

An Approach for Knowledge-Aided-Design (KAD) of Microwave Circuits using Artificial Neural Networks

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Abstract — This paper points out that appropriately trained artificial neural networks can be used to develop knowledge-aided-design (KAD) modules for RF and microwave design. The approach is illustrated by examples of the reflection type and the loaded line type phase shifters. It also is applicable to other types of circuits and subsystems. KAD modules were developed and verified by using available microwave CAD software.

Keywords — Knowledge-aided design, Microwave circuits, Neural networks, Phase shifters

I. INTRODUCTION

Most of the RF and microwave design tools available today presume that the designer has an initial design ready before using the tool. Then, the CAD softwares allow the designer to carry out a computer-aided analysis or simulation of the initial design and to modify the initial design that one had started with, to be refined to the final optimized design by using powerful computer-aided optimization methods. Thus, whereas the available microwave CAD softwares do serve a very useful purpose, there is a well-recognized need for computer aids for helping the designers to arrive at the initial design. This paper introduces a neural network based technique for developing knowledge-aided design (KAD) modules suitable for this purpose.

Section II brings out the need for knowledge-aided design modules, and Section III describes an approach for developing KAD modules by embedding knowledge in appropriately trained ANN modules. Two examples of KAD modules for design of reflection type phase-shifters and loaded line phase shifters respectively, are presented in Section IV. Concluding remarks in Section V emphasize the enormous potential of neural nets as knowledge-embedding nuggets for KAD applications.

II. NEED FOR KAD DESIGN TOOLS

The sequence of various steps in a typical RF and microwave design process (actually for any design!) [1] is shown in Fig. 1. In this Figure arrows pointing upward indicate possible need for feedback to and reworking of earlier steps. One starts with problem identification. This phase is concerned with determining the need for a product. A product is identified, resources allocated, and end-users are targeted. The next step is drawing up the product design specification (PDS), which describes the requirements and performance specifications of the product. This is followed by a Concept Generation stage where preliminary design decisions are made. Several alternatives will normally be considered. Decisions taken at this stage determine the general configuration of the product and, thus, have enormous implications for the remainder of the design process. At each of these design stages, there is usually a need for feedback to earlier stages and reworking of the previous steps. The analysis and evaluation of the conceptual design lead to concept refinement, for example, by placing values on numerical attributes. The performance of the conceptual design is tested for its response to external inputs and its consistency with the design specifications. These steps lead to an initial design.

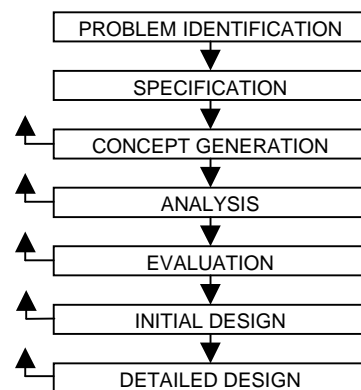


Fig. 1. Sequence of steps in a typical design process

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The step from initial design to the final detailed design involves modeling, computer-aided analysis, and optimization. CAD tools currently available to us for RF and microwave design primarily address this step only. However, it is in the initial steps of the design process (leading to the initial design) that important and expensive design decisions are made. Here, the previous experience of the designers plays a significant role and a *knowledge-based system* is the most likely candidate technology that could help designers. This paper outlines an approach for a part of this process.

III. NEURAL NET BASED APPROACH FOR KAD MODULES

Artificial Neural networks have been used extensively [1] for developing models for RF and microwave components. These models become part of the design tools for computer-aided analysis and design of microwave circuits. The ANN models may be viewed as nuggets containing the knowledge about the component behavior. Here we present an extension of this concept to develop KAD modules for design of RF and microwave circuits and subsystems. Inputs for these modules are desired circuit performance specifications and the outputs are the design parameters for the circuit. This circuit design can be further optimized if needed by using circuit simulation and optimization tools. Various steps in developing these KAD modules may be listed as follows:

1. Choose the class of circuits for which a KAD module needs to be developed. (For example, a reflection-type phase-shifter or a class-E high efficiency amplifier.)
2. Select a class of non-designable components needed for the circuit. These would be switching devices or transistors for the two examples respectively in item 1 above.
3. Develop or obtain a model of the non-designable component (switching device or the transistor in the above examples) suitable for the specific design to be developed. Neural networks may be used for this model also. Most of the currently reported applications of neural networks are for this purpose.
4. Decide on the range of circuit performance parameters for which the KAD module needs to be designed. Using the design of experiments methodology, select suitable sample designs to be used for training the neural network for the KAD module.

5. Carry out the designs for the selected set of parameters in item 4 above. Available knowledge from various sources and/or iterative analysis/simulation or optimization techniques need to be used for this purpose. This is the process of embedding knowledge in the KAD module. This process can be further organized by segmenting the target circuits into subcircuits. For example, an amplifier design can be divided into design of input matching network and output matching network separately. In this case the first step in the design process will consist of arriving at the specifications for the two matching circuits; and, in the second step the two matching networks are designed. Two separate neural nets may be trained separately for the two steps and then coupled together in the KAD module.
6. Verify the KAD module by designing the circuit for performance parameters that are different from the samples used for training the neural net.

The next Section presents two examples of developing KAD modules using this methodology.

IV. EXAMPLES

Two of the examples for which KAD modules have been developed are presented in this Section.

A. Reflection Type Phase Shifter

Reflection-type phase-shifters are commonly used for electronic steering of phased array antennas. Although the design configurations for these phase-shifters are well known, an actual design taking switching device parameters into account needs multiple optimization steps. The KAD module developed and reported in this Section may be used as a good initial design, even by an inexperienced designer. The circuit configuration [2] used is shown in Fig. 2. Switching devices may be Pin diodes or MESFETs operating in passive mode, and are characterized by a low impedance state reactance X_r , a high impedance state reactance X_r and a series resistance R_s .

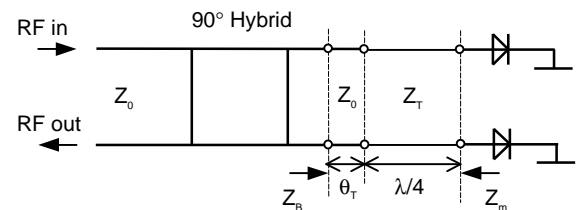


Fig. 2. Circuit configuration of a reflection-type phase shifter for which a KAD module has been developed.

The input parameters of the KAD module shown in Fig. 3 are the desired differential phase shift $\Delta\phi$, the reactances in the two states X_f and X_r and the series resistance R_s of the device. The output of the KAD module yields the circuit parameters. These are the impedance Z_T of the quarter-wave transformer and the electrical length θ_T of the transmission line between hybrid and quarter-wave transformer shown in Fig. 2. A multi-layer perceptron architecture with three layers (MLP3) was used for the ANN.

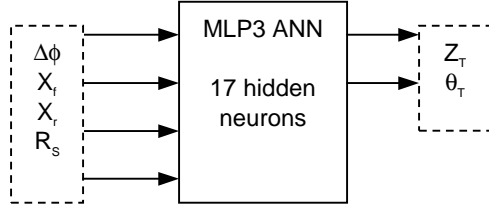


Fig. 3. Trained ANN as a KAD module for a reflection type phase shifter.

The range of differential phase for the KAD module was selected to be 11.25° to 90° . The ranges of device parameters were selected as follows:

$R_s = 0\Omega$ to 20Ω (5 values, linear spacing)
 $X_f = 1\Omega$ to 26Ω (6 values, linear spacing)
 $X_r = -100\Omega$ to -1500Ω (30 values, log spacing)

The numbers of values used for training the KAD module are shown in parentheses. The corresponding number of values for $\Delta\phi$ was 11. A total of 9,900 data samples were generated using a Matlab program based on the design procedure outlined in [2]. The ANN was trained using Neuromodeler, which is available in its introductory version in [1]. The training with this data results in a training error of 0.8%. In order to verify how well the trained ANN performs as a KAD module,

we generate another file with 5,000 data samples. The design input parameters thereby are chosen randomly within their respective data ranges. Testing the ANN with this data results in an overall average error of 0.66%.

The KAD module for reflection-type phase-shifters has been verified by comparing the results with those from the conventional design procedure. Comparison of typical results is shown in Table I.

B. Loaded Line Type Phase Shifter

As the second example we look at the design of loaded line phase shifters. The configuration selected in this case is the one with stub mounted switching devices with two stubs a quarter wavelength apart along the main line as shown in Fig. 4.

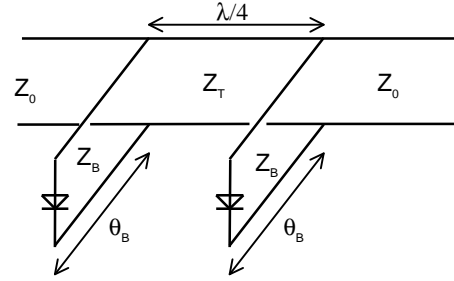


Fig. 4. Circuit configuration of a loaded line type phase shifter selected for developing a KAD module.

For the first version of the KAD module we assumed the switching devices to be lossless, i.e. the device impedances in the two states are pure reactances

As shown in Fig. 5, the input parameters for the KAD module are the desired phase shift $\Delta\phi$ and the device forward and reverse bias reactances X_f and X_r . The output circuit design parameters are the stub impedance Z_B , the electrical stub length θ_B and the impedance of the quarter-wave transmission line between the stubs Z_T .

TABLE I
COMPARISON OF RESULTS FROM ANN-KAD-MODEL AND CONVENTIONAL DESIGN
REFLECTION TYPE PHASE SHIFTER

Design Input				ANN-KAD-Model			Conventional Design		
$\Delta\phi$	R_s	X_f	X_r	Z_T	θ_T	$\Delta\phi^1$	Z_T	θ_T	$\Delta\phi^1$
22.5	0	5	-400	321.04	5.64	22.2	319.14	5.48	22.500
22.5	5	10	-800	457.42	5.36	21.9	451.34	5.48	22.504
45.0	15	2	-1200	363.29	11.33	48.9	380.97	11.21	45.009
45.0	10	15	-300	192.11	10.08	46.5	195.77	10.11	44.998
90.0	10	4	-600	177.17	22.29	88.2	174.42	22.04	89.952

¹ Computed using a network simulator

The design method available in [2] is used for generating data to train the KAD module.

We select the following ranges and numbers of training data points for the input parameters:

$$\begin{aligned}\Delta\phi &= 11.25^\circ \text{ to } 90^\circ && (8 \text{ values, linear spacing}) \\ X_r &= 1\Omega \text{ to } 26\Omega && (6 \text{ values, linear spacing}) \\ X_r &= -80\Omega \text{ to } -1530\Omega && (30 \text{ values, linear spacing})\end{aligned}$$

A Matlab program was written to generate data for these 1,440 samples. When the device losses are considered, we could get these training samples from a simulation/optimization in a microwave circuit simulator like Agilent's ADS.

An MLP3 ANN as shown in Fig. 5 is trained for this KAD module. In this case, the final training error is 1.6%. In order to verify how well the trained ANN performs as a KAD module, we generate another file with 5,000 data samples. The design input parameters thereby are chosen randomly within their respective data ranges.

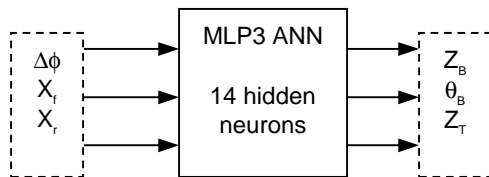


Fig. 5. Trained ANN as a KAD module for a loaded line type phase shifter.

Testing the ANN leaves us with an overall average error of 1.6%. Looking at the error distribution we see that the most errors occur where the relationship between the input and the output parameters is strongly non-linear. This occurs at the low values of the phase shift $\Delta\phi$ and high impedance state reactance X_r . Therefore a better model is obtained when the linear spacing of these two parameters is replaced by a logarithmic spacing.

We select:

$$\begin{aligned}\Delta\phi &= 11.25^\circ \text{ to } 90^\circ && (10 \text{ values, log spacing}) \\ X_r &= -80\Omega \text{ to } -1530\Omega && (35 \text{ values, log spacing})\end{aligned}$$

We also increase the number of hidden neurons from 12 to 14. The training of an ANN with this data results in a training error of 0.7%. Testing this ANN with the same test data as above gives an average error of 0.794%.

As before, the KAD module for loaded line phase shifters is verified by comparing the results with the conventional design. A comparison of typical results is given in Table II.

V. CONCLUSION

Results reported here demonstrate that appropriately trained neural networks may be used as KAD building blocks. This leads to a potential very powerful methodology for developing Knowledge-Aided Design tools for RF and microwave CAD applications. The impact of these tools is likely to be more profound in the cases where the initial circuit design is more complicated and no closed form design synthesis methods are available.

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- [2] K. C. Gupta, "Microwave Control Circuits", Chapter 12 in *Microwave Solid State Circuit Design*, (Eds. I. J. Bahl and P. Bhartia), New York: John Wiley and Sons, 1988.

TABLE II
COMPARISON OF RESULTS FROM ANN-KAD-MODEL AND CONVENTIONAL DESIGN
LOADED LINE PHASE SHIFTER

Design Input			ANN-KAD-Model				Conventional Design			
$\Delta\phi$	X_r	X_r	Z_B	θ_B	Z_T	$\Delta\phi^1$	Z_B	θ_B	Z_T	$\Delta\phi^1$
22.5	5	-400	173.41	121.78	49.105	22.1	171.16	122.57	49.039	22.500
22.5	10	-800	208.99	125.34	49.017	22.0	205.06	126.41	49.039	22.430
45.0	2	-1200	117.39	131.15	46.244	42.6	111.96	131.82	46.194	45.002
45.0	15	-300	105.98	121.01	46.221	41.8	101.00	121.47	46.194	44.987
90.0	4	-600	52.851	129.57	35.454	83.1	49.857	130.33	35.355	89.999

¹ Computed using a network simulator