

# Microwave LNA Design Based On Adaptive Network Fuzzy Inference and Evolutionary Optimization

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**Abstract**—This paper presents a novel approach for the design of microwave circuits using Adaptive Network Fuzzy Inference Optimizer (ANFIO). The method takes advantage of direct synthesis of subsections of the amplifier using very fast and accurate ANFIO models based on exact simulations using ADS. A mapping from course space to fine space known as space mapping is also used. The proposed synthesis approach takes into account the noise and scattering parameters due to parasitic elements to achieve optimal results. The overall ANFIO system is capable of designing different LNAs at different noise and scattering criteria. This approach offers significantly reduced time in the design of microwave amplifiers within the validity range of the ANFIO system. The method has been proven to work efficiently for a 2.4GHz LNA example. The  $S_{21}$  of 10.1 dB and noise figure (NF) of 2.7 dB achieved for ANFIO while  $S_{21}$  of 9.05 dB and NF of 2.6 dB achieved for ANN.

**Keywords**—fuzzy system, low noise amplifier, microwave amplifier, space mapping

## I. INTRODUCTION

THE VAST advancements in semiconductor technology have enabled the design of high-performance microwave circuits to meet the increasing demands of the present wireless communication systems. However, with the increase of the frequency of analog signals as well as integrated microwave circuits, the layout interconnect parasitic elements produce high degree of complexity for the design problems.

Microwave manufacture oriented designs require high accuracy and first pass success. Therefore, accurate extraction of circuit model for on-chip design has become a very critical part of the whole design methodology [1]. The electromagnetic (EM) based modeling is in general the most favored approach for these methods. There has been a lot of research effort focused on this approach in the literature [2 and 3].

However, the drawback is quite evident. Fine model simulation requires large number of computations even for simple high frequency devices. Moreover, the modeling time increases for semi-conductor devices as the complexity of the design configuration increases. For design of a circuit one must employ iterative optimization using the model to predict behavior at each epoch. In large scale production

environments, different designs with different characteristics need to be optimized over multiple bandwidths, center frequencies, and for example gain, noise factor (NF), phase margin and such parameters. It requires a large increase in modeling, simulation and optimization. This is excessive with the current computer aided design methods and therefore a novel alternative approach is elaborated in this paper.

Space mapping have recently been introduced to the microwave design area as a fast and flexible tool to microwave modeling, simulation and optimization [4]. The method is based on mapping a fast coarse model to complex fine model, achieving short time and accurate simulation results. The ANFIS model is presented to produce a good approximate of nonlinear relationships between high frequency semi-conductor properties, parasitic elements, geometrical parameters and micro strip interconnections. Different implementations of space mapping are proposed for ANFIS model and the results are evaluated. The conclusions confirmed that the proposed space mapping methods could provide an accurate computation of the characteristic of an active microwave circuit.

In this paper, a new space mapping approach based on adaptive neuro-fuzzy inference system (ANFIS) is presented for the microwave LNA design with practical profile. It combines the neural network adaptive capabilities and the fuzzy qualitative approach. The trained ANFIS networks are used in high level simulation and design. There have recently been numerous efforts on modeling transmission line components, parasitic components, microwave filter designs, etc. [2,4 and 5]. However there are a few reports on application of fuzzy modeling or microwave active circuit design [6 and 7]. In this paper, we apply a direct and a hybrid ANFIS model for fast design of LNA in S-band for a center frequency of 2.4 GHz, noise factor of 2.6 dB and gain of 9.5 dB.

## II. HYBRID ANFIS MODEL DEVELOPMENT

Method of tuning an ideal coarse model according to an accurate fine model in order to diminish the design duration is known as space mapping [4]. ANFIS structures are suitable candidates for modeling nonlinear, multi-dimensional, complicated systems. They combine the learning ability of neural networks (NN's) and the generalization property of fuzzy qualitative inference. Owing to their ability of learning, the complex system nature could be recognized. The proposed surrogate model in this paper contains a developed ANFIS model which is trained with circuit coarse-model and a space mapping ANFIS. Coarse-model implementation and optimization causes the following enhancements:

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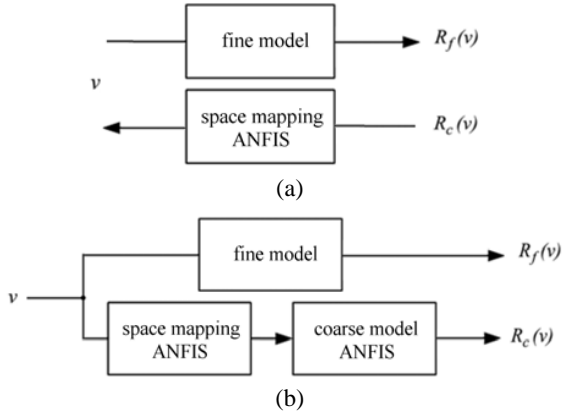


Fig. 1. (a) Inverse ANFIO design system and (b) standard space mapping ANFIO implementation.

- Number of free design variables in coarse-model is less than fine-model.
- Data acquisition based on coarse-model proceeds readily.
- Coarse functional model can be embedded in a smaller network size and therefore reduces the training effort.
- Fast optimization process is achieved using trained neural model with coarse domain parameters.

The space mapping function  $F$  is a mapping from fine model parameters  $v_f$  to coarse model parameters  $v_c$  as  $v_c = F(v_f)$  such that

$$R_c(F(v_f)) \approx R_f(v_f). \quad (1)$$

in a semi-definite region of interest in which  $R_c$  and  $R_f$  are the responses of coarse and fine models respectively. The optimization problem is defined as

$$\hat{v}_f = \arg \min_{v_f} R_c(F(v_f)). \quad (2)$$

where  $v$  is the vector of design parameters,  $R$  is a vector of responses of the model,  $F$  is the desired cost function and  $v^*$  is optimal solution to be achieved. The optimization duration diminishes due to solving (2) for  $v_c$  instead of  $v_f$ . Inverse model design approach is depicted in Fig. 1(a) and space mapping optimizer is constructed according to Fig. 1(b).

Let  $R_f: V_f \rightarrow R^m$ ,  $V_f \subseteq R^n$ , and  $R_c: V_c \rightarrow R^m$ ,  $V_c \subseteq R^n$  denote the fine and coarse model response vectors. For example,  $R_f(\omega)$  and  $R_c(\omega)$  may represent the magnitude of a transfer function at  $m$  chosen frequencies. We denote  $V_R \subseteq V_f$  by the region of interest in which we want an enhanced matching between the surrogate and fine model. We assume that  $V_R$  is an  $n$ -dimensional interval in  $R^n$ . ANFIS surrogate model  $\bar{R}_s$  is defined as

$$\bar{R}_s(V_R) = R_c(F(v_f, w, d)) \quad (6)$$

Where  $W$  is the adaptive network weights and  $d = [d_1 \dots d_n]^T$  determines the region of interest in  $V_f$ .  $W$  and  $d$  are obtained by the parameter optimization

$$(W, d) = \arg \min_{(\Psi, \delta)} \sum_{k=1}^N \|R_f(v_f^k) - \bar{R}_s(v_f^k, \Psi, \delta)\| \quad (7)$$

in which  $N$  is the number of base points in fine domain. Let us introduce the characteristic distance  $\lambda = \lambda(d, n)$  of the base set depending on the size of the region of interest and the number of base points, defined as

$$\lambda(d, N) = \frac{2}{nN} \sum_{i=1}^n d_i \quad (8)$$

If the base points are uniformly distributed in  $X_R$ ,  $\lambda = \lambda(d, N)$  is just an average distance between neighboring points. Parameter  $\lambda$  characterizes and compares different base sets  $X_R$ .

We use fuzzy interpolation of the difference between the fine model  $R_f$  and standard surrogate on top of the standard space-mapping. Fuzzy systems have been successfully used in the microwave area by other authors [7 and 8]. In this study, we use a fuzzy system with triangle membership functions and centroid defuzzification. Membership functions for the  $i$ th variable are defined as shown in Fig. 1. Each interval  $[v - d, v + d]$  is divided into  $K$  fuzzy regions. The number  $K$  corresponds to the number of base points and is given by the formula  $K = \lfloor N \frac{1}{n} \rfloor - 1$ .  $K$  is chosen in such a way that the maximum number of rules is not larger than the number of base points.

The division of  $[v_i^o - d_i^o, v_i^o + d_i^o]$  into  $K$  subintervals creates  $k+1$  values  $v^{ik}, k=1,2,3,\dots$ . In the case of a uniform base set, points  $v^q = [v^{1q_1} \dots v^{nq_n}]^T, q \in \{0,1,\dots, k\}^n$  coincide with the base points. Value  $v^{ik}$  corresponds to the fuzzy region for  $[v^{i(k-1)}, v^{i(k+1)}]$  for  $k=1,2,\dots,k-1$ . We also use the symbol  $v^q$  to denote the  $n$ -dimensional fuzzy region  $[v^{1q_1} \dots v^{nq_n}]^T$ . For any given  $v$ , the value of membership function  $m_{ik}(v)$  determines the degree of  $x$  in the fuzzy region  $x^{ik}$ . Having defined the membership functions, we need to generate the fuzzy rules from given data pairs. We use if-then rules of the form IF  $v^k$  is in  $v^q$ , THEN  $y = R^k$ , where  $y$  is the response of the rule. At the level of vector components it means

$$\text{IF } v_{k1} \text{ is in } v^{1q_1} \text{ AND } v_{k2} \text{ is in } v^{2q_2} \text{ AND } \dots \\ \dots \text{ AND } v_{kn} \text{ is in } v^{nq_n} \text{ THEN } y = R^k \quad (5)$$

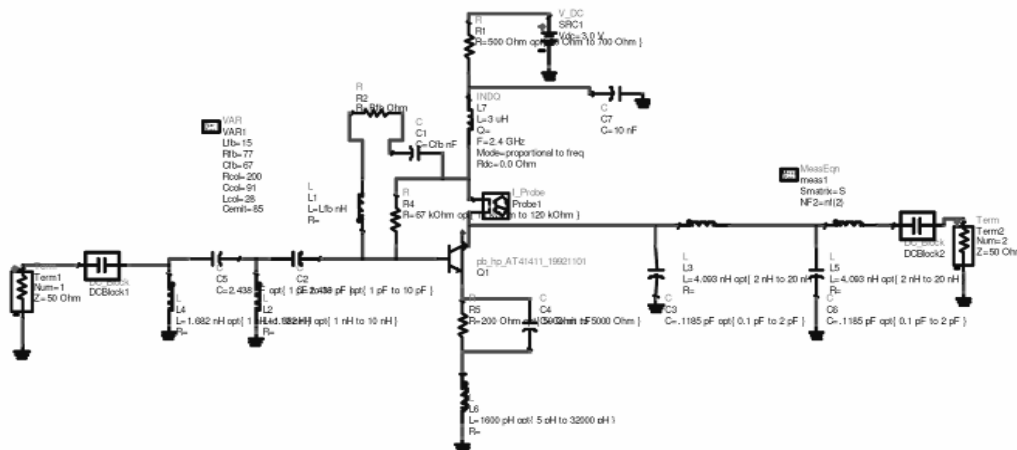


Fig. 2. LNA circuit diagram.

where  $v_{ki}, i=1,2,\dots,n$  are components of vector  $v^k$ . Our surrogate model  $R_s$  combining the standard space-mapping surrogate  $\bar{R}_s$  and the fuzzy system  $\hat{R}_s$  is defined as

$$R_s(v) = \bar{R}_s(v) + \hat{R}_s(v) \quad (11)$$

It should be noted that although the idea of combining space-mapping with fuzzy systems is similar to the idea of combining space mapping with radial basis function interpolation described in [7], the latter technique is more difficult to implement. In particular, the problem of determining interpolation coefficients may be ill conditioned, especially if the number of base points is large. Moreover, the radial basis function interpolation may be very sensitive to control parameters, and typically, some sort of adjusting algorithm is necessary in order to find the proper values of these parameters. Fuzzy systems are free of these problems.

### III. LNA DESIGN AND OPTIMIZATION

A LNA design experiment performed using agilentADS simulation software on 3.2 GHz Intel Pentium 4 computer with 2 GB of RAM. Circuit diagram based on AT41411 is depicted in Fig. 2. Center frequency of 2.4 GHz is chosen. Bias circuit is designed for appropriate current gain.  $L_3$ ,  $C_5$  and  $R_2$  are chosen to satisfy the stability of the amplifier.  $L_1$ ,  $L_2$ ,  $C_2$  and  $C_3$  provide input impedance matching and  $L_6$ ,  $L_7$ ,  $C_7$  and  $C_8$  provide output impedance matching. The optimization problem is mainly selection of impedance matching elements to achieve both minimum noise factor and maximum gain. Exact simulations of the circuit are used as fine model and a reduced version of circuit with only four matching elements is used as coarse model. Two optimization methodologies based on inverse modeling and space mapping are examined. ANFIS model and NN model are used for each method.

TABLE I  
MEAN SQUARE ERROR FOR INVERSE MODEL

Element	Mean Square Error
$L_1$	0.0067
$L_2$	0.0028
$C_2$	0.0143
$C_3$	0.0102
$L_6$	0.0023
$L_7$	0.0016
$C_7$	0.0084
$C_8$	0.0092

#### A. Inverse Mode Design Method

Inverse model is trained by vector  $[S_{11} S_{21} S_{22} NF]$  as input and vector  $[L_1 L_2 C_2 C_3 L_6 L_7 C_7 C_8]$  as output. 20 pairs of base points are used for training inverse model. An adaptive network consists of 20 hidden layer neurons is used for both ANFIS and NN modelers. ANFIS inverse model output is depicted in Fig. 3 compared to fine model parameters. Mean square error is depicted in Table I. The output error is almost equal for ANFIS and NN in base points. However the results for regions out of the base points are much more accurate for ANFIS. This could be cause of qualitative generalization property of fuzzy systems.

#### B. Space Mapping Optimization

ANFIO is used as a design tool in this section. As described before it is a strategy to map the responses of a coarse, un-accurate model with reduced computational cost to a fine, accurate model with long duration. It overcomes inverse model design because that may not be practical in all design problems, especially circuits with complex characteristics. However, ANFIO could be globalized to a wide range of design problems. It will be shown that fast optimization is achieved without reduction of design accuracy. The main reason of using ANFIO system regardless of inverse modeling, ordinary standard space mapping and neural network models arises from their accuracy, robustness and also ability of generalization to estimate the values which are not learned in training phase. Moreover, the employed training method can avoid being trapped in local minimums.

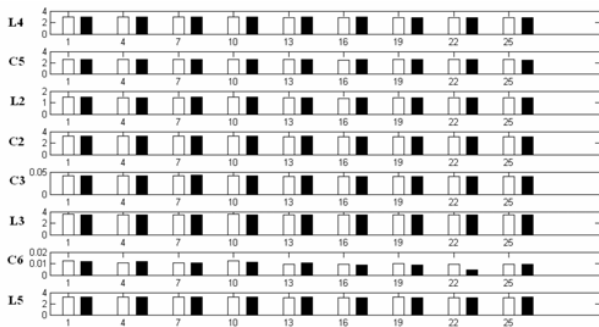


Fig. 3. ANFIS inverse model output (white bars) compared to fine model (black bars) parameters.

TABLE II  
MEAN SQUARE ERROR FOR INVERSE MODEL

Element	Mean Square Error
$L_1$	0.0045
$L_2$	0.0007
$C_2$	0.0035
$C_3$	0.0123
$L_6$	0.0009
$L_7$	0.0002
$C_7$	0.0014
$C_8$	0.0029

Coarse model is trained by vector  $v_c = [L_1 \ C_2 \ L_6 \ C_7]$  as input and vector  $R_c = [S_{11} \ S_{21} \ S_{22} \ NF]$  as output. 20 pairs of input-output pairs are used for training inverse model. An adaptive network consists of 20 hidden layer neurons is used for both ANFIS and NN modelers. Another ANFIS structure with 10 neurons in hidden layer is used for space mapping. ANFIS inverse model output is depicted in Fig. 3 compared to fine model parameters. Mean square error is depicted in Table II. The results of optimization are shown in Fig. 4 for several test points in the region of interest. The mean square errors between fine model and ANFIO are within a very small region. The ANN space mapping optimizer responses are depicted in Fig. 5 and ANFIO results are depicted in Fig. 6. Optimization for minimum noise factor leads to  $S_{21}$  of 9.2 dB and NF of 2.7 dB for ANN optimization and  $S_{21}$  of 10.5 dB and NF of 2.6 dB for ANFIO. The results show that ANFIO could be used as a useful tool for rapid solution of complex optimization problems in microwave circuit design. The results of the proposed design methodology dominates the inverse modeling and standard space mapping approaches due to deductive learning ability of elaborated fuzzy system. There is not certain limitative constraint for ANFIO and it could be used in a wide range of microwave design circuits and systems.

#### IV. CONCLUSIONS

In this paper, an efficient methodology was presented for the generation of adaptive fuzzy rules for modeling the complex systems and structures was proposed for application of the model to optimize design problems. The objective was to use hierarchical qualitative information from lower

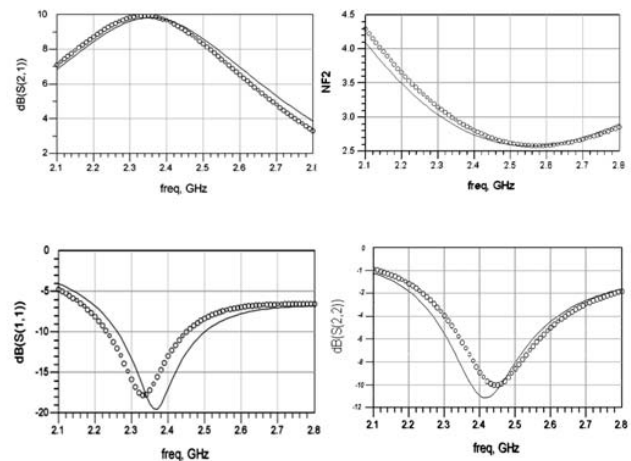


Fig. 4. Results of optimization for  $S_{21}$ , NF,  $S_{11}$  and  $S_{22}$  parameters on 2.1-2.8 GHz.

hierarchical layers in the form of fuzzy network inference hyper surfaces. It was shown that under certain region of interest these lower level rules in combination with lower order coarse model can indeed be used to extract performance information of the accurate model avoiding time consuming circuit level simulations. Advantages of this approach are the limited dimension of the high level design space, the storage memory reduction by modeling the fine model, the significant speedup of the optimization algorithm, while the quality of the eventually generated high level performance is maintained. The optimizer generated by this methodology can be used by an analog designer to a priori choose circuit parameters that best meets the given specifications for coarse model and hereby immediately determines the values of all design parameters of final design.

#### REFERENCES

- [1] J.W. Bandler, Q.S. Cheng, N.K. Nikolova, and M.A. Ismail, "Implicit space mapping optimization exploiting preassigned parameters," IEEE Trans. Microwave Theory Tech., vol. 52, no. 1, pp. 378-385, Jan. 2004.
- [2] S. Koziel, J.W. Bandler, and K. Madsen, "A space mapping framework For engineering optimization: theory and implementation," IEEE Trans. Microwave Theory Tech., vol. 54, no. 10, pp. 3721-3730, Oct. 2006.
- [3] A. Hennings, E. Semouchkina, A. Baker, and G. Semouchkin, "Design optimization and implementation of bandpass filters with normally fed Microstrip resonators loaded by high-permittivity dielectric," IEEE Trans. Microwave Theory Tech., vol. 54, no. 3, pp. 1253-1261, March 2006.
- [4] J. W. Bandler, Q. S. Cheng, S. A. Dakroury, A. S. Mohamed, M. H. Bakr, K. Madsen, J. Sondergaard, "Space Mapping: The State of the Art," IEEE Trans. On Microwave Theory Tech., vol. 52, pp. 337-361, 2004.
- [5] J.W. Bandler, Q.S. Cheng and S. Koziel, "Simplified space mapping approach to enhancement of microwave device models," Int. J. RF and Microwave Computer-Aided Eng., vol. 16, no. 5, pp. 518-535, 2006.
- [6] J. Zhu, J. W. Bandler, N. K. Nikolova and Koziel, "Antenna Optimization Through Space Mapping," IEEE Trans. on Antennas and Propagation, vol. 55, pp. 651 – 658, 2007.
- [7] S. Koziel, J. W. Bandler, "A Space-Mapping Approach to Microwave Device Modeling Exploiting Fuzzy Systems," IEEE Trans. on Microwave Theory and Tech., vol. 55, pp. 2539 – 2547, 2007.
- [8] B. Karlik, H. Torpi, M. Alci, "A fuzzy-neural approach for the characterization of the active microwave devices," 12th International Conference on Microwave and Telecomm. Tech., pp. 114 – 117, 2002.