adjoint system that helps optimize the model's outputs based on mathematical formulations or constraints, making them particularly useful in physics and engineering. KBNNs with Adaptive Mappings further enhance the model by allowing it to adapt the embedded knowledge as it learns from new data, improving its flexibility and ability to generalize to new situations. These approaches help reduce the reliance on large datasets and improve the model's performance in complex, knowledge-rich domains. A comparison of Basic KBNN, Knowledge-Based Models with Adjoint Neural Networks, and KBNNs with Adaptive Mappings is given in Table II.

Table II
Comparison of knowledge-based neural networks techniques

	Basic KBNN	Knowledge-Based Models with Adjoint Neural Networks	KBNNs with Adaptive Mappings
Requirement of prior knowledge	No	Yes	Yes
Neural Networks no.	One	One	Multiple
Complexity of the model	Simple	Complex	Complex
Samples size	Large	Small to medium	Small to medium

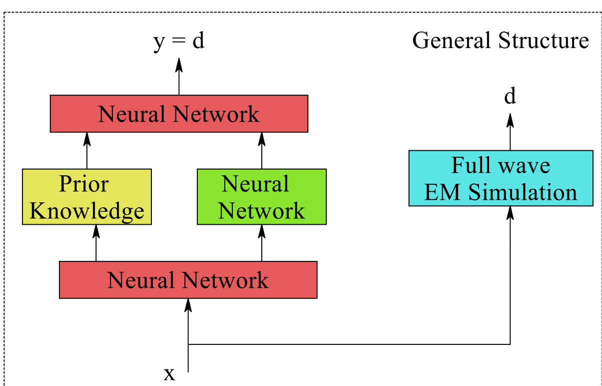

Fig.7 Basic KBNN model [1].

VI. SURROGATE MODELING

Surrogate modeling is a macro modeling technique with a solid mathematical basis, increasing the ability to develop engineering models. It operates on the fundamental principle of simplifying complex systems by creating effective analytical models when conventional methodologies face limitations [85]. When the direct modeling of intricate systems becomes impractical or computationally burdensome, surrogate models offer a viable alternative by employing standard mathematical representations. These surrogate models, characterized by their simplicity, are designed to emulate the input-output dynamics of complex systems, providing a more tractable understanding of their behavior. By calibrating these models using available data from the original system, surrogate modeling establishes a connection between inputs and outputs, enabling efficient solution space exploration [86]. Surrogate modeling balances simplistic macromodels with precise yet computationally intensive computer simulations. These macromodels can be made using various methods, for instance, Polynomial basis functions [87], Neural Network-Based Models [88],[89], Machine Learning-Based Models [90], and

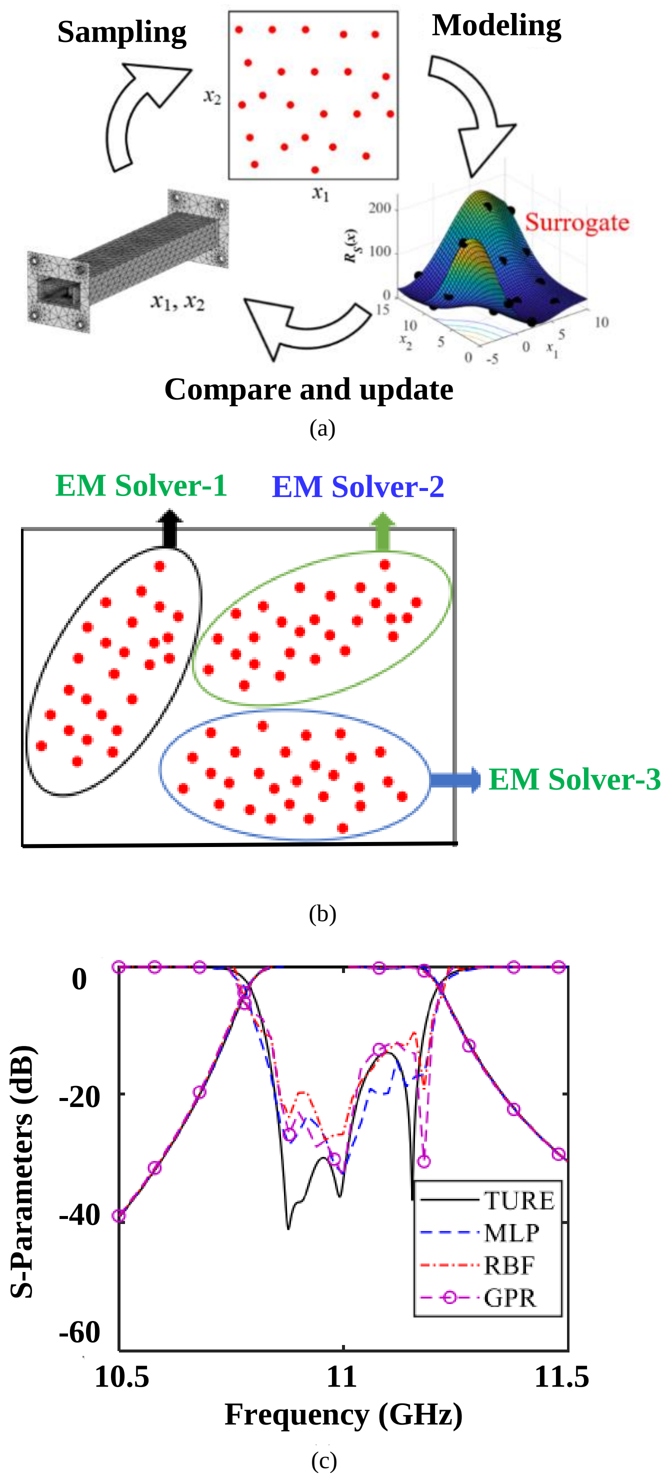

Fig.12 (a) Workflow of data-driven surrogate modelling; (b) parallel parameter sampling; (c) comparison of different surrogates [88].

Kriging Basis Functions [91]. Researchers successfully applied surrogate modelling methods to design various microwave circuit devices, including power dividers [85], low pass filters [89], low noise amplifiers [92], couplers [93]-[94], impedance matching transformers [94], power amplifier [95], and microwave filter [96]. In [93], a compact branch line and rat-race coupler with folded transmission lines were designed employing dimensionality-reduced constrained surrogates.

Surrogate modeling is suitable for linear and nonlinear problems and provides a high convergence rate. However, this technique is suitable for small data sizes.

VII. PARAMETRIC YIELD OPTIMIZATION

Parametric Yield Optimization (PYO) is a crucial process that strives to maximize the production yield of acceptable products within a given set of parameters. This optimization strategy is important in diverse fields, with particular applications in designing integrated circuits, refining manufacturing processes, and strategic production planning. The primary goal is to enhance the efficiency of manufacturing operations by identifying and fine-tuning the key parameters that influence the yield of acceptable products. In the context of integrated circuit design, for instance, parametric yield optimization involves adjusting various design parameters to ensure that a high percentage of manufactured circuits meet specified quality standards.

It operates on the fundamental principle of enhancing the production process by strategically adjusting specific parameters to maximize the yield of acceptable products. The process begins with identifying critical parameters that significantly influence the quality and quantity of the final products, with meticulous quantification and measurement establishing a baseline. Data analysis and modeling explore relationships between these parameters and product yield, often employing mathematical models and statistical techniques. Optimization algorithms are then implemented to systematically fine-tune the values of identified parameters to discover the optimal combination that yields the highest acceptable product output. The goal of yield optimization in EM optimization is to maximize yield by adjusting design parameters to account for variability in component values in the manufacturability-driven design of microwave passive components [97]-[98]. Over the past two decades, various techniques for yield-driven EM optimization have been developed. One such technique is space mapping [99]-[102], while another group includes feature-based methods [103]-[104].

Feature-based methods have recently garnered attention for their application in yield estimation and optimization of microwave structures [105]-[107]. Typically, each iteration in the yield optimization process involves yield value prediction. Recently, polynomial chaos expansion (PCE) [108] has emerged as a promising alternative for yield estimation and statistical analysis within the microwave field [109]-[110]. The PCE method provides significant computational benefits over traditional Monte Carlo analysis, establishing it as a powerful tool for statistical analysis and yield estimation in microwave structures.

Several RF circuits were designed using PYO, e.g., couplers [95], [105], filters [106], and interconnects [109]. The PYO can be used to optimize circuits when the data is large. This technique is suitable for nonlinear problems, and its convergence is fast. But the training time for this technique is large.

VIII. COMPARISON AND SELECTION OF A TECHNIQUE

A comparison of the design techniques in terms of inherent characteristics has been presented in Table.III. Each ML and global optimization design technique has its inherent characteristics. It is noted that surrogate modelling is used when data is limited, NNs are suitable when data is large, and the relationship between the parameters is nonlinear. Therefore, the NN training is expensive and time-consuming. However, RL is used when the design problem involves sequential decision-making or optimization over multiple stages. GAs are used for global optimization in large, complex search spaces, especially when robustness is needed against local minima. PSO is used for global optimization similar to GA, with the added benefit of simplicity and good convergence properties.

The selection of the technique in designing a given RF circuit depends on the characteristics of the technique and that of the circuit. ANN is capable to learn non-linear relationship from data, thus it is well suited for designing non-linear circuits like power amplifier. RL can make sequential decision and capable for adaptive tuning problems that makes them suitable for designing matching networks because it can optimize parameters as load impedance changes. And surrogate modeling is suited to reduce the computational cost of complex problems. Thus SM with ANN is more suitable to design RF PA.

Table. III
Comparison of characteristics of the optimization techniques

Technique	GA	NN	RL	SM	PSO	PYO
Sample size (range)	100 - 1000	1000 – 100000	10000 – 1000000	100 – 10000	100 – 1000	10000 – 1000000
Training time (sec)	0.1 - 100	10 - 10000	100 – 100000	0.1 - 1000	0.1 - 100	1000 – 100000
Computational complexity (average)	O(n * m)	O(n^ 2) - O(n^ 3)	O(n^ 2) - O(n^ 3)	O(n^ 2) - O(n^ 3)	O(n^ 2) - O(n^ 3)	O(n)
Optimization Goal	Global	Prediction, Classification	Sequential Decision making	Regression, Classification	Global	Object detection
Parameter Sensitivity	High	High	Moderate	Moderate	Moderate	High
Convergence Speed	Moderate	Slow to moderate	Slow to fast	Fast	Fast	Fast
Suitability for Linear/Nonlinear Problems	Both	Highly nonlinear	Highly nonlinear	Both	Both	Nonlinear

IX. CONCLUSION

As documented in existing literature, we have provided an in-depth review of machine learning and global optimization techniques utilized in designing RF circuits. It has explored key design methodologies, including genetic algorithms, neural networks, surrogate modeling, yield optimization, particle swarm optimization, and reinforcement learning. The article begins with an introduction to the fundamentals of these techniques before delving into their specific applications in RF circuit design. A comparative analysis is also presented, offering insights into the relative performance of these techniques. Additionally, the paper offers guidance on selecting the appropriate technique based on specific engineering requirements. We hope this review will be a valuable resource for researchers and RF and microwave engineering engineers.

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