

A Novel Modeling Technique for Operational Amplifier Using RBF-ELM

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Received 22 June 2016; Accepted 9 September 2016

Abstract

This paper formulates a new modeling technique for the analog circuits like OPAMP (Operational Amplifier). One of the fastest learning techniques, extreme learning machine along with best suitable kernel Radial Basis Function has been implemented for modeling. The simulated result shows that the training speed is very high and can handle a large set of data without compromising accuracy.

Keywords: Analog Circuit, Gaussian Kernel, Machine learning, Feed-Forward Network, Mean Square Error.

1. Introduction

In recent years, researchers have shown greater interest in the modeling of circuits as the designing of circuits has come into a level of saturation. So, designers are taking the help of traditional design systems to integrate as well as modified forms to enhance the performance of the circuits. The modeling of analog, digital and mixed signal circuits has been carried out since several decades ago and presently the designers are depending on these modeling techniques to formulate some new designs [1, 2]. These formulations will help the designers in scaling the designs to its lower level by compromising the specifications into very less margin and hence can improve the efficiency of the circuit into a greater extent. The modeling of the circuits can be done on various aspects like behavioral form, analytical form, symbolic form, etc., without going into the details how each component is affecting the behavior of the circuit. That means the designer need not to be an expert in circuit design, he can analyze the relation between the output variations in accordance with the input.

So, on the basis of mapping of the analog circuits of various models, many modeling techniques have been formulated [3]. To them various machine-learning algorithms are available which are able to map these circuits with reliable models which work as similar to the circuits [4, 5]. Machine learning is an area of artificial intelligence where various algorithms are formulated to develop various systems which can be able to perform classification, clustering, regression and many other activities. The prerequisites for these learning algorithms are the data which will help the system to develop a model which can be able to make predictions. So, in the conceptual modeling of analog circuits, RBF-ELM can play one of the best modeling techniques.

2. Proposed Technique

Huang et al. [6] in 2004 proposed Extreme Learning Machine to provide a speedier approach to the neural networks for analyzing big data. In recent years, ELM (Extreme Learning Machine) has become one of the most preferable alternatives in machine learning algorithms. These machines are working on the principle SLFNN (Single Layer Feedforward Neural Network). SLFNN is an extension of neural network, which can be used to estimate a function from a given set of inputs and their corresponding outputs. It relates the inputs by choosing random weights with the outputs within an error β results to a trained network. For learning and tuning the input parameters slow gradient method is used. An activation function is provided to tune the network accordingly on the finite number of inputs and number of hidden neurons [7, 8].

ELM is mainly used for the problems where classification, clustering, regression are the main objectives of the systems. As they contain a single layer of hidden nodes or neurons where the weights connecting inputs to hidden neurons are randomly assigned. These assigned nodes are never trained or updated unlike other machine learning techniques, especially ANN (Artificial Neural Network) [9]. So, these hidden neurons, which are connected to the outputs, are learned in a single step. The fast training algorithm proceeded from non-iterative method is an aisle to the domain of large data set problems.

It has been proven that when the sample of data approaches infinity the error between the estimated and actual result becomes zero [7]. So it becomes a very important factor regarding the variables which are used as inputs and their respective estimated outputs. So the designer who is training the ELM must preanalyze the data, whether there is any aberration or not. Adding RBF kernel to ELM will help the circuit designers achieve some vital design parameters to formulate new specification based circuits. If these things are not taken into consideration then the model may approach to over-fitting condition which will

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create a hectic for the designer to modify the model appropriately.

Kernel functions are basically the feature maps for the data points which can be able to classify or analyze the same easily. In recent years, many researchers have formulated many kernels. One of such kernel is a Gaussian kernel (RBF). Due to its implacable functionality, it can help the learning machine to enhance its classification or regression capability [10, 11]. So, RBF-ELM can be a fruitful method to implement the analog circuit modeling. A proposed flow diagram for the analog circuit modeling using modeling concept has been shown in figure 1.

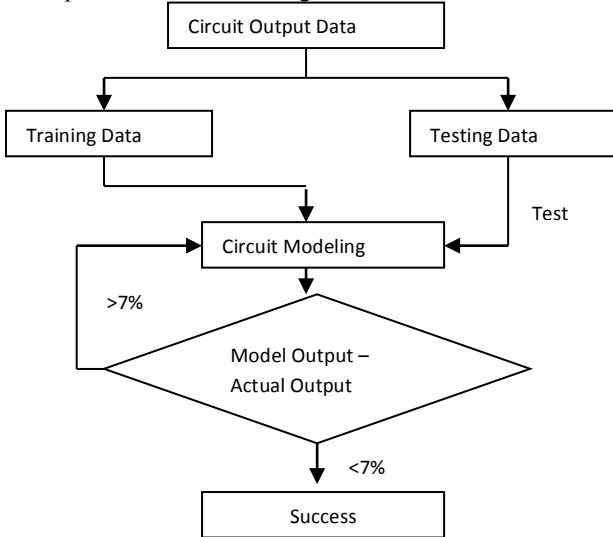


Fig. 1. Flow chart of proposed analog circuit modeling

3. ELM Algorithm

This machine learning can be implemented for both classifications as well as regression problems. For regression problem, let there are N distinct training samples (x_i, y_i) where $x_i = [x_{i1}, x_{i2}, \dots, x_{in}]^T \in \mathbb{R}^n$ and

$y_i = [y_{i1}, y_{i2}, \dots, y_{im}]^T \in \mathbb{R}^m$. The learning mechanism for ELM is attained in two stages:

(i) In the first stage, the activation function $g(x)$ is calculated by randomly assigning the weights between the input parameters and the hidden neurons. The other parameters which are connecting output and hidden neurons, which are optimized during the training time of the machine.

So, the relationship between input set x_j and output set o_j can be written mathematically as

$$\sum_{i=1}^{n_h} \beta_i g(w_i^T \times x_j + b_i) = o_j \quad (1)$$

Where $w_i = [w_{i1}, w_{i2}, \dots, w_{in}]^T$ are the set of weight vectors between the i_{th} hidden neuron and the input neurons, $\beta_i = [\beta_{i1}, \beta_{i2}, \dots, \beta_{im}]^T$ are the set of weight vectors between i_{th} hidden neuron and the output neurons and b_i is the threshold value for the i_{th} hidden neuron.

(ii) In the second stage, the value of β_i is calculated from the above equation (1), which forms a system of linear equations and hence obtained as

$$\min_{\beta \in \mathbb{R}^{n_h \times m}} 0.5(|\beta|^2 + C \sum_{i=1}^N |e_i|^2), \text{ s.t. } H\beta = Y - E \quad (2)$$

Where C is the penalty coefficient of the training errors and $e_i \in \mathbb{R}^m$ is the error vector with respect to i_{th} training input sample data and

$$H(w_1, \dots, w_{n_h}, b_1, \dots, b_{n_h}, x_1, \dots, x_N) = \begin{pmatrix} g(w_1 x_1 + b_1) & \dots & g(w_{n_h} x_1 + b_{n_h}) \\ \vdots & \ddots & \vdots \\ g(w_1 x_N + b_1) & \dots & g(w_{n_h} x_N + b_{n_h}) \end{pmatrix}_{N \times n_h}$$

$$\beta = [\beta_1^T \dots \beta_{n_h}^T]^T_{n_h \times m},$$

$$Y = [y_1^T \dots y_{n_h}^T]^T_{N \times m} \text{ and}$$

$$E = [e_1^T \dots e_{n_h}^T]^T_{N \times m}$$

So, by solving the equation (2), the minimized value of the vectors β_i can be estimated on the following cases which are mentioned below:

(a) If the training set is larger than the number of hidden neurons (i.e. $N > n_h$), then

$$\beta = \left(H^T H + \frac{I_{n_h}}{C} \right)^{-1} H^T Y \quad (3)$$

Where I_{n_h} is the identity matrix of dimension n_h .

(b) If the number of hidden neurons is larger than the training set (i.e. $n_h > N$), then

$$\beta = H^T \left(H^T H + \frac{I_N}{C} \right)^{-1} Y \quad (4)$$

where, I_N is the identity matrix of dimension N.

But in this paper, the training data set is taken in thousands. So, the case (a) is taken for modeling the circuit using ELM. The parameters which are used to train the network are the weights of the inputs along with the bias.

4. Implementation and Results

The modeling technique has been implemented on one of the most common two stage transconductance operational amplifier (OTA) which is shown in figure 2. The OTA was designed in gpdk 45 nm technology and simulated using Cadence Spectre. The inputs to the model are the width of the transistors. So, from the circuit 5 variables are taken and their range was set from 120nm to 1um. Two most important output parameters [12] Gain and CMRR of the OTA were

considered in this modeling analysis. The data set generated from the Cadence Spectre was then made used for modeling by ELM was implemented in MATLAB.

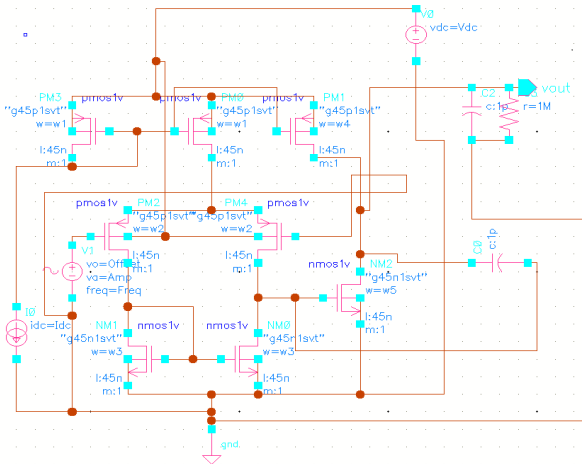


Fig. 2. A two stage operational amplifier

In total 16875*5 data points have been considered. Out of them 10% of the data taken for testing purpose and rest for training purpose. So, accessing and training so much of data, requires very less time. Also, RBF-ELM has been trained by taking 100 hidden neurons. If the numbers of hidden neurons are enhanced accuracy can be enhanced by compromising the training time. Here accuracy is analyzed by taking the help of Mean Square Error. Table 1 illustrates the training and testing time as well as accuracy of the models designed using RBF-ELM. Similarly, the decreasing error rate with increase in number of hidden neurons have been shown in figure 3.

Table 1. Estimating accuracy and training and testing time for different models

Sl.No.	Type of Model	Training Time	Testing Time	Testing Accuracy
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1	Gain	0.90 s	0.05 s	0.07
2	CMRR	0.80 s	0.03 s	0.02

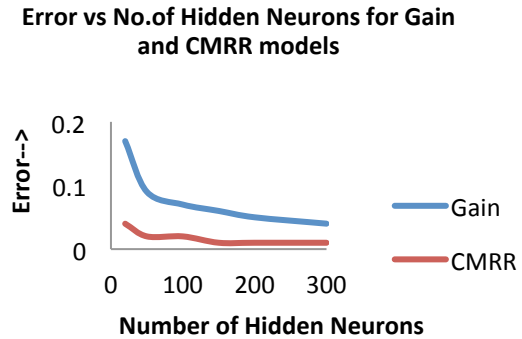


Fig. 3: Graph showing error for the different models

5. Conclusion and Future Scope

From the results it can be accomplished that the modeling time taken by RBF-ELM machine learning technique is taking very few seconds to formulate the model. This advantage can lead to very less time for the circuit designers for supplying chips to market will be very less. Also, if the designers need to make the model, they have to compromise a little in the time factor. So, the chip industry will not wait for a long to get the appropriate circuit. This modeling technique can be further implemented for synthesis techniques to reduce the burdens for the circuit designers. Also, adding multi output modeling may enhance the modeling of circuits to a greater level.

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