ELECTROMAGNETICS-BASED DESIGN OF HIGH-SPEED CIRCUITS USING ARTIFICIAL NEURAL NETWORKS

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I. INTRODUCTION

Artificial Neural Networks (ANNs) are inspired in the behavior of rudimentary biological neuronal functions. A biological neural network may be thought of as a sophisticated signal processor, in which the strength of each synapse (i.e., the synaptic weight), the bias and threshold values of each neuron at steady state constitute the network's program. ANNs are conceived as information processing systems that aproximate biological neural networks: they emulate the ability of the human brain to learn from observation and generalize by abstraction.

The modern era of artificial neural networks started in the 1940's and explosively developed in the 1980's, finding applications in many areas of science, engineering, management and other disciplines.

Neural network applications in RF and microwave engineering have been reported since the 1990's. Description of artificial neural networks and key issues, namely architectures, paradigms, training methods, data set formation, learning and generalization errors, learning

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speed, etc., in the context of RF and microwave CAD, has been extensively reported [1-6]. An excellent compilation and review of the main issues and initial applications of artificial neural networks in the microwave arena was made by Burrascano and Mongiardo [6]. Patnaik and Mishra [7] developed an abbreviated review of ANN techniques to microwave modeling, design, and measurement problems (with some emphasis on antenna applications). Another excellent review on ANNs for RF circuits, high-speed interconnects and microwave modeling is the work by Zhang et al. [8], which includes a comprehensive foundation to neural model development as well as a list of practical microwave neuromodels. It is clear that neural networks have been widely used for modeling microwave devices and high-speed circuits in several innovative ways. The training and testing data for these models are typically obtained from full-wave EM simulators, from physics-based models, or from measurements. In the case of massive simulation tasks such as those required in RF/microwave subsystems (e.g., front ends for mobile and personal communications), the training and testing data can be obtained from standard Harmonic Balance simulations using detailed circuit models [9]. The resultant neural models are excellent vehicles for fast and accurate simulation. Examples of neuromodeled microwave structures are in Table I.

In contrast, the use of neural networks for microwave design by optimization is at a less developed stage. This Chapter aims at reviewing the relevant work in electromagnetics-based design and optimization of RF and microwave circuits exploiting artificial neural networks (ANNs). Measurement-based design of high-speed circuits using ANNs is also treated. This Chapter is based on the author's review paper [10], which is here updated and expanded.

The conventional and most popular microwave neural optimization approach is reviewed in Section II. Advantages and drawbacks of this strategy are emphasized. Improvements of this "black-box" approach through segmentation, decomposition, hierarchy, design of experiments (DoE) and clusterization are considered.

The main limitations of the conventional neural optimization approach can be alleviated by incorporating available knowledge into the neural network training scheme. Several innovative strategies that exploit knowledge are described in Section III, including the Difference Method (also called Hybrid EM-ANN), the Prior Knowledge Input (PKI) method, the Knowledge-Based ANN approach (KBNN), the Neural Space Mapping (NSM) optimization method, the Extended Neural Space Mapping approach, and the Neural Inverse Space Mapping (NISM) optimization algorithm. Practical examples using these techniques are illustrated.

Another strategy for ANN-based design of high-speed, RF and microwave circuits is described in Section IV, which consists of developing synthesis neural networks, also called "inverse neural models". A synthesis neural network is trained to learn the mapping from the responses to the design parameters of the microwave circuit. Difficulties in developing synthesis neural networks are indicated. Several cases of successful inverse modeling are described.

Section V deals with several methods for EM-based statistical design using neural networks. An industrially relevant microwave problem is used to illustrate the application of neural networks for efficient and accurate yield optimization.

The key issues on transient EM-based design using neural networks are described in Section VI. Suitable paradigms for approximating nonlinear dynamic behavior are mentioned, such us Recurrent Neural Network (RNN) and their corresponding training techniques.

In Section VII the exploitation of ANNs in the so called "Global Modeling" technique is described. "Global modeling" refers to a technique for unifying the EM analysis of passive structures and the semiconductor theory related to the active devices, by coupling the transport equations with Maxwell's equations. The use of neural networks to speed up "global modeling" for EM-based design of MMICs is briefly described.

Some future directions of ANN techniques for designing high-speed, RF and microwave circuits are proposed in Section VIII. Finally, in Section IX some conclusions are drawn.

II. THE CONVENTIONAL NEURAL OPTIMIZATION APPROACH

The most common strategy for optimizing high-speed, RF and microwave circuits using neural networks consists of generating a neuromodel of the circuit within a certain training region of the design parameters, and then applying conventional optimization to the neuromodel to find the optimal solution that yields the desired response. This technique is illustrated in Fig. 1. Examples of this neural optimization approach can be found in [11-14].

The neuromodel is trained such that it approximates the fine model responses $\boldsymbol{R}_f$, in a region of interest for the design parameters $\boldsymbol{x}_f$ and operating conditions $\boldsymbol{\psi}$, as illustrated in Fig. 1a. The fine model responses $\boldsymbol{R}_f$ are typically obtained from an EM simulator; in general, they represent the responses of an accurate but computationally expensive model (the term "fine model" comes from the space mapping literature [15]). The operating conditions are in vector $\boldsymbol{\psi}$, which might contain any required combination of independent variables according to the nature of the simulation, such as the operating frequencies, bias levels, excitation levels, risetime, falltime, initial conditions, temperature, etc. Vector $\boldsymbol{w}$ contains the internal free parameters of the ANN (weighting factors, bias, etc.).

If $\boldsymbol{N}$ represents the input-output relationship of the ANN, the process of training the neuromodel (see Fig. 1a) can be formulated as an optimization problem, where an optimal vector of the ANN parameters $\boldsymbol{w}^*$ is found by minimizing the difference between the ANN outputs and the fine model responses at all the learning samples,

$$\boldsymbol{w}^* = \arg\min_{\boldsymbol{w}} \left\| [\boldsymbol{e}_1^T \quad \ldots \quad \boldsymbol{e}_L^T]^T \right\| \tag{1}$$

where ||·|| denotes a suitable norm (typically Euclidean, Manhattan or Huber), L is the total number of learning samples and $\boldsymbol{e}_k$ is the error vector for each of those samples,

$$\boldsymbol{e}_k(\boldsymbol{w}) = \boldsymbol{R}_f(\boldsymbol{x}_{f_i}, \boldsymbol{\psi}_j) - \boldsymbol{N}(\boldsymbol{x}_{f_i}, \boldsymbol{\psi}_j, \boldsymbol{w}) \tag{2}$$

with

$$i = 1, \ldots, l \tag{3a}$$

$$j = 1, \ldots, \tau \tag{3b}$$

$$k = j + \tau(i-1) \tag{3c}$$

where l is the number of training base points for the design parameters and τ is the number of independent variable points. It is seen that the total number of learning samples is $L = l\tau$.

The complexity of the ANN must be properly selected: the number of internal free parameters has to be sufficiently large to achieve a small learning error, and sufficiently small to avoid poor generalization performance, i.e., ANNs that are too small cannot approximate the desired input-output relationship, while those with too many internal parameters perform correctly on the learning set, but give large errors at points not seen during training [16]. The generalization ability of the neuromodels is controlled during the training process (1) by using validation data and testing data, also obtained from fine model evaluations (typically full-wave EM simulations or measurements).

Multilayer feedforward perceptrons are the most common paradigm for implementing the neuromodels [6]. In principle, they offer an accurate vehicle to model complex phenomena, since it has been shown [17] that standard multilayer feedforward networks can approximate any measurable function to any desired level of accuracy, provided a deterministic relationship between input and target exists.

Once an appropriate ANN is trained with sufficient learning samples and adequate generalization performance, i.e., once the optimal free parameters $\boldsymbol{w}^*$ are determined, the ANN can be used for fast and accurate simulations within the region of interest. It can also be used for inexpensive optimization, to find an approximation of the optimal fine model solution $\boldsymbol{x}_f^*$ that yields the desired response $\boldsymbol{R}_f^* = \boldsymbol{R}_f(\boldsymbol{x}_f^*)$ (see Fig. 1b). The design problem consists of finding $\boldsymbol{x}_f^*$ such that

$$\boldsymbol{x}_f^* = \arg\min_{\boldsymbol{x}_f} U(\boldsymbol{N}(\boldsymbol{x}_f, \boldsymbol{\psi}, \boldsymbol{w}^*)) \tag{4}$$

where U is the objective function (typically minimax) expressed in terms of the design specifications.

When the already trained neuromodel is optimized to find the optimal fine model solution $\boldsymbol{x}_f^*$, conventional optimization methods [18,19] are typically used.

In [20,21], a modified version of the training algorithm used to develop the neuromodel is employed for searching the optimal design. In this case the backpropagation algorithm with a modified learning rule where the weights are kept fixed while the input design parameters are considered as free parameters, is used to find the optimal design. In this sense, the neural network is considered in [20,21] as a "bi-directional model", and the process of training the ANN with $\boldsymbol{x}_f$ as free parameters is considered as a "reverse modeling" process. This reverse modeling approach is illustrated in [20,21] by designing microwave HBT amplifiers.

In any case, the conventional approach to ANN-based design allows us to search for multiple solutions if different starting points for the design parameters are used.

A. Segmentation and Decomposition

The neuromodel to be used for design by optimization can be developed for the microwave circuit as a whole, or in a decomposed manner, where small neuromodels are developed for each individual section in the circuit, which are later connected by circuit theory. Full wave EM simulations are typically employed to generate the training, validation and testing data for each section of the microwave circuit. Examples of this decomposed approach are found in [22,23]. The design of a microstrip corporate feed embedded in the middle of a duroid substrate is realized in [23] by characterizing each junction in the corporate feed using neural networks.

A different technique for neuromodeling decomposition can be used when the complete set of responses contained in $\boldsymbol{R}_f$ are difficult to approximate with a single ANN. In those cases, the learning task can be distributed among a number of ANNs, which in turn divides the output space into a set of subspaces. The corresponding ANNs are trained individually, to match each response (or subset of responses) contained in $\boldsymbol{R}_f$. The technique is illustrated in Fig. 2. Examples of this approach are found in [24]. For instance, each output current and complex admittance parameter of a MESFET transistor is approximated in [24] by an individual neural network within a certain region of bias voltages and operating frequencies.

B. Exploiting Hierarchy

Practical CAD tools require abundant libraries of accurate and computationally efficient models. If neuromodels are to be used for efficient microwave design, the development of these libraries demands a more intelligent approach than developing individual neuromodels for each component of each library, otherwise massive fine model data generation and repetitive model training would be necessary. As a response to this challenge, a Hierarchical Neural Network approach is proposed in [25], which basically consists of two stages. In the first one the fundamental performance of a family of components of a library is identified and the corresponding basic (or low-level) neuromodels are developed. In the second stage a neural network based on a suitable combination of the low-level neuromodels is trained to map the low-level responses to the fine model responses of each component in that family. Examples of high-speed interconnect libraries and physics-based MESFET libraries are developed in [25] following this approach.

C. Final Remarks on the Conventional ANN-based Design Approach

The conventional approach to ANN-based design described before, which is also known as the "black-box" approach [26], has three main disadvantages: the time required to generate sufficient training, validation and testing samples, the unreliability of the optimal solution when it lies outside the training region (due to the well known poor extrapolation performance of ANNs), and the "curse of dimensionality", which refers to the fact that the number of learning samples needed to approximate a function grows exponentially with the ratio between the dimensionality and its degree of smoothness [27]. Essentially, the number of fine model evaluations needed in this approach grows exponentially with the number of design parameters in the circuit.

An alternative to reduce the size of the learning set in the black-box approach is to carefully select the learning points using the Design of Experiments (DoE) methodology, to ensure adequate parameter coverage, as in [28,29].

Another way to speed up the learning process is proposed in [6] by means of preliminary neural clusterization of similar responses using the Self Organizing Feature Map (SOM) approach. An interpretation of the general concept is illustrated in Fig. 3. Vector $\boldsymbol{w}_b$ represents the internal free parameters of a basic ANN that is taken as a rough approximation of the fine model in the region of interest, while vector $\boldsymbol{w}_s$ represents the internal free-parameters of the

SOM network. The SOM is developed such that it can automatically identify a number of classes of behavior (or groups of similar responses) according to some previously defined criteria. Then individual neural networks (multiple-layer perceptrons) are trained with the data associated with each class. Experiments are reported in [6] showing reduction in the overall training time of up to 80% with respect to that required by a single neural network model.

The conventional neural optimization approach is indeed very suitable when the device's physics is not fully understood (i.e., when there is no empirical model available for the device), but the device's outputs for specified inputs are available, either from measurements or from accurate simulations. On the other hand, an important advantage of the conventional neural optimization approach is its adequacy for full automation. An algorithm for automatic development of conventional (black-box) neuromodels of microwave circuits is proposed by Zhang et al. [30]. This algorithm can automatically generate a neuromodel for any desired accuracy within a user-defined region of interest. The process of generating fine-model training data, as well as the process of regulating the ANN complexity is fully automated. Once the neural model automatically developed is available, the algorithm could be in principle expanded to automated design by optimization given a number of user-defined specifications and constraints, although this has not been reported yet.

III. NEURAL EM-DESIGN EXPLOITING MICROWAVE KNOWLEDGE

The three main limitations of the conventional neural optimization approach can be alleviated by incorporating available microwave knowledge into the neural network training scheme. Several innovative strategies have been proposed to incorporate this knowledge.

A. The Difference Method

Also known as the Hybrid EM-ANN method, the Difference Method makes use of the difference in S-parameters between an available coarse model and the fine model to train the corresponding neural network, as illustrated in Fig. 4a. The coarse model responses $\boldsymbol{R}_c$ are typically obtained from an empirical, circuit equivalent model, which is very fast to evaluate but is not sufficiently accurate in all the regions of interest for the design parameters and operating conditions (the term "coarse model" comes from the space mapping literature [15]). Training the neuromodel in the Difference Method can be formulated as (1-3) but replacing (2) by the error vector

$$\boldsymbol{e}_k(\boldsymbol{w}) = [\boldsymbol{R}_f(\boldsymbol{x}_{f_i}, \boldsymbol{\psi}_j) - \boldsymbol{R}_c(\boldsymbol{x}_{f_i}, \boldsymbol{\psi}_j)] - \boldsymbol{N}(\boldsymbol{x}_{f_i}, \boldsymbol{\psi}_j, \boldsymbol{w}) \tag{5}$$

Once the ANN is trained to approximate the difference between the fine and coarse model responses in the region of interest, it can be combined with the coarse model as in Fig. 4b to yield an inexpensive and accurate approximation of the fine model, which can be used for conventional optimization. The design problem is then formulated as finding $\boldsymbol{x}_f^*$ such that

$$\boldsymbol{x}_f^* = \arg \min_{\boldsymbol{x}_f} U(R_c(\boldsymbol{x}_f, \boldsymbol{\psi}) + \boldsymbol{N}(\boldsymbol{x}_f, \boldsymbol{\psi}, \boldsymbol{w}^*)) \tag{6}$$

It has been reported [31] that the number of fine model simulations needed to train the ANN can be significantly reduced in the Difference Method. However, it is recognized in [32] that this reduction in training samples is achieved only when the mapping from the difference between the fine and coarse model responses to the input parameters is simpler than the original target relationship, which is not always possible, depending on the coarse model accuracy. The Hybrid EM-ANN approach was used in [33] to design an end-coupled band-pass filter in a 2-layer configuration.

To illustrate how the difference between the fine and coarse model responses can be as complex as the fine model responses themselves, consider the HTS microstrip filter in [34]. Fig. 5 shows the coarse model responses at 13 base points, the corresponding fine model responses, and the absolute difference between them. It is seen that the difference between both models look like filter responses too, due to the severe misalignment of the coarse model responses. Modeling the difference by a neural network would represent almost the same effort as modeling the fine model directly.

B. The Prior Knowledge Input (PKI) Method

In the Prior Knowledge Input (PKI) method proposed by Gupta et al. the coarse model responses are used as inputs for the ANN in addition to the other inputs, as illustrated in Fig. 6. The neural network is trained such that its response is as close as possible to the fine model response for all the data in the training set (see Fig. 6a). Once it is trained, it can be used with the coarse model to realize efficient optimization (see Fig. 6b). It has been reported [32,35] that the PKI approach exhibits better accuracy than the Hybrid EM-ANN approach, at the expense of a more complex ANN. The PKI method is used in [36] to optimize a CPW patch/slot antenna on Duroid.

C. The Knowledge-Based ANN (KBNN) Approach

In the so called Knowledge-Based ANN approach (KBNN), developed by Zhang et al. [37], the available knowledge is inserted in the internal structure of the ANN, as illustrated in Fig. 7. This knowledge takes the form of microwave empirical or semi-analytical information.

Knowledge-Based ANNs have non fully connected architectures, with one or several layers assigned to the microwave knowledge in the form of single or multidimensional vector functions, usually obtained from available closed-form expressions based on quasi-static approximations.

By inserting the microwave empirical formulas into the neural network structure, the empirical formulas can be refined or adjusted as part of the overall neural network training process. Since these empirical functions are used for some neurons instead of standard activation functions, KBNNs do not follow a typical multilayer perceptron architecture and are trained using other methods than the conventional backpropagation [37]. In Fig. 7a, vector $\boldsymbol{w}$ contains not only the typical free parameters of an ANN (weights, bias, etc.), but also the adjustable parameters of the microwave empirical functions.

KBNNs have been extensively used for developing models of microwave circuits [37, 38,39]. In contrast, there are no microwave design examples using KBNNs (as defined here) reported in the literature. Nevertheless, once a KBNN model is appropriately trained, it could be used as an accurate and inexpensive model for realizing conventional optimal design (see Fig. 7b).

D. Sensitivity of Knowledge-Based Neural Networks

Sensitivity information is very important in design by optimization. The evaluation of the output derivatives with respect to the design variables without resorting to finite-difference schemes can improve the numerical performance of a large class of optimization methods typically employed for design. When conventional feed-forward neural networks are used, the Jacobian of the ANN outputs with respect to its inputs can be obtained in closed form [40]. When a generic knowledge-based neural network is used, i.e., when microwave functions are embedded within the ANN topology, the KBNN sensitivity information can be obtained using the formulation proposed by Zhang et al. [41,42]. In this formulation two ANNs are used: the original neural network and other called the adjoint neural network. The adjoint neural network is defined such that once the original neural network is trained using the input/output data, the outputs of the adjoint neural network automatically becomes the derivatives of the output data with respect to the input data. This formulation is used in [42] to find by optimization the solution of feasible regions of VLSI interconnect geometries given a budget on electrical performance.

E. Neural Space Mapping (NSM) Optimization

NSM optimization follows a space mapping (SM) approach to design [43,15], where the mapping function $\boldsymbol{P}$ from the fine to the coarse model parameter space is implemented by an ANN. NSM optimization represents the first algorithmic formulation of ANN-based design of microwave circuits [44]. A simplified flow diagram for NSM optimization is illustrated in Fig. 8.

NSM starts by finding the optimal coarse model solution $\boldsymbol{x}_c^*$ that yields the desired response $\boldsymbol{R}^*$ by applying conventional optimization to the coarse model. In Fig. 8, $U(\cdot)$ represents the same objective function used in (4) and (6). $2n$ additional points centered at $\boldsymbol{x}_c^*$ are selected as the initial training set to develop an SM-based neuromodel [45], where n is the number of design parameters ($\boldsymbol{x}_c, \boldsymbol{x}_f \in \Re^n$). Training the neuromapping is formulated as (1-3) but replacing (2) by the error vector

$$\boldsymbol{e}_k(\boldsymbol{w}) = \boldsymbol{R}_f(\boldsymbol{x}_{f_i}, \boldsymbol{\psi}_j) - \boldsymbol{R}_c(\boldsymbol{N}(\boldsymbol{x}_{f_i}, \boldsymbol{\psi}_j, \boldsymbol{w})) \tag{7}$$

Once an SM-based neuromodel is trained (see Fig. 9a), it is used as an improved coarse model (also called "surrogate model"), optimizing its parameters to generate the desired response. The solution to the optimization problem

$$\boldsymbol{x}_f^{(i+1)} = \arg\min_{\boldsymbol{x}_f} U(\boldsymbol{R}_c(\boldsymbol{N}(\boldsymbol{x}_f, \boldsymbol{\psi}, \boldsymbol{w}^*))) \tag{8}$$

becomes the next iterate and is included in the learning set (see Fig. 9b).

The fine model response at the new point is calculated and compared with the desired response. If they are not close enough, the SM-based neuromodel is re-trained over the extended set of learning samples and the algorithm continues, otherwise, the algorithm terminates.

An interesting feature of NSM optimization is that the independent variable $\boldsymbol{\psi}$ can also be transformed through the neural network in order to improve the alignment between the fine and coarse model responses. Additionally, NSM allows us to map only some of the design parameters. This flexibility yields a number of different techniques to establish the neuromapping $\boldsymbol{N}$, all of them illustrated in [45,34] for linear frequency-domain cases. An extension of the neural space mapping modeling technique [45] applicable for nonlinear device modeling and large signal simulation is in [46].

NSM optimization is used in [34] to design a high-temperature superconducting (HTS) quarter-wave parallel coupled-line microstrip filter, as well as a bandstop microstrip filter with quarter-wave resonant open stubs. NSM optimization has only been reported for frequency domain design problems.

F. Extended Neural Space Mapping Approach

Although the original formulation of space mapping optimization considers $\boldsymbol{x}_c$ and $\boldsymbol{x}_f$ with different dimensions [43] and even with different design variables [15], the initial versions of SM-based algorithms were implemented and illustrated assuming that the optimization variables of the fine and coarse models are the same. Typically, $\boldsymbol{x}_c$ and $\boldsymbol{x}_f$ are vectors with the same dimension containing corresponding physical parameters (lengths, widths, heights, dielectric constants, etc.). This is true in [43,15,47-52], and NSM optimization is no exception. This constraint was probably motivated by the fact that the mapping between both models can be easily initialized with a unit mapping, and that the Broyden updating formula usually considers $\boldsymbol{x}_c$ and $\boldsymbol{x}_f$ with the same dimensionality, i.e., a system of n nonlinear equations with n unknowns is assumed [53].

More recent versions of SM-based optimization algorithms allow different dimensionality in $\boldsymbol{x}_f$ and $\boldsymbol{x}_c$, but still it is assumed they are of the same nature ($\boldsymbol{x}_f$ contains a subset of the design variables contained in $\boldsymbol{x}_c$). That is the case in [54,55], where the coarse model optimization variables include not only the fine model optimization variables but also some pre-assigned parameters. The novel output space mapping [56] relates the mapped coarse model responses to the fine model responses, so that the mapped vectors (responses) are also of the same nature and dimensionality.

In the most general case of input space mapping, the optimization variables of the fine and coarse models could be of different nature and dimension, hence the term "extended space mapping". For instance, $\boldsymbol{x}_c$ might contain the element values of an equivalent lumped circuit of a microwave structure, while $\boldsymbol{x}_f$ might contain the physical dimensions and material constants of that structure.

An SM-based optimization algorithm for this general or extended mapping was proposed in [57], by using two different mappings, one for the parameters with the same design variables (the normal linearized mapping, which is updated using Broyden's formula), and a second one called "knowledge mapping", which is used to translate from the circuit to the physical variables in the coarse model using empirical formulas. The technique described in [57] realizes the coarse model optimization phase and the parameter extraction phase at the circuit parameter level and not at the physical parameter level. Several LTCC filters are designed in [57] following this scheme. Another example of extended space mapping optimization is in [58], where $\boldsymbol{x}_f$ contains n geometrical parameters of a multiplexer channel, while $\boldsymbol{x}_c$ contains the corresponding m coupling matrix elements.

In contrast, an ANN-based design approach for this general case of extended space mapping has not been reported in the literature, only a neural modeling strategy was proposed in [59,60], where $\boldsymbol{x}_c$ contains the element values of a conventional small signal equivalent circuit of an HEMT (whose physical dimensions are fixed), while $\boldsymbol{x}_f$ contains the bias voltages. $\boldsymbol{R}_f$ contains the S-parameters measured at various bias settings. In this manner, once a suitable ANN is properly trained, the combination of the ANN and the small signal equivalent circuit approximates the large signal behavior of the active device (see Fig. 10) in the region of training.

G. Neural Inverse Space Mapping (NISM) Optimization

NISM optimization is another algorithmic approach to ANN-based design, where the inverse of the mapping between the fine and coarse models is implemented with a neural network [61]. NISM optimization follows an aggressive approach in the sense of not requiring a number of up-front fine model evaluations to start building the inverse mapping.

As in any other space mapping algorithm, NISM starts by finding the optimal coarse model solution $\boldsymbol{x}_c^*$ that yields the desired response by optimizing the coarse model, followed by a fine model evaluation at $\boldsymbol{x}_c^*$. Next, parameter extraction is performed, which consists of finding the coarse model parameters that make $\boldsymbol{R}_c$ as close as possible to $\boldsymbol{R}_f$ (see Fig. 11a). The inverse of the mapping is trained with all the accumulated points from previous parameter extractions, as illustrated in Fig. 11b. Training the inverse neuromapping at the ith iteration is formulated as

$$\boldsymbol{w}^* = \arg \min_{\boldsymbol{w}} \left\| [\ldots \quad \boldsymbol{e}_l^T \quad \ldots]^T \right\| \tag{9}$$

with

$$\boldsymbol{e}_l = \boldsymbol{x}_f^{(l)} - \boldsymbol{N}(\boldsymbol{x}_c^{(l)}, \boldsymbol{w}), \quad l = 1, \ldots, i \tag{10a,b}$$

The next iterate is calculated by simply evaluating the current inverse neuromapping at the optimal coarse model solution (see Fig. 11c),

$$\boldsymbol{x}_f^{(i+1)} = \boldsymbol{N}(\boldsymbol{x}_c^*, \boldsymbol{w}^*) \tag{11}$$

If the relative changes in the fine model parameters are small enough, NISM stops, otherwise a new parameter extraction is realized and the algorithm continues. A simplified algorithm for NISM optimization is illustrated in Fig. 12.

NISM is used in [62] to design a capacitively-loaded 10:1 two-section impedance transformer, a bandstop microstrip filter with open stubs, and an HTS quarter-wave parallel coupled-line microstrip filter. NISM optimization is compared in [63] with NSM optimization as well as with the trust region Aggressive Space Mapping algorithm exploiting surrogates [52]. It is found in [63] that, in all the examples considered, NISM optimization not only requires fewer fine model evaluations, but also arrives at a solution closer to the solution of the original optimization problem (the direct optimization of the fine model).

As in the case of NSM optimization, NISM optimization has only been illustrated for frequency domain design problems, where $\boldsymbol{x}_c$ and $\boldsymbol{x}_f$ are the same optimization variables.

IV. SYNTHESIS NEURAL NETWORKS

Another strategy for ANN-based design of microwave circuits consists of using synthesis neural networks, also called "inverse neural models". A synthesis neural network is trained to learn the mapping from the responses to the design parameters of the microwave circuit. In this sense, a conventional neuromodel becomes an analysis neural network. The problem of training a synthesis neural network is known as the inverse modeling problem, since the input and output variables are interchanged. This idea is illustrated in Fig. 13, where the ANN is trained such that it can synthesize the design parameters $\boldsymbol{x}_f$ for a given response $\boldsymbol{R}_f$.

The analysis problem is characterized by a single-value mapping: given a vector of design parameters we have only one possible vector of responses. However, for inverse problems, the mapping can often be multi-valued: a given vector of responses can be generated by several different vectors of design parameters. This might lead the synthesis neural network to make poor generalizations. Another complication of the inverse modeling problem is the coverage of the input space by the training data, since the full characterization of the input space (microwave circuit responses) is usually not available.

A successful case of synthesis ANN development is reported by Selleri et al. [64,65], where an inverse neuromodel was obtained for predicting the position x and the radius r of a cylindrical post in a rectangular waveguide given a frequency sweep of $|S_{21}|$ obtained from full wave finite element EM simulations. The synthesis neural network is trained with a number of vectors $\boldsymbol{x}_f = [x \quad r]^T$ and $\boldsymbol{R}_f = [|S_{21}(f_1)| \quad |S_{21}(f_2)| \ \ldots]^T$. It is reported in [64] that the synthesis ANN yields high accuracy for 3 testing points (3 frequency sweeps) not seen during training.

An interesting approach is employed in [64] to design a profiled corrugated circular horn antenna by using synthesis neural networks. In this problem, the effects of the multi-valued design relationship is overcome by taking a subset of the original design parameters (keeping constant the rest of them), by considering only some of the original responses (with *a posteriori* validation), and by imposing a selection criterion on the geometries predicted by the neural network.

A dedicated algorithm for the design of multilayer asymmetric coupled transmission structures using a combination of analysis neural networks, synthesis neural networks and equivalent lumped circuits was successfully developed Gupta et al. [66]. In that work, the input space of the synthesis neural network is not the set of S parameters, but a set of lumped circuit parameters that are later translated into the conventional responses. The physical parameters (the width of each line and the spacing between their edges) are the outputs of the synthesis ANN and the inputs of the analysis ANN. Similarly, the output space of the analysis ANN is not the set of scattering parameters but a set of LC parameters used in an equivalent lumped circuit that generates the actual responses.

Developing synthesis neural networks for general microwave design appears to be far from automation. The most serious difficulty is the multi-valued relationship in the inverse model. User intervention is most likely needed in terms of choosing suitable design parameters, i.e., in determining selection criteria to impose a one-to-one relationship. It appears that only dedicated algorithms for very specific design problems are amenable to automation.

V. ANN-BASED STATISTICAL DESIGN

Accurate statistical analysis and yield optimization of microwave components are crucial ingredients for manufacturability-driven designs in a time-to-market development environment. Yield optimization requires intensive simulations to cover the entire statistic of possible outcomes of a given manufacturing process. In practice, random variations in the manufacturing process of a microwave device may result in a significant percentage of the produced devices not meeting the specifications. When designing, it is essential to account for these inevitable uncertainties. Given the recognized accuracy of EM full-wave field solvers, it is desirable to include them in the statistical analysis and yield-driven design of microwave circuits. Unfortunately, their high computational cost imposes serious constraints for their direct intensive usage.

Significant contributions have been made to the EM-based statistical analysis and design of microwave circuits. Yield-driven EM optimization using multidimensional quadratic models that approximate the EM model responses for efficient and accurate evaluations was proposed in [67]. A more integrated CAD system for statistical analysis and design was proposed by Bandler et al. [68], where quadratic modeling and interpolation techniques were unified.

A. Yield Analysis and Design Using ANNs

The most basic approach to ANN-based EM statistical design consists of applying conventional neuromodeling over a certain region of interest (see Section II) and then applying conventional Monte Carlo analysis techniques and conventional yield optimization techniques to the inexpensive but accurate neuromodel. In [11], the yield for the gain and input VSWR of an X-band amplifier is optimized by using conventional neuromodels. In [13], a conventional neuromodeling procedure is followed to develop a fast and accurate model of an E-plane metal-insert waveguide filter, within a region defined by certain nominal manufacturing tolerances. This neuromodel is later used to efficiently predict the yield on a large set of outcomes.

The exploitation of neuromodels to estimate IC parametric yield is demonstrated by Creech and Zurada [108]. Here the neuromodel is developed in a decomposed fashion (see Section IIa), using training data obtained from measurements, including doping concentrations, layer thicknesses, planar geometries, resistivities, device voltages and currents in MESFET devices. Inverse neuromodels are also developed to perform yield optimization. Excellent agreement between the neuromodel yield prediction and the actual yield is reported.

The use of SM-based neuromodels to perform accurate and efficient yield analysis and optimization of microwave devices is proposed by Bandler et al. [69]. Here it is assumed that the SM-based neuromodel is already available, obtained either from a modeling process [45] or from an optimization process [34]. It is shown in [69] that if the SM-based neuromodel is properly developed, the sensitivities of the fine model responses, $\boldsymbol{J}_f$, can be approximated using

$$\boldsymbol{J}_f \approx \boldsymbol{J}_c \boldsymbol{J}_N \tag{12}$$

where $\boldsymbol{J}_c$ denotes the Jacobian of the coarse model responses with respect to the coarse model parameters and mapped independent variable, while $\boldsymbol{J}_N$ denotes the Jacobian of the neuromapping with respect to the fine model parameters. $\boldsymbol{J}_c$ can be inexpensively computed using the coarse model, while $\boldsymbol{J}_N$ can be calculated in exact closed form if conventional architectures are used for the ANN (e.g., three-layer perceptrons).

B. An Example of Yield Optimization through Neural Space Mapping

Consider optimizing the yield of a high-temperature superconducting (HTS) quarter-wave parallel coupled-line microstrip filter [69], whose physical structure is illustrated in Fig. 14. L_1, L_2 and L_3 are the lengths of the coupled-line sections and S_1, S_2 and S_3 are the corresponding separations. The width W is the same for all the sections as well as for the input and output lines, of length L_0. A lanthanum aluminate substrate with thickness H and dielectric constant ε_r is used. The design specifications are $|S_{21}| \geq 0.95$ in the passband and $|S_{21}| \leq 0.05$ in the stopband, where the stopband includes frequencies below 3.967 GHz and above 4.099 GHz, and the passband lies in the range [4.008GHz, 4.058GHz].

OSA90/hope™ [70] built-in elements for microstrip lines, two-coupled microstrip lines and open circuits connected by circuit theory over the same substrate definition are taken as the "coarse" model. Sonnet's ***em***™ [71] with a high-resolution grid is used as the fine model.

The SM-based neuromodel of the HTS filter obtained in [45] is used to perform yield analysis and optimization. This model was obtained assuming that the design parameters are $\boldsymbol{x}_f = [L_1\ L_2\ L_3\ S_1\ S_2\ S_3]^T$, and taking L_0 = 50 mil, H = 20 mil, W = 7 mil, ε_r = 23.425, loss tangent = 3×10^{-5}; the metalization was considered lossless. The corresponding SM-based neuromodel is illustrated in Fig. 15, which implements a frequency partial-space mapped neuromapping with 7 hidden neurons, mapping only L_1, S_1 and the frequency (3LP:7-7-3). L_{1c} and S_{1c} in Fig. 15 denote the corresponding two physical dimensions as used by the coarse model, i.e., after being transformed by the mapping, while ω represents the operating frequency (as used by the fine model), and ω_c is the frequency used by the coarse model (transformed by the neuromapping).

To realize yield analysis, it was considered a 0.2% of variation for the dielectric constant and for the loss tangent, as well as 75 micron of variation for the physical dimensions, as suggested in [72], with uniform statistical distributions. The SM-based neuromodel was first optimized, and the statistical analysis was realized around this optimal nominal solution with 500 outcomes using OSA90/hope™. The responses for 50 of those outcomes are shown in Fig. 16. The yield calculation is shown in Fig. 17. A yield of only 18.4% is obtained, which is reasonable considering the well known high sensitivity of this filter.

Yield optimization was then applied to the SM-based neuromodel with 500 outcomes using the Yield-Huber optimizer available in OSA90/hope™. The corresponding responses for 50 of those outcomes are shown in Fig. 18. The yield is increased from 18.4% to 66%, as shown in Fig. 19. An excellent agreement is observed between the fine model response and the SM-based neuromodel response at the optimal yield solution (see Fig. 20). More details on this example, as well as a creative technique for considering asymmetric variations due to tolerances, can be found in [69].

VI. TRANSIENT EM-DESIGN USING NEURAL NETWORKS

Although large-signal S-parameters might be employed to characterize the behavior of nonlinear microwave circuits [73-75], other techniques are usually preferred to fully describe the dynamic performance of such circuits [76]. In the frequency-domain, the two most popular techniques for analyzing nonlinear microwave circuits are Harmonic-Balance and Volterra-Series. The steady-state time-domain response can be easily obtained from the corresponding frequency-domain response by applying inverse Fourier transformation. This allows us to realize steady-state time-domain design by employing frequency-domain simulators.

If the transient response of the nonlinear circuit is an issue, either measurements or direct time-domain simulators with nonlinear models must be employed. If neural network techniques are to be exploited in this case, more suitable paradigms than feed-forward perceptrons should be used.

A neural network with nonlinear dynamic behavior can be realized by adding feedback loops with some unit-delay elements to static multilayer perceptrons with nonlinear activation functions, as in a Recurrent Neural Network (RNN). Fig. 21 conceptually illustrates the process of developing a neural dynamic model of a nonlinear microwave circuit. Vector $\boldsymbol{\psi}(t)$ contains the input waveforms evaluated at the current discrete time t, while $\boldsymbol{R}_f(t)$ contains the corresponding fine model output waveforms amplitudes. Banks of unit-delays are denoted by z^{-1}. Vector $\boldsymbol{x}_f$ contains the design variables as well as any other time invariant circuit parameter. The free-parameters (weights, bias, etc.) of the feed-forward multiple-layer perceptron (MLP) are adjusted during training, such that the RNN best approximates the fine model response in the region of interest. An extension of the standard back-propagation algorithm, the back-propagation through-time (BPTT) algorithm [77], is typically used for training the RNN.

A macromodeling approach for nonlinear microwave circuits using RNNs is proposed by Zhang et al. [78], where macromodels of an RFIC power amplifier and a Gilbert cell mixer are successfully developed.

In addition to the typical issues that have to be considered for training ANNs, there are two parameters that must be carefully chosen while training RNNs, namely the sampling cycle and the number of unit-delay elements in each bank of delays (see Fig. 21). The first one can be estimated from the highest frequency of the input transient waveforms, while the second one is more difficult to predict and it is usually determined heuristically, as in [78].

Following the same procedure as in [78], a macromodeling example of a p-MOSFET transistor is developed in [79]. This example also illustrates the eventual need of a separate RNN to model very fast responses at the beginning of the simulation. An comparison between the performance of standard neural networks (without feedback) and RNNs in transient-regime modeling is described in [79], confirming the RNNs advantages for dynamic systems.

An interesting ANN formulation for modeling nonlinear microwave circuits is realized in [80,81]. Here the neuromodel, called dynamic neural network (DNN) model, is developed as a reduced-order representation in state equations form of the original circuit. The DNN model is trained with frequency-domain information or with time-domain information. The training data used for the examples in [80,81] is in the form of input/output harmonic spectra (obtained from harmonic balance simulations), and the corresponding time-domain data is obtained by inverse Fourier transformation. Training the DNN is implemented in two stages: an initial training in the time-domain, and a refinement step in the frequency-domain. Examples of dynamic modeling of an amplifier, a mixer, and a combination of both to simulate a DBS receiver sub-system are reported in [80,81], where the DNNs are compared with the corresponding original circuits (in both time and frequency domains), showing excellent agreement, and an important reduction in simulation time. A similar approach is used in [82] to develop time-domain neural models for embedded passives. Since the training data used in [80,81] to develop the neural models is in the steady-state regime (obtained from harmonic balance simulations within a finite frequency band), the corresponding DNNs can not in general, for any kind of excitation, reproduce the transient responses of the microwave circuit, but only the steady-state time domain responses. Nevertheless, given their general formulation based on reduced-order state equations, DNNs are in principle capable of simulating transient responses if appropriate training data is employed. A more advanced technique is proposed in [83], where an adjoint of the DNN along with a Lagrange formulation is used to facilitate the DNN training directly from transient data. Transient modeling of nonlinearly terminated high speed interconnects is illustrated in [83].

Examples of time-domain optimization of microwave circuits using ANNs (or RNNs) have not been reported in the literature. More research is also needed on the stability of RNNs when used as models for microwave circuits (Lyapunov stability theory, [16,84]). This is related to the problem of choosing the number of delay-unit elements mentioned above, which determines the order of the dynamic model. Especially important is the stability of RNNs if they are used as computational models in optimization.

VII. GLOBAL MODELING EXPLOITING ANNS

At sufficiently high frequencies, microwave and millimeter-wave CAD tools require full-wave EM analysis of MMICs to accurately predict the wave interactions and behavior of not only the passive structures but also the active devices. Usually, only the passive periphery around the active device is characterized by a full-wave analysis, while the active device is characterized by a lumped equivalent circuit whose element values are provided by parameter extractions based on measurements. When the active device is electrically large (as in the case of wide-gate field-effect transistors), a lumped equivalent circuit is no longer reliable, since it can not predict the effects of possible standing waves along the device itself [85].

On the other hand, simple analytical models based on the drift-diffusion formulation were sufficiently accurate to simulate the electrical performance of the earlier semiconductor devices. However, as semiconductor devices were scaled into the submicrometer scenario, the assumptions underlying the drift-diffusion model lost their validity, leading to the need of full hydrodynamic models based on the Boltzmann's transport equations [86].

The so called "Global Modeling" technique [87] aims at unifying both the electromagnetic analysis of passive structures and the semiconductor theory related to the active devices, by coupling the Boltzman transport equations with Maxwell's equations using space-time discretization. The solution is computed on a non-uniform grid to improve accuracy and convergence: a coarse grid is used on the neutral zones far from the depletion region, while a fine grid is used where high carrier-density gradients are found (under the gate and in the active layer). Since the mesh density in the active device region is much higher than the one in the passive structures, this approach is computationally very expensive, and so far unpractical for direct use into commercial software. Time-domain diakoptics [88] has been proposed to speed up this process.

The use of neural networks to speed up "global modeling" for full-wave design of MMICs was proposed by Goasguen and El-Ghazaly [89]. Here the transistor is implemented in an extended FDTD code, where the nonlinearities of the active device are described by the ANN that updates the circuit parameter values inside the FDTD mesh according to the calculated electromagnetic field. The extended FDTD method uses current/voltage sources to substitute the device in the corresponding cells of the FDTD grid. Lumped elements are also included in the FDTD marching time algorithm (each lumped element is distributed in the cells of the active region).

A MESFET was successfully simulated in [89] using this method. By using the ANN the computation time was dramatically reduced with respect to the simulation time required by a hydrodynamic model or complete global modeling approach.

VIII. SOME FUTURE DIRECTIONS

Finally, an attempt to predict general future developments of microwave design techniques using neural networks is presented here. These are suggested in addition to those specific issues mentioned throughout the paper that require more research.

A. More Algorithmic On-Line Approaches to EM-Based Design

Off-line approaches to ANN-based design consist of developing a neuromodel from reliable data and using it as a fast and accurate approximation of the actual microwave device for optimization. We have seen that this can be realized in several ways. Off-line approaches afford many training, testing and validating data points obtained from fine model evaluations. In contrast, on-line approaches to design should generate as few fine model data points as possible, where local neuromodels (which could be considered as "ANN-based surrogates") are gradually improved at each design iteration. We need more algorithms for on-line ANN EM-based design. These algorithms should allow the microwave engineer to design on a feasible interactive framework, i.e., computationally efficient software engines must be used. At the same time, the microwave engineer should not be concerned with the typical ANN decisions (neural network topology, number of hidden layers, number of hidden neurons, selection of training or testing data, etc.). All of these parameters should be transparent to the user, who should only be concerned with the microwave engineering aspects of the problem.

Zhang et al. [90] proposed an algorithm for Knowledge-based Automatic Model Generation (KAMG), which implements in a automated fashion the development of some of the neuromodeling techniques mentioned in this paper: the Difference Method, the PKI method, the KBNN approach and the SM neuromodeling technique. KAMG aims at generating very accurate microwave neural models using the fewest possible fine model data points. The KAMG algorithm exploits the adaptive sampling technique [30], by which the region where the worst training errors are found is further divided into smaller sub-regions for additional training and validation data. KAMG is an algorithm for modeling. The models generated by KAMG can later be used for design. KAMG is then an off-line approach to ANN EM-based design. We still need an automated on-line design algorithm, as described before.

B. An Integrated Transient and Frequency Domain ANN-Based Design Approach

A number of innovative techniques for microwave design have been described in the previous sections. All of them have been developed and/or demonstrated either for the frequency-domain or for the transient domain. An integrated transient and frequency domain ANN-based design approach has not been reported yet. Although it seems simple, the complexity of this task should not be overlooked.

C. More ANN EM-Based Design Methods Exploiting Circuit Models

Microwave engineers have been developing circuit models of microwave structures for decades. These equivalent circuit models have been successfully used as vehicles for design in countless practical microwave problems. They represent a rich collection of knowledge the microwave community should not abandon. The most successful ANN design techniques will be those that exploit this knowledge more intelligently. Section III describes a number of ANN design techniques that exploit circuit models to make more efficient use of the EM simulator during the design process. By observing Figs. 4, 6, 7, 9 and 11, it is clear that there might be several more ways to efficiently combine the ANN, the fine and the coarse models. New strategies will certainly emerge.

IX. CONCLUSIONS

Significant contributions to the area of electromagnetics-based design and optimization of high-speed, RF and microwave circuits exploiting artificial neural networks are described in this Chapter. Measurement-based design of high-speed circuits using ANNs is also reviewed. The conventional microwave neural optimization approach is described. Advantages and drawbacks of this strategy are treated. Improvements of this approach through segmentation, decomposition, hierarchy, design of experiments (DoE) and clusterization are considered. Innovative strategies for ANN EM-based design that exploit knowledge are reviewed, including the Difference Method, the Prior Knowledge Input (PKI) method, the Knowledge-Based ANN approach (KBNN), the Neural Space Mapping (NSM) optimization method, the Extended Neural Space Mapping approach, and the Neural Inverse Space Mapping (NISM) optimization algorithm. ANN-based design of microwave circuits using synthesis neural networks or inverse neural models is reviewed. Difficulties in developing synthesis neural networks are indicated. Several cases of successful inverse modeling are described. Methods for EM-based statistical design using neural networks are described. An industrially relevant microwave problem illustrates the use of a neural space mapping technique to efficient and accurate yield optimization. The key issues in transient EM-based design using neural networks are described. Suitable paradigms for approximating nonlinear dynamic behavior are mentioned, such us Recurrent Neural Network (RNN) and their corresponding training techniques. The application of ANNs to speed up Global Modeling for EM-based design of MMICs is briefly described. Finally, some future directions of ANN techniques for high-speed, RF and microwave circuit design are predicted.

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TABLE I
NEURAL MODELS FOR MICROWAVE COMPONENTS

Passive Components	Selected References
MMIC spiral inductors	[28,91,92]
Capacitors	[93,94]
Embedded resistors	[95]
Microstrip interconnects	[31,96]
Microstrip vias	[31,35]
Microstrip bends	[97,98]
Microstrip lines on PBG	[99]
CPW components	[22,100,101]
Waveguide elements	[102-104]
PBG waveguides	[99]
Active Devices	**Selected References**
Diodes	[105,106]
MESFETs	[11,24,37,46,107-110]
HBTs	[2,46,111,112]
HEMTs	[29,39,59,60,113]
Circuits and Systems	**Selected References**
Filters	[2,6,13,33,45,95,98,101]
Amplifiers	[9,11,24,26,46,77,109,114]
Mixers	[78,80]
VLSI interconnects	[10,12,83]
Antennas	[115-122]
Radar target recognition	[123,124]

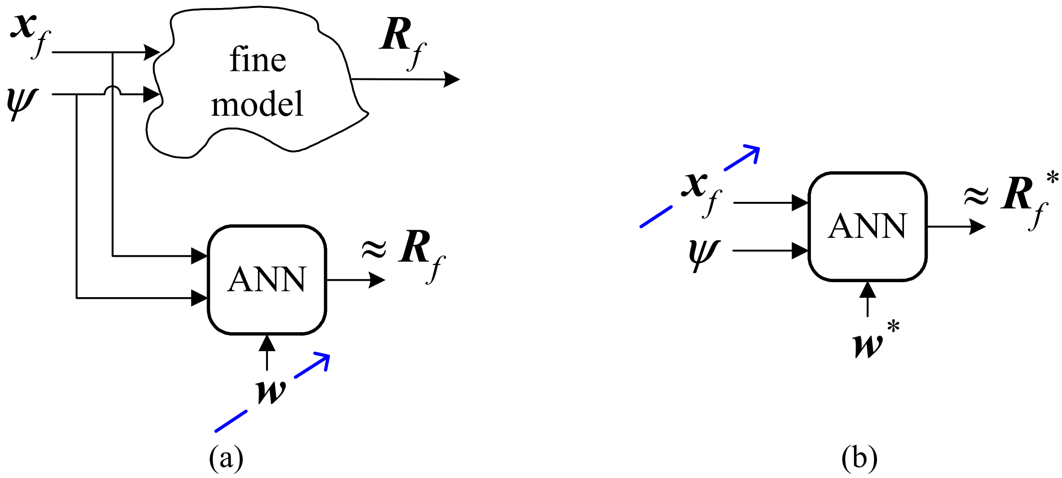


Fig. 1. Conventional neural optimization concept: (a) training the ANN to approximate the fine model responses in a region of interest, (b) designing with the already trained neuromodel.

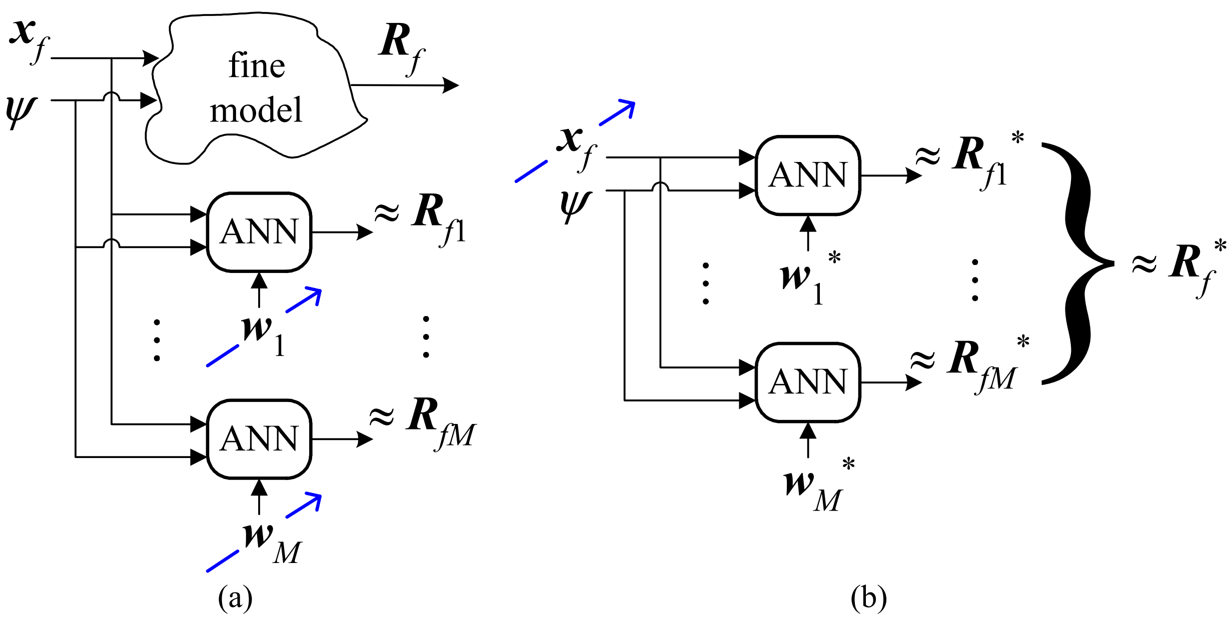


Fig. 2. Decomposed conventional neural optimization concept: (a) training the M neural networks to approximate the individual responses, (b) designing with the already trained decomposed neuromodel.

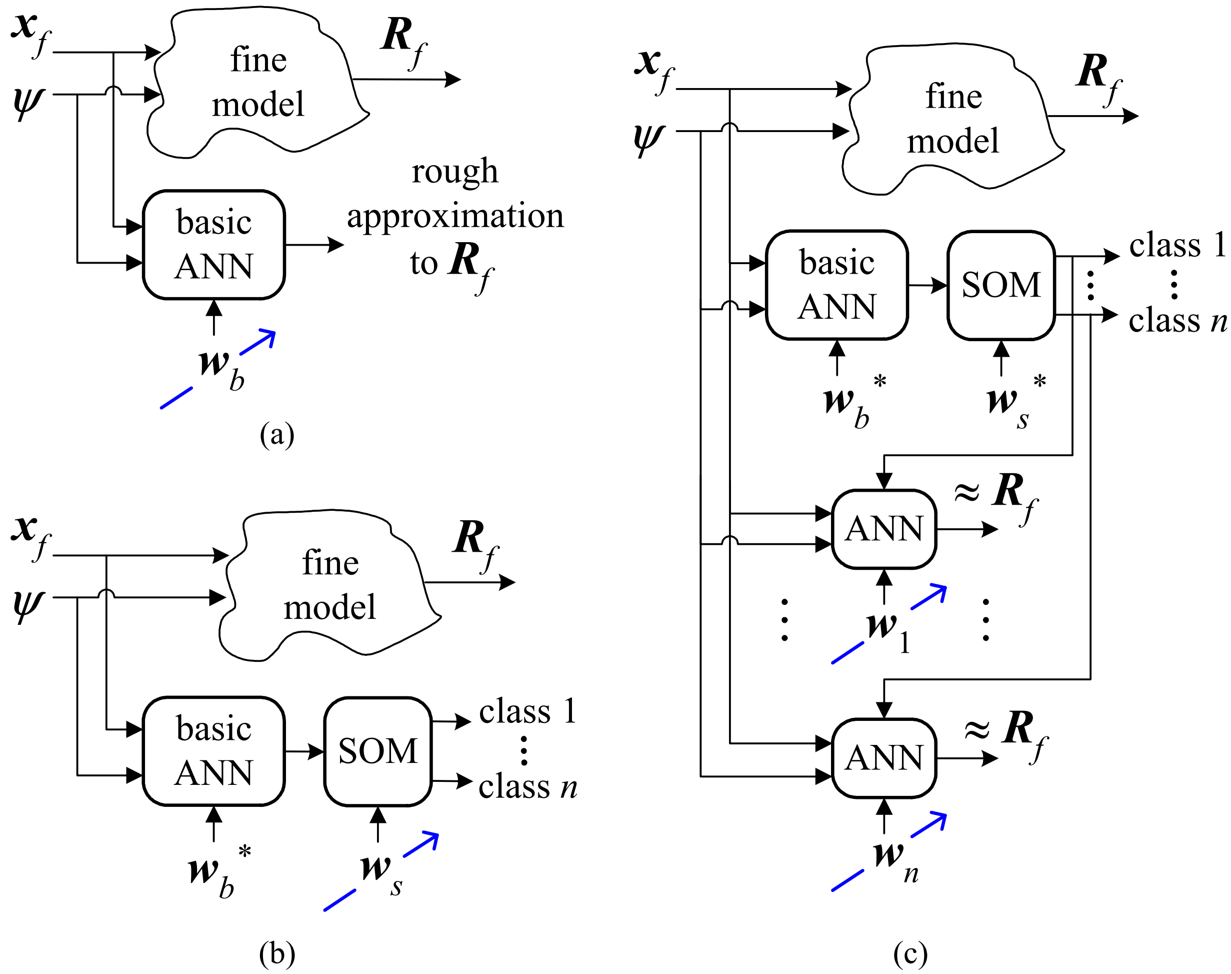


Fig. 3. Neuromodeling by preliminary clusterization of similar responses using the Self Organizing Feature Maps (SOM): (a) training a small ANN as a first-order approximation of the fine model, (b) training a SOM network to detect the classes of responses, (c) training small ANNs, each of them specialized on a class of responses.

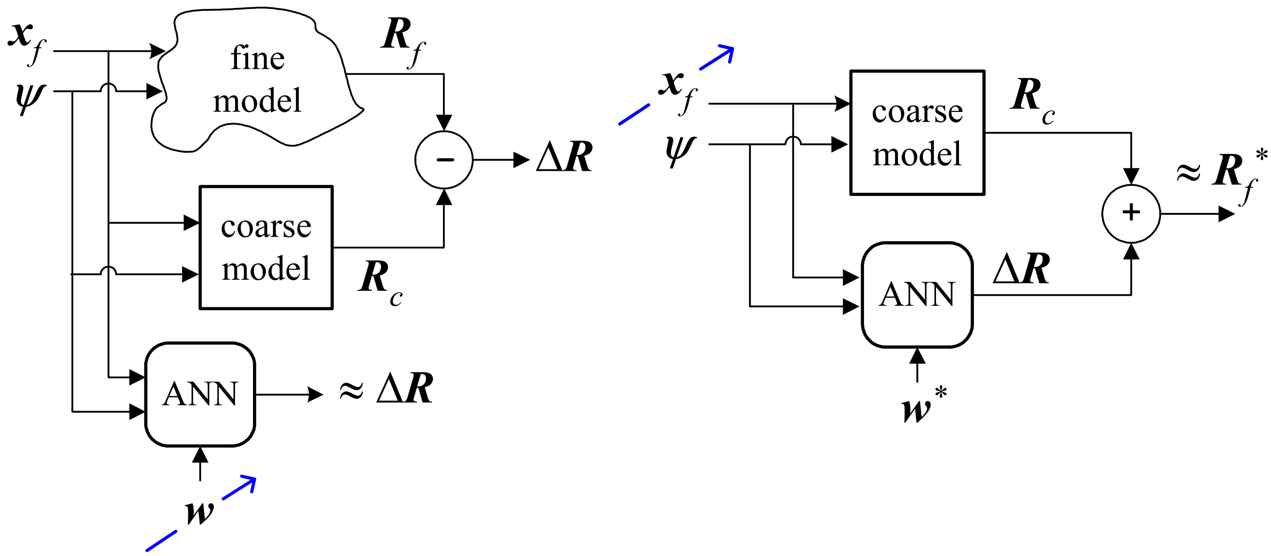


Fig. 4. The Hybrid EM-ANN or Difference Method for neural optimization: (a) training the ANN to approximate the difference between the fine and coarse model responses, (b) designing with the already trained Hybrid EM-ANN neuromodel.

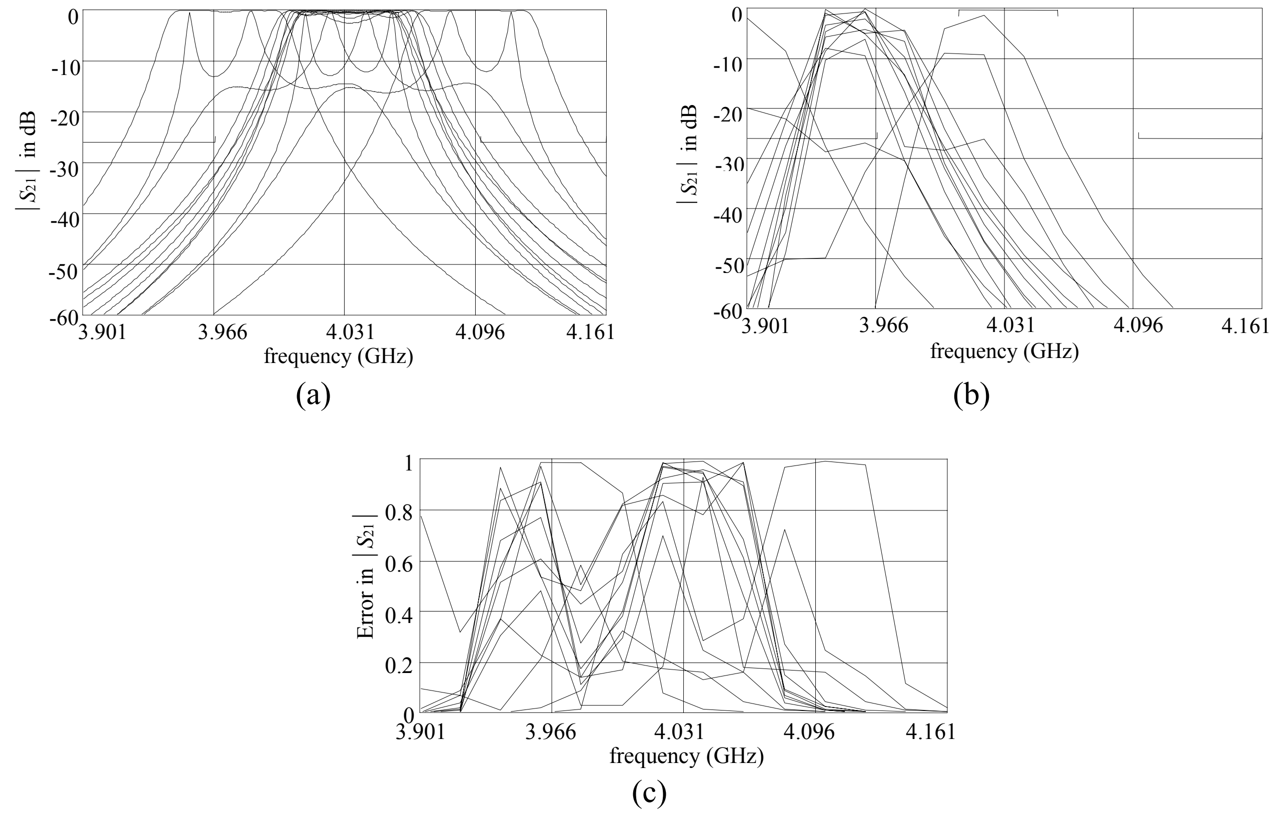
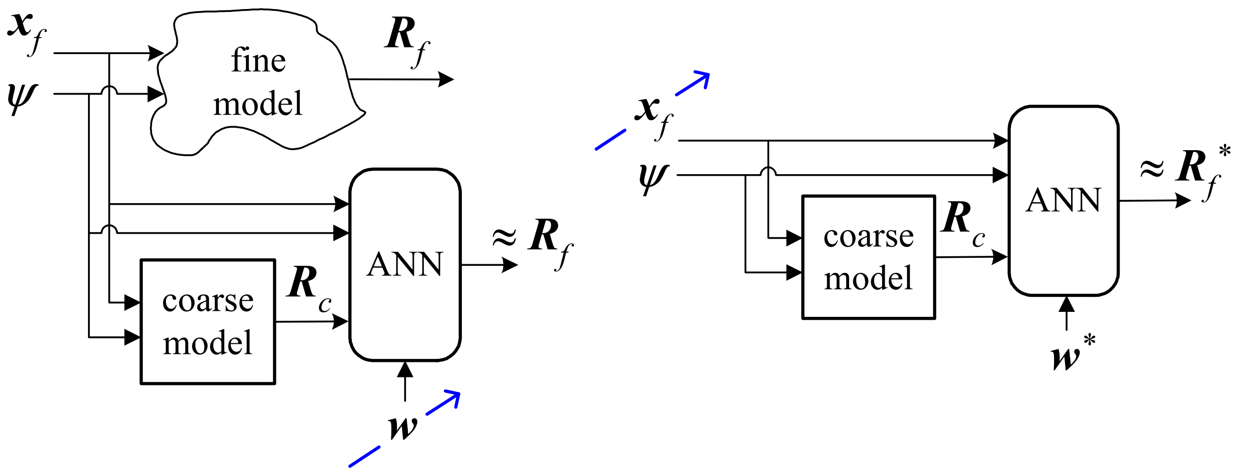
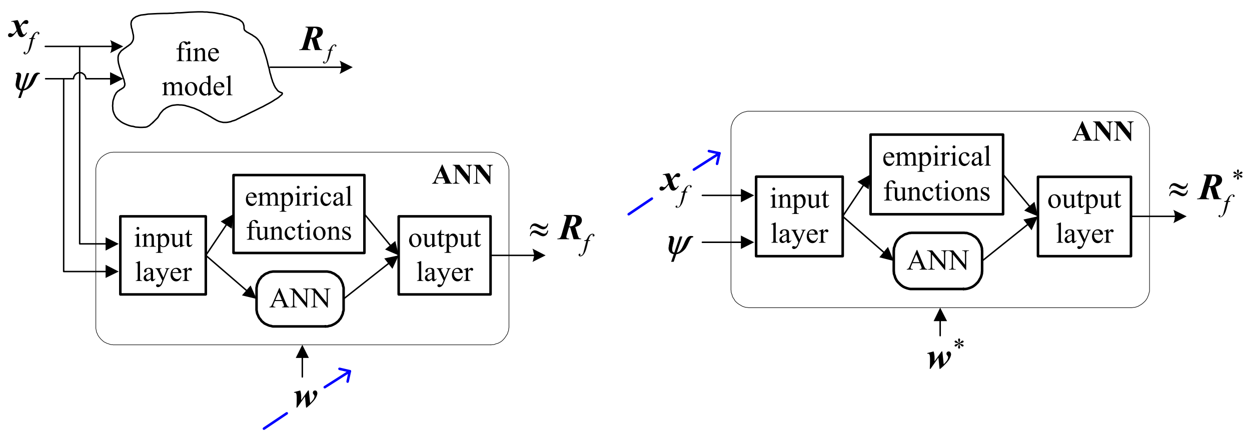


Fig. 5. Illustrating how the difference between the fine and coarse model responses can be as complex as the fine model responses themselves. This example corresponds to the HTS microstrip filter reported in [34]: (a) coarse model responses (OSA90/hope™) at 13 base points, (b) fine model responses (Sonnet's ***em***™) at the same base points, (c) absolute difference between fine and coarse model responses.



(a) (b)

Fig. 6. The PKI Method for neural optimization: (a) training the ANN to approximate the fine model responses, considering the coarse model responses as additional inputs to the ANN, (b) designing with the already trained PKI neuromodel.



(a) (b)

Fig. 7. The Knowledge-Based Neural Network (KBNN) approach to neural optimization of microwave circuits: (a) training the KBNN model (the empirical functions and formulas are embedded in the ANN internal structure), (b) designing with the already trained KBNN model.

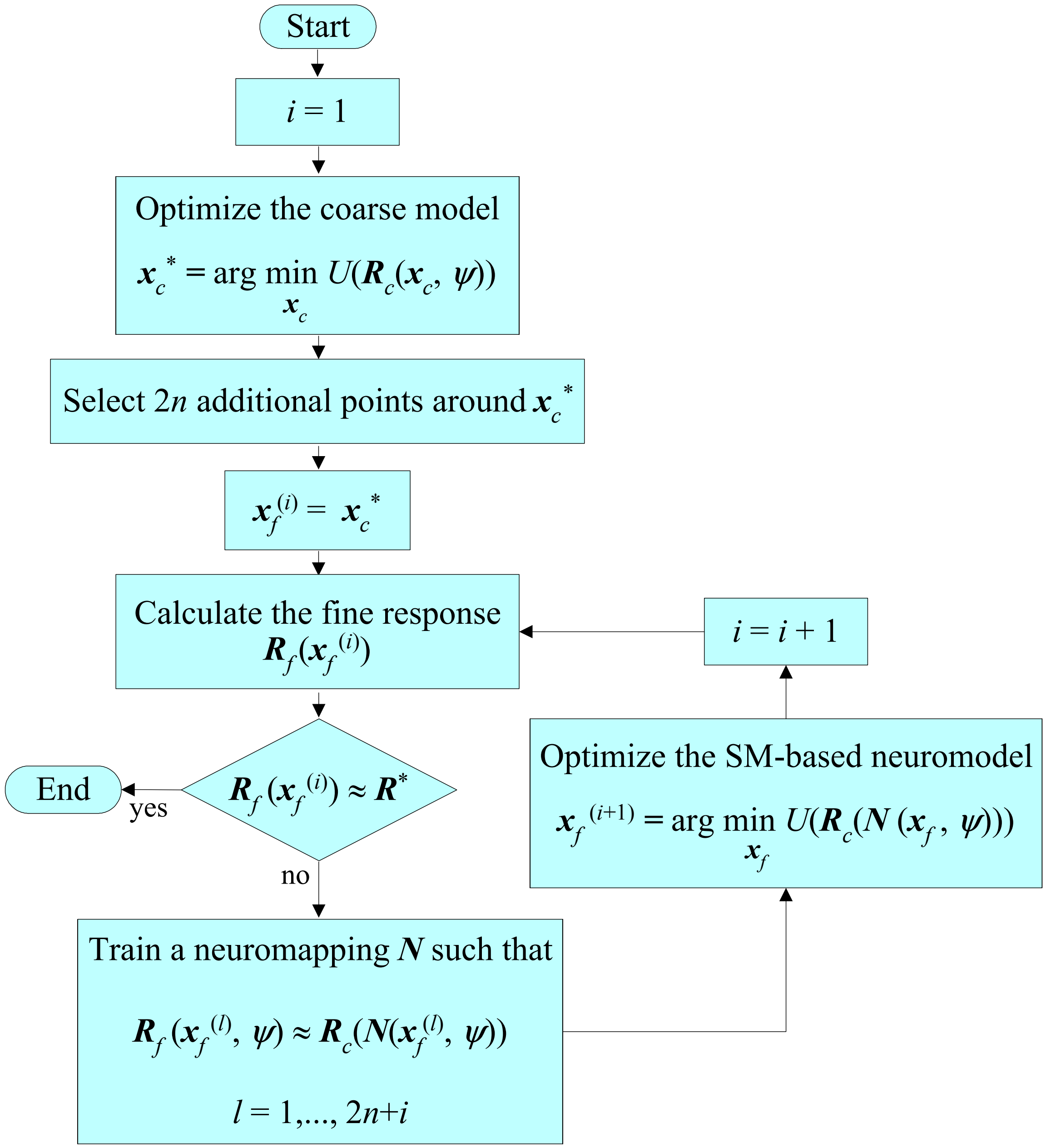


Fig. 8. A simplified flow diagram for Neural Space Mapping (NSM) optimization.

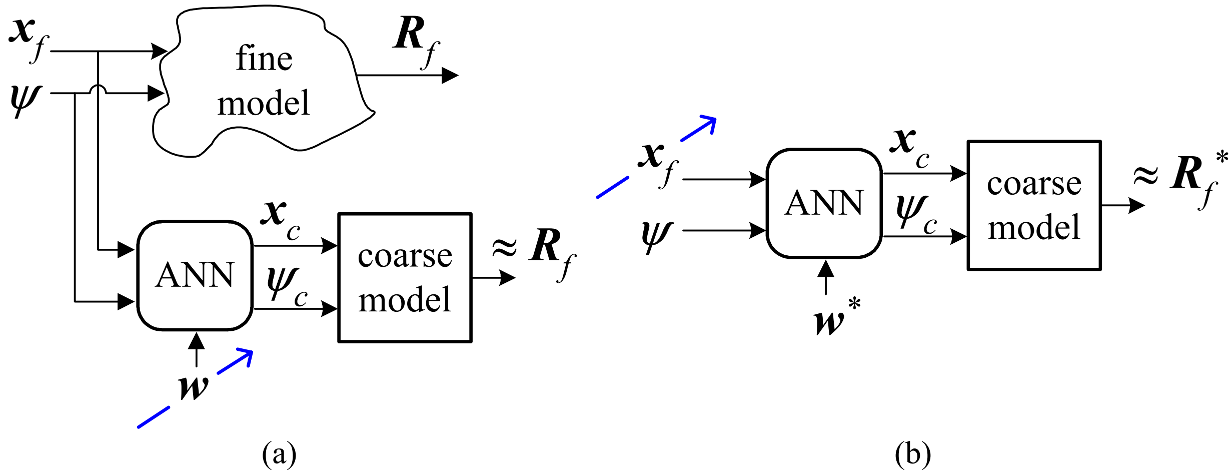


Fig. 9. Main conceptual steps in Neural Space Mapping (NSM) optimization: (a) training the space mapped based neuromodel on all the accumulated learning points, (b) calculating the next iterate by designing with the already trained space mapped based neuromodel.

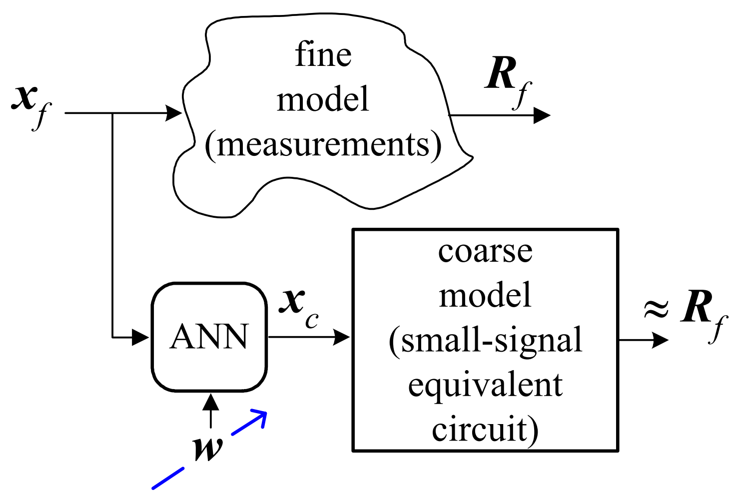


Fig. 10. An extended neural space mapping modeling approach used in [37,38] for modeling an HEMT. The ANN output contains the bias-dependent intrinsic elements, $\boldsymbol{x}_c = [C_{gs}\ \ R_i\ \ C_{gd}\ \ g_m\ \ \tau\ \ g_{ds}\ \ C_{ds}]^T$. Once the ANN is trained, the combination of the ANN and the small signal equivalent circuit approximates the large-signal behavior of the active device. Here, the physical structure of the device is fixed, and the design variables are the bias levels, $\boldsymbol{x}_f = [V_{GS}\ \ V_{DS}]^T$. $\boldsymbol{R}_f$ contains the S-parameters measured at various bias settings.

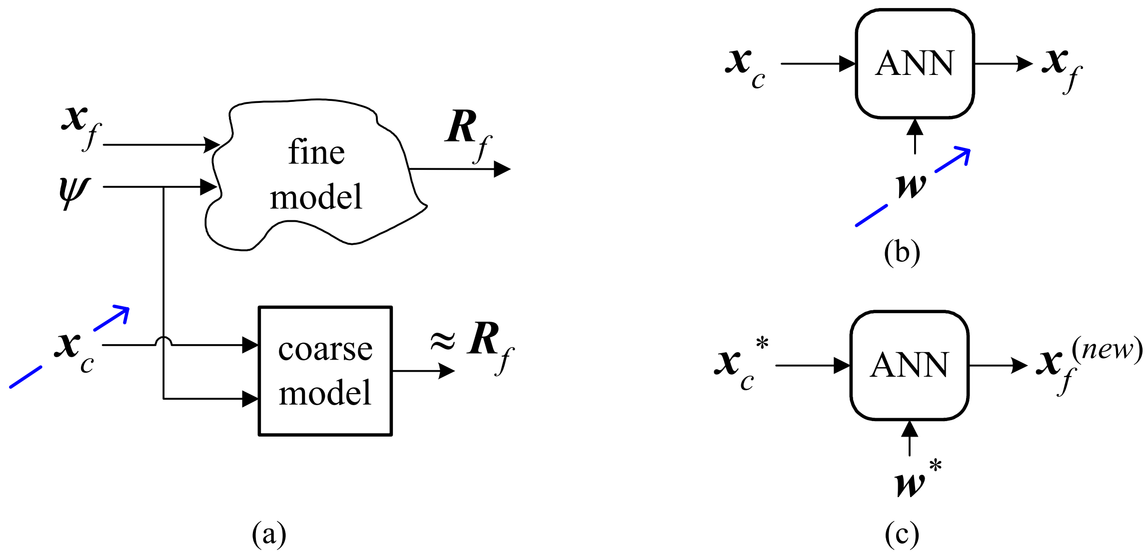


Fig. 11. Main sub-processes in Neural Inverse Space Mapping (NISM) optimization: (a) parameter extraction, (b) training the inverse of the mapping using all the accumulated points, (c) predicting the next iterate by evaluating the current inverse mapping at the optimal coarse model solution.

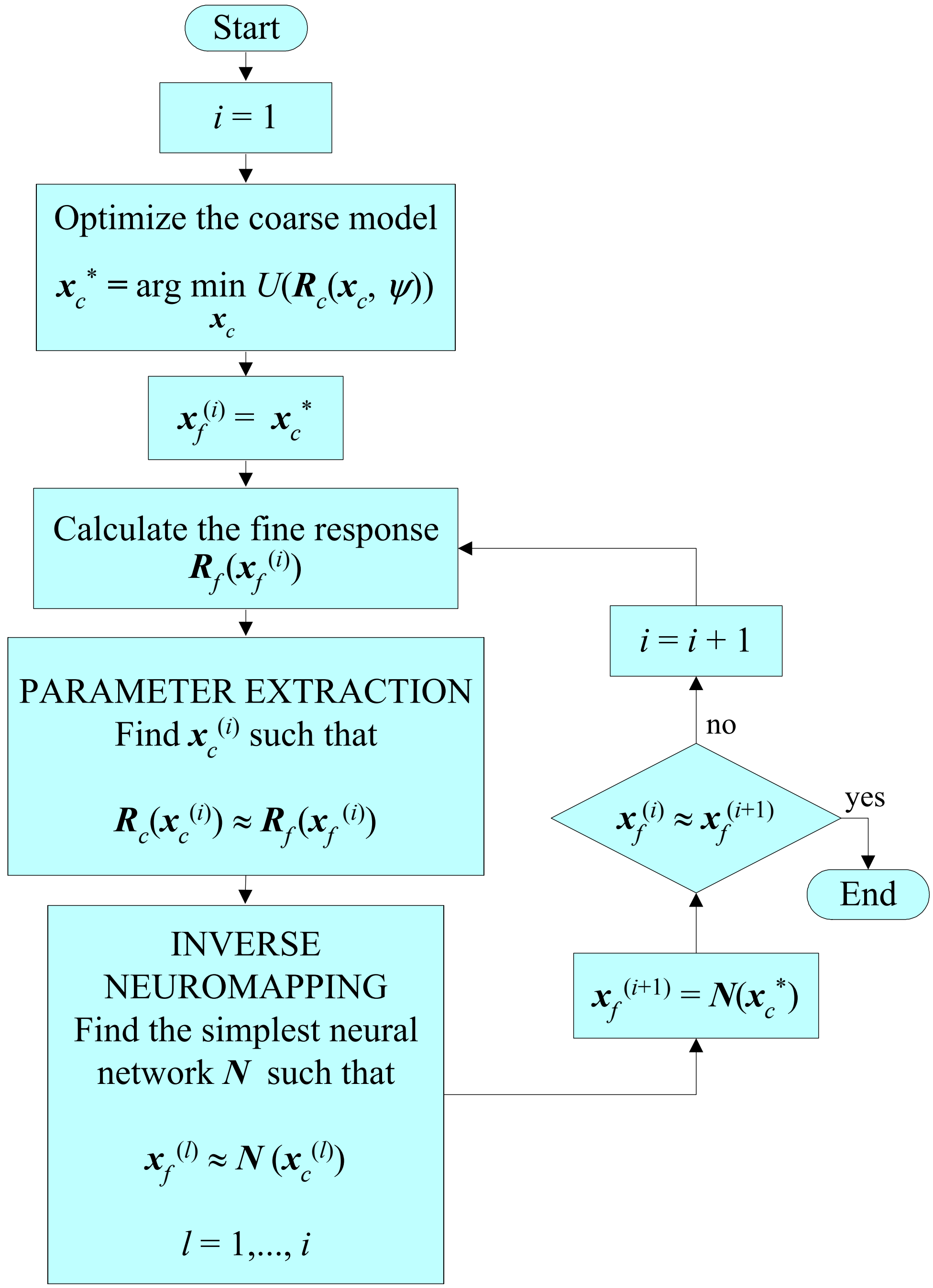


Fig. 12. A simplified flow diagram for Neural Inverse Space Mapping (NISM) optimization.

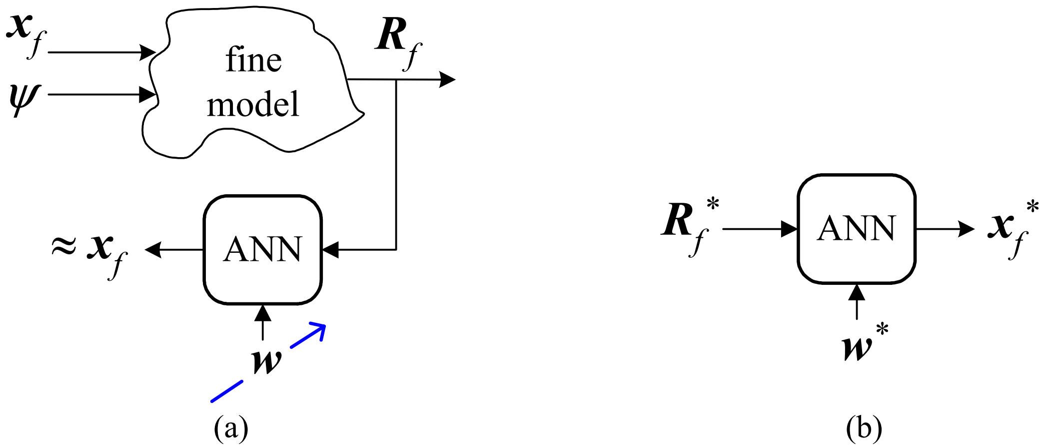


Fig. 13. Synthesis neural networks for microwave design: (a) training the synthesis ANN to approximate the design parameters that generate each response, (b) designing with the already trained inverse neuromodel in principle consists of simply evaluating the synthesis neural network at the desired response.

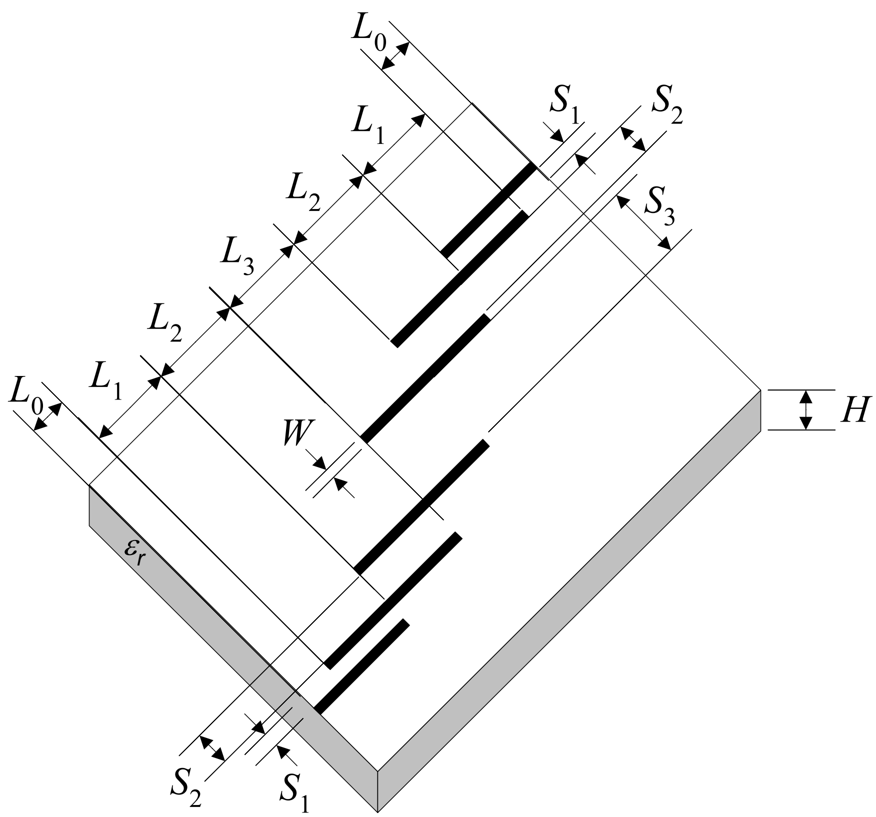


Fig. 14. High-temperature superconducting (HTS) quarter-wave parallel coupled-line microstrip filter.

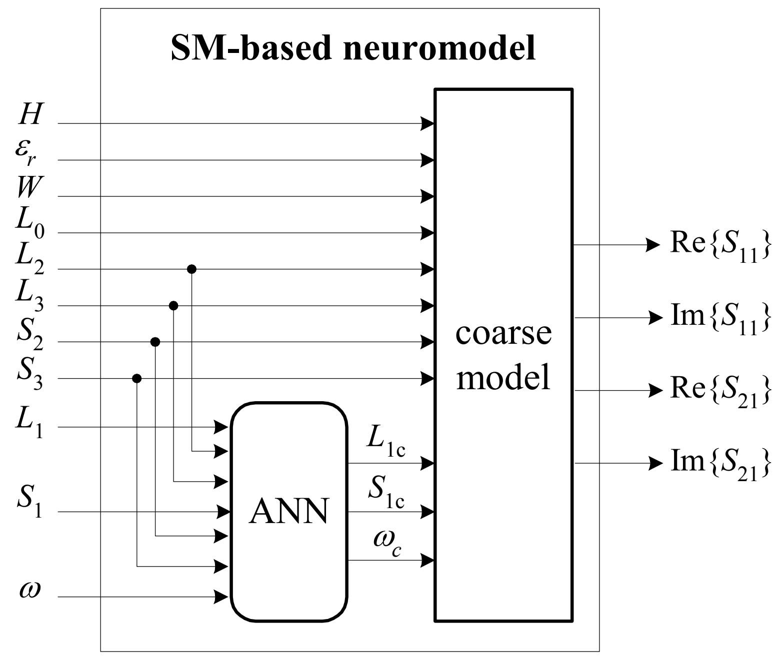


Fig. 15. SM-based neuromodel of the HTS filter for yield analysis and optimization. L_{1c} and S_{1c} correspond to L_1 and S_1 after transformation by the neuromapping (as used by the coarse model).

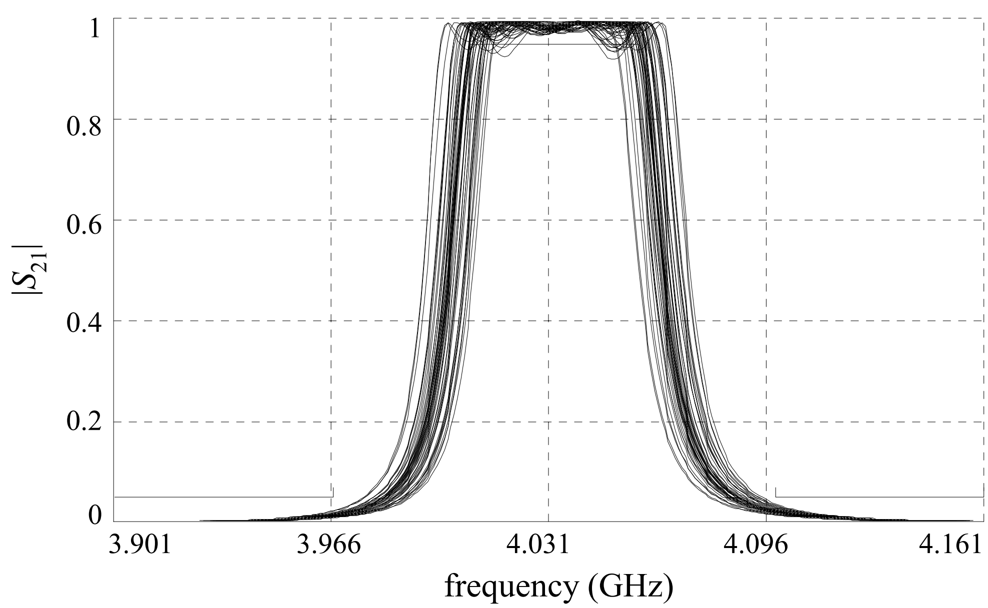


Fig. 16. Monte Carlo yield analysis of the SM-based neuromodel responses around the optimal nominal solution with 50 outcomes.

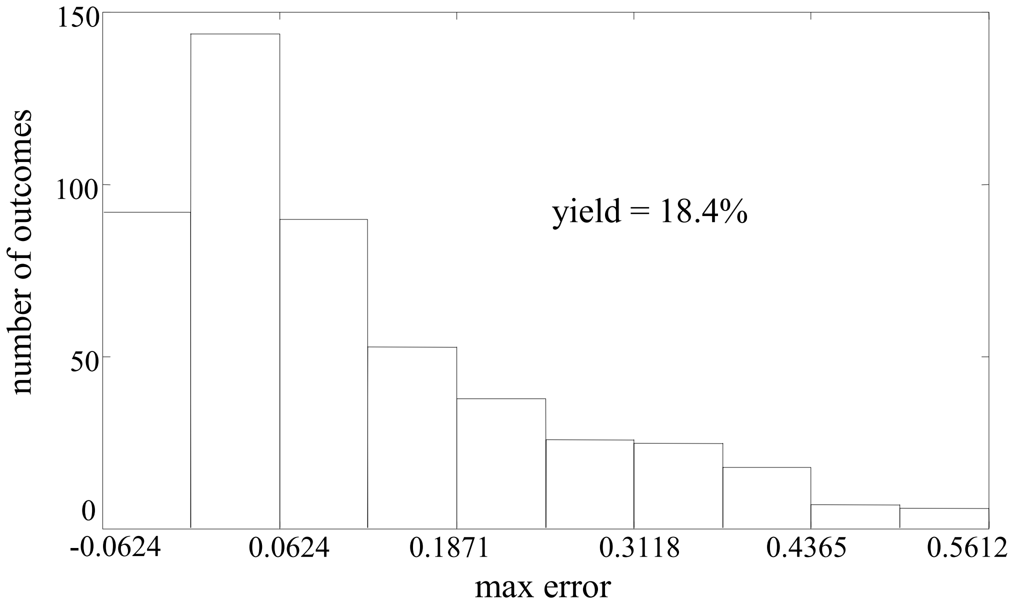


Fig. 17. Histogram of the yield analysis of the SM-based neuromodel around the optimal nominal solution with 500 outcomes.

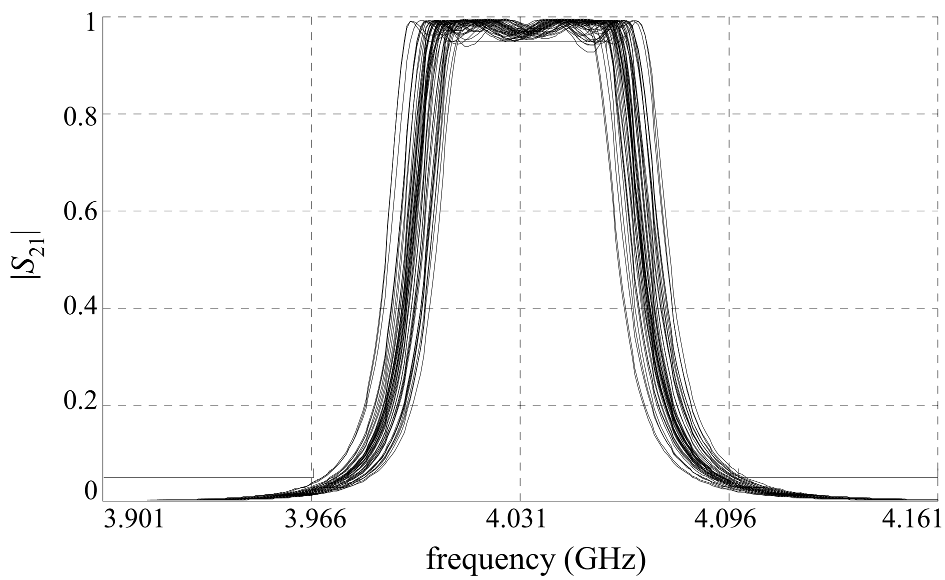


Fig. 18. Monte Carlo yield analysis of the SM-based neuromodel responses around the optimal yield solution with 50 outcomes.

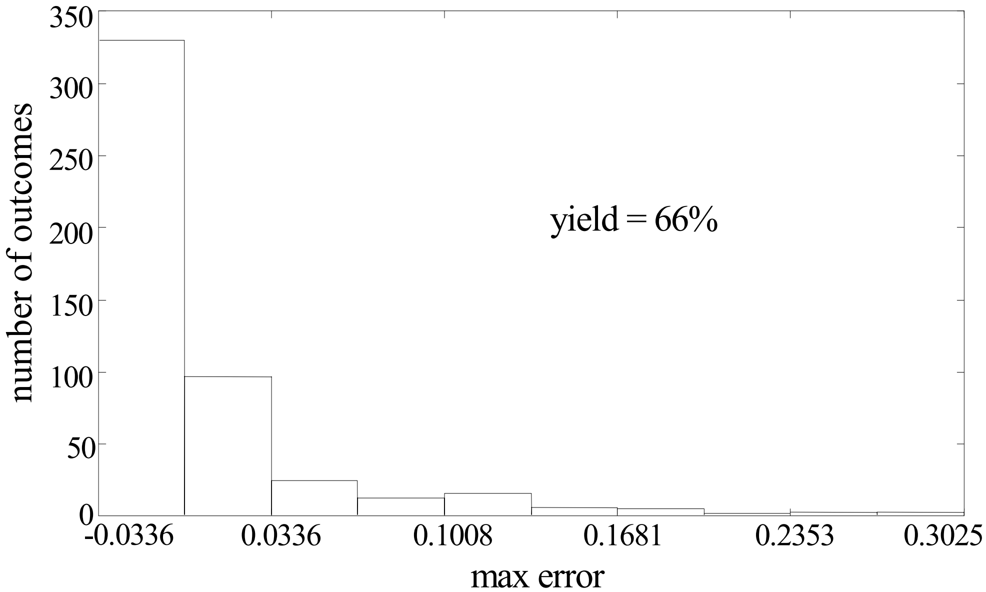


Fig. 19. Histogram of the yield analysis of the SM-based neuromodel around the optimal yield solution with 500 outcomes.

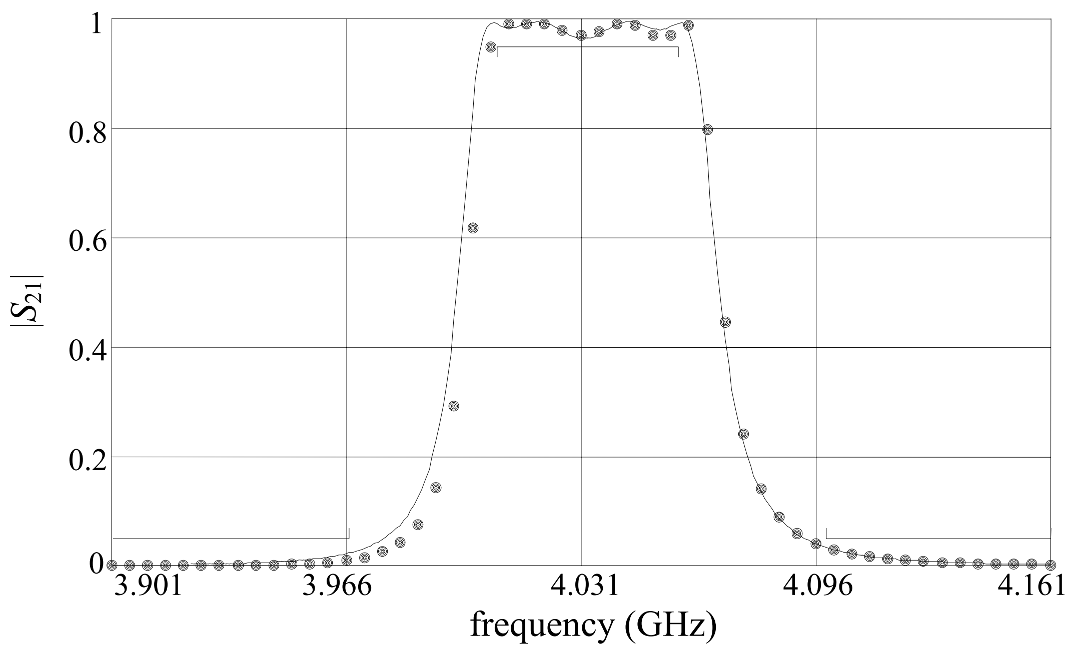


Fig. 20. Fine model (Sonnet's ***em***™) response (•) and SM-based neuromodel response (−) at the optimal yield solution.

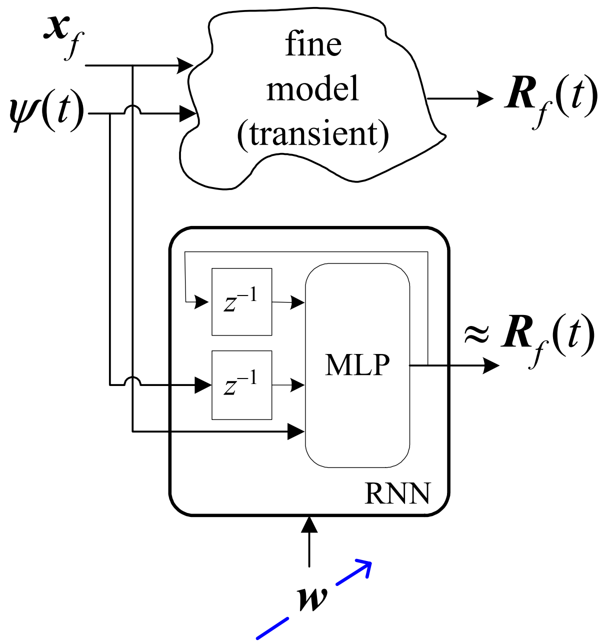


Fig. 21. Developing a neurodynamic model of a nonlinear microwave circuit. A recurrent neural network (RNN) is used to model the transient response of the microwave device. Banks of unit-delays are denoted by z^{-1}. A nonlinear multiple layer perceptron (MLP) with feedback forms the basis of the RNN.