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FET SMALL-SIGNAL MODELLING BASED ON THE DST AND MEL FREQUENCY CEPSTRAL COEFFICIENTS

R. R. Elsharkawy

Microstrip Department, Electronics Research Institute
Dokki, Cairo 12622, Egypt

S. El-Rabaie

Faculty of Electronic Engineering
Menouf 32952, Egypt

M. Hindy and R. S. Ghoname

Microstrip Department, Electronics Research Institute
Dokki, Cairo 12622, Egypt

M. I. Dessouky

Faculty of Electronic Engineering
Menouf 32952, Egypt

Abstract—In this paper, a new technique is proposed for field effect transistor (FET) small-signal modeling using neural networks. This technique is based on the combination of the Mel frequency cepstral coefficients (MFCCs) and discrete sine transform (DST) of the inputs to the neural networks. The input data sets to traditional neural systems for FET small-signal modeling are the scattering parameters and corresponding frequencies in a certain band, and the outputs are the circuit elements. In the proposed approach, these data sets are considered as forming random signals. The MFCCs of the random signals are used to generate a small number of features characterizing the signals. In addition, other MFCCs vectors are calculated from the DST of the random signals and appended to the MFCCs vectors calculated from the signals. The new feature vectors are used to train the neural networks. The objective of using these new vectors is to characterize the random input sequences with much more features to be robust against measurement errors. There are two benefits

Corresponding author: R. R. Elsharkawy (raniarefaat85@yahoo.com).

for this approach: a reduction in the number of neural networks inputs and hence a faster convergence of the neural training algorithm and robustness against measurement errors in the testing phase. Experimental results show that the proposed technique is less sensitive to measurement errors than using the actual measured scattering parameters.

1. INTRODUCTION

Knowledge of the equivalent circuit of an FET is very useful for the device performance analysis. Therefore, it is very important to use efficient tools to predict the small-signal circuit elements. Two major solution categories have been proposed by researchers to solve the small-signal modeling problem of transistors. The first trend is based on the direct extraction of the small-signal circuit elements through analytic solutions [1–4]. This trend is very complicated because it depends on finding closed form expressions to relate the scattering parameters of the FET to the small-signal circuit elements.

The second trend is directed towards optimizing the component values to closely fit the small-signal microwave scattering parameters measured or published for the device [5–8]. However, the equivalent circuit determination needs accurate broad-band S-parameters measurements. In fact, there are inherent errors in vector network analyzer measurements, which cannot be avoided easily. Therefore, there is a need of a new approach which is more robust to errors in the scattering parameters measurements.

Several modeling approaches based on artificial neural networks and belonging to the second category of solutions have been presented in the literature [9–11]. Neural networks have the ability to simulate nonlinear relations with high accuracy. They can achieve a trade-off between efficiency and accuracy. Based on these advantages of neural networks, they found a great popularity in modeling the nonlinear relations between the measured or published FET scattering parameters and the values of the small-signal circuit elements. The traditional approach for this purpose is to build a single neural network to relate all the measured scattering parameters to the small-signal circuit elements, but this approach is time consuming and does not guarantee convergence in the training phase of the neural network.

In this paper, the MFCCs of the neural inputs in the traditional method and the MFCCs of their DSTs are extracted and concatenated to form feature vectors to be used as the new neural input vectors. The paper presents a study of the sensitivity of the traditional and proposed neural models to measurement errors in the testing phase. The paper is organized as follows. Section 2 gives the basics of neural small-signal modeling. Section 3 gives the small-signal models for two metal semiconductor field effect transistors (MESFETs), which will be used throughout the paper. Section 4 presents the proposed technique for FET small-signal modeling. Section 5 gives the experimental results. Finally, Section 6 gives the concluding remarks.

2. NEURAL SMALL-SIGNAL MODELLING

Artificial Neural Networks are programming paradigms that seek to emulate the microstructure of the brain, and they are used extensively in artificial intelligence problems from simple pattern-recognition tasks to advanced symbolic manipulation. Generally, artificial neural networks are basic input and output devices, with the neurons organised in layers. They have the ability to model nonlinear relations such as the relations between the scattering parameters and small-signal circuit elements in FETs. Several neural structures can be implemented for this purpose. The multilayer perceptron (MLP) Network is one of such configurations [12, 13]. It is a feed-forward artificial neural network that maps sets of input data onto a set of appropriate outputs. A standard MLP neural network is shown in Fig. 1. It consists of an input and an output layer with one or more hidden layers of nonlinearly-activated nodes. Each node in a layer connects with a certain weight w_{ij} to every other node in the following layer, but there are no connections between the same layer neurons.

An MLP with one or more hidden layers can be used for FET small-signal modeling. The sigmoid function $F(u) = 1/(1 + e^{-u})$ can

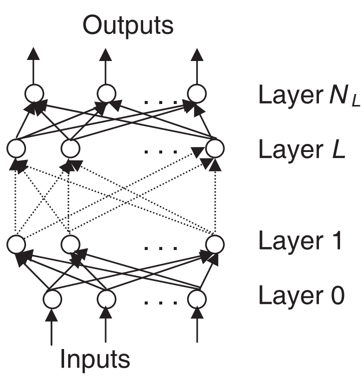


Figure 1. Standard MLP neural network.

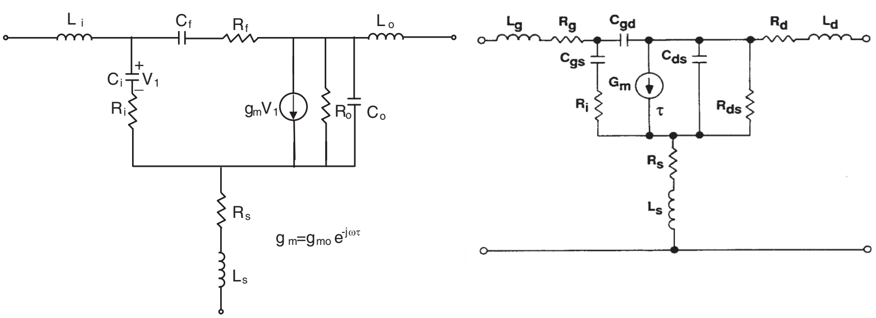
be used as an activation function for the hidden layers, and the neurons from the input and output layers can have linear activation functions. Let $\mathbf{X}$ be the input vector to a single hidden layer neural network, the output vector $\mathbf{Y}$ can be obtained according to the following matrix equation [12, 13]:

$$\mathbf{Y} = \mathbf{W_2} * F(\mathbf{W_1} * \mathbf{X} + \mathbf{B_1}) + \mathbf{B_2} \tag{1}$$

where $\mathbf{W}_1$ and $\mathbf{W}_2$ are weight matrices between the input and hidden layers and between the hidden and output layers, respectively. $\mathbf{B}_1$ and $\mathbf{B}_2$ are bias matrices for the hidden and output layers, respectively. The neural network learns the relationship among sets of input/output data (training sets) that represents the characteristics of the component under consideration. First, input vectors are presented to the input neurons and output vectors are computed. These output vectors are then compared with desired values, and errors are computed. Error derivatives are then calculated and summed up for each weight and bias until the whole training set has been presented to the network. These error derivatives are then used to update the weights and biases for neurons in the model. The training process proceeds until errors become lower than the prescribed values or until the maximum number of epochs is reached. Once a neural network is trained, its structure remains unchanged, and it will be capable of predicting outputs for all inputs whether they have been used for the training or not.

3. FET SMALL-SIGNAL MODELS

Many researchers are interested in FET small-signal modeling. They introduced several models. Of such models, the model presented by



(a) Vendelin model for a GaAs MESFET. (b) The model of the CF001-01 MESFET.

Figure 2. Two MESFET small-signal models.

Vendelin for a GaAs MESFET [14] and the model of the Mimix CF001-01 MESFET published in its datasheet in 2008. These models are illustrated in Fig. 2. The Vendelin model is valid up to 12 GHz, and the model of the CF001-01 MESFET is valid up to 26 GHz. The Mimix CF001-01 MESFET is a 300 µm gate in width, sub-half-micron gate in length GaAs device with Silicon Nitride passivation. The purpose of using these two models in the paper is to prove that the proposed technique for FET small-signal modeling is valid for different device types such as MESFETs and for different circuit configurations. Application of the proposed technique for other devices can be performed in the future work.

4. PROPOSED NEURAL MODELLING TECHNIQUE

A direct approach to generate a neural model for a MESFET is to use the frequency values, magnitude and phase of the S-parameters as inputs to a single MLP neural network and circuit elements as the outputs. In the proposed technique, we take the parameters of the GaAs MESFET shown in Table 1 or the CF001-01 MESFET as inputs to several neural networks and circuit elements as outputs for each network, separately. A training process can be performed with these data sets or other data sets.

Using all the data in any of Tables 1 or 2 as inputs for the neural network and circuit elements as outputs in a single neural structure as in the traditional method causes two problems. The first problem is that the amount of data will be very large. The second one is that the convergence will not be guaranteed. Thus, the proposed technique will be used to achieve convergence and reduce the amount of input data.

Table 1. Published S-parameters for which, the Vendelin small-signal elements are given by $R_f = 100\,\Omega$, $R_o = 192\,\Omega$, $C_f = 0.018\,\text{pF}$, $C_i = 0.5\,\text{pF}$, $C_o = 0.16\,\text{pF}$, $R_i = 6.5\,\Omega$, and $g_m = 43\,\text{mS}$.

f	S_{11}		S_{21}		S_{12}		S_{22}	
(GHz)	Mag.	Angle	Mag.	Angle	Mag.	Angle	Mag.	Angle
2	0.96	−36°	2.95	151°	0.61	−15°	0.021	73°
4	0.89	−65.3°	2.49	128°	0.6	−28.56°	0.036	61°
6	0.83	−87.8°	2.05	109.7°	0.6	−40.34°	0.043	55.6°
8	0.78	−104.4°	1.69	95°	0.6	−51.18°	0.047	54.8°
10	0.75	−116.9°	1.41	83°	0.61	−61°	0.049	57°
12	0.73	−126°	1.2	73.55°	0.63	−70.13°	0.052	63.4°

Table 2. Published S-parameters for which, the values of the small-signal elements of the CF001-01 MESFET are given by $L_g = 0.19\,\mathrm{nH}$, $Rg = 1\,\Omega$, $C_{gs} = 0.32\,\mathrm{pF}$, $R_i = 1.9\,\Omega$, $C_{gd} = 0.023\,\mathrm{pF}$, $G_m = 66\,\mathrm{mS}$, $\tau = 2.7\,\mathrm{ps}$, $C_{ds} = 0.12\,\mathrm{pF}$, $R_{ds} = 161\,\Omega$, $R_d = 1.3\,\Omega$, $L_d = 0.21\,\mathrm{nH}$, $R_s = 1.1\,\Omega$, $L_s = 0.04\,\mathrm{nH}$.

f	S_{11}		S_{21}		S_{12}		S_{22}	
(GHz)	Mag.	Angle	Mag.	Angle	Mag.	Angle	Mag.	Angle
2	0.98	−24°	4.56	156°	0.02	73°	0.53	−10°
4	0.93	−51°	4.31	136°	0.04	62°	0.5	−25°
6	0.88	−72°	3.83	118°	0.05	51°	0.48	−35°
8	0.84	−98°	3.47	100°	0.06	38°	0.43	−51°
10	0.79	−122°	2.99	82°	0.06	23°	0.38	−68°
12	0.79	−140°	2.64	67°	0.07	18°	0.38	−83°
14	0.78	−154°	2.41	55°	0.07	10°	0.39	−93°
16	0.78	−166°	2.27	44°	0.07	5°	0.36	−101°
18	0.77	178°	2.16	30°	0.08	−2°	0.32	−113°
20	0.76	159°	2.04	15°	0.09	−13°	0.27	−131°
22	0.79	141°	1.82	−2°	0.09	−20°	0.27	−163°
24	0.78	132°	1.52	−13°	0.09	−21°	0.3	176°
26	0.81	129°	1.31	−21°	0.09	−19°	0.39	168°

The steps of the proposed technique can be summarized as follows:

1. Calculate the MFCCs for the original input data considering it as a random signal.
2. Calculate the DST for the original data.
3. Calculate the MFCCs for the output of step 2.
4. Make a concatenation between the two vectors obtained from steps 1 and 3 and use them as input for multiple neural networks to estimate each circuit element, separately.
5. In the training phase, use the output of step 4 with each circuit element of the training set to train a neural network belonging to this element.
6. In the testing phase, the measured S-parameters with measurement errors are used to predict the circuit elements with their neural networks.

The MFCCs technique is used to reduce the amount of input data as all the inputs are replaced by a small number of MFCCs.

Measurement errors are similar in nature to random noise. It is known in speaker identification, that the MFCCs can be used to characterize speech signals in the presence of noise rather than using all the signal samples in the identification process. The same idea is exploited here considering the measurement errors as noise. Extracting the MFCCs from the DST of the neural inputs can add more features to characterize the neural inputs in the presence of measurement errors leading to more robust modeling.

4.1. The Discrete Sine Transform

The DST is a mathematical transform that uses sine functions oscillating at different frequencies to transform time signals into a

Table 3. Number of epochs required in the training phase for modelling the relation between each circuit element in the Vendelin model and the published device parameters with the different modelling methods.

Method of Estimation	R_0	g_m	R_f	R_i	C_i	C_o	C_f	Avg. Epoches
Traditional Method single layer	119	1668	1308	3780	333	2079	1027	1473
Traditional Method two layers	9844	959	355	154	552	2705	3434	2572
MFCC Method single layer	138	78	1092	7	4	135	22	211
MFCC Method two layers	2984	329	465	12	10	8	8	545
MFCC+DST Method single layer	5	46	478	572	140	198	155	228
MFCC+DST Method two layers	10	71	297	21	345	15	10	110

Table 4. Number of epochs required in the training phase for modelling the relation between each circuit element of the intrinsic elements in the model of the CF001-01 and the published device parameters with the different modelling methods.

Method of Estimation	C_{gs}	R_i	C_{gd}	g_m	τ	C_{ds}	R_{ds}	Avg. Epoches
Traditional Method single layer	57	93	647	1264	137	82	694	425
Traditional Method two layers	256	257	606	4746	843	934	3389	1576
MFCC Method single layer	39	19	272	727	4	12	1057	304
MFCC Method two layers	9	22	9	21	12	7	8585	1238
MFCC+DST Method single layer	753	95	2918	225	15	28	251	612
MFCC+DST Method two layers	77	8	127	9	10	21	13	38

different domain. If features are extracted from signals in more than one domain, this can help in an accurate characterization of that signal. The DST is defined by the following equation [15–17]:

$$X(k) = \sum_{n=0}^{N-1} x(n) \sin\left(\frac{\pi k n}{N+1}\right) \quad k = 0, \ldots, N-1 \tag{2}$$

where $x(n)$ is a 1-D signal representing the neural inputs, and $X(k)$ is the 1-D DST of that signal. The MFCCs will be extracted from $X(k)$ to add more features to those extracted from $x(n)$. The concatenation of the feature vectors extracted from $x(n)$ and $X(k)$ will give a more robust feature vector to characterize $x(n)$, even in the presence of measurement errors in the testing phase.

Table 5. Number of epochs required in the training phase for modelling the relation between each circuit element of the extrinsic elements in the model of the CF001-01 and the published device parameters with the different modelling methods.

Method of Estimation	L_g	R_g	R_d	L_d	R_s	L_s	Avg. Epoches
Traditional Method single layer	64	92	6793	58	5818	1365	2365
Traditional Method two layers	598	8846	8325	473	10000	1756	5000
MFCC Method single layer	6	6	6	138	13	226	66
MFCC Method two layers	285	10	198	8	36	19	93
MFCC+DST Method single layer	23	511	4	36	57	1655	381
MFCC+DST Method two layers	243	747	11	215	22	141	230

4.2. Extraction of the MFCCs

The MFCCs of a data sequence are a representation of the short-term coefficients derived from a type of cepstral transformation of this data sequence. The calculation of the MFCCs is based on a linear cosine transform of a log power spectrum on a nonlinear Mel-scale of frequencies [14]. The MFCCs of a signal are commonly derived as follows:

1. Take the Fourier transform of the signal.
2. Map the powers of the spectrum obtained above onto the Mel-scale, using triangular overlapping windows.
3. Take the logs of the powers at each of the Mel-frequencies.

4. Take the DCT of the list of Mel log powers, as if they constitute a signal.
5. The MFCCs are the amplitudes of the resulting spectrum.

The Mel scale is calculated as follows:

$$Mel(f) = 2595 \log_{10} \left(1 + \frac{f}{700}\right) \tag{3}$$

where *Mel(f)* gives the Mel-scale frequency corresponding to the actual frequency f. If the energy of the mth Mel-filter output is $\tilde{S}(m)$, the MFCCs will be given as follows [2]:

$$c_j = \sqrt{\frac{2}{N_f}} \sum_{m=1}^{N_f} \log\left(\tilde{S}(m)\right) \cos\left(\frac{j\pi}{N_f}(m - 0.5)\right) \tag{4}$$

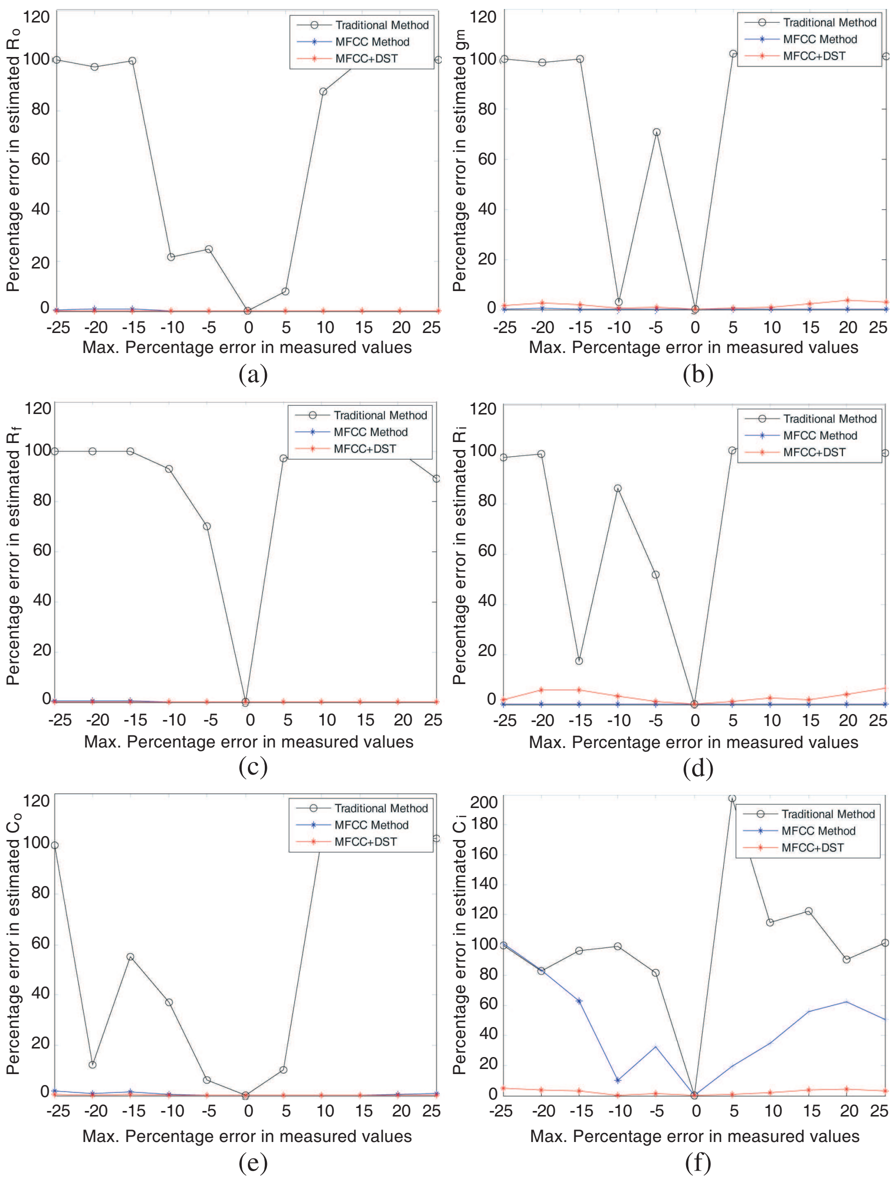
where $j = 0, 1, \ldots J - 1$, J is the number of MFCCs; N_f is the number of Mel-filters; c_j are the MFCCs. The number of resulting MFCCs is chosen between 12 and 20, since most of the signal information is represented by the first few coefficients. The 0th coefficient represents the average log energy of the data sequence. We will choose 13 coefficients in our experiments.

5. EXPERIMENTAL RESULTS

In this section, several experiments are carried out to test the proposed technique for FET small-signal modeling. The published S-parameters at certain frequencies for two small-signal models are used in these experiments. The models used are the Vendelin small-signal model of a GaAs MESFET and the small-signal model of the Mimix CF001-01 GaAs MESFET. The published S-parameters for these models are tabulated in Tables 1 and 2.

Three methods are tested for creating neural models to estimate the small-signal circuit elements from the published parameters. These methods are the traditional neural network modeling method using all published data as inputs, the proposed method using the MFCCs of the published data, and the proposed method using a concatenation of the MFCCs obtained from the original data and MFCCs obtained from the DST of this data. For all the experiments, a neural network is created through training to relate each circuit element to the neural inputs, whether they are the published data or features extracted from this data.

Two types of neural networks are considered and compared to create the neural models with different three methods for each circuit element, single and two hidden layer networks. The error back-propagation algorithm is used in the network training phase for each case. The average numbers of epochs required in the training phase for each neural network are tabulated in Tables 3 to 5. From these tables, it is clear that the number of epochs required for creating the



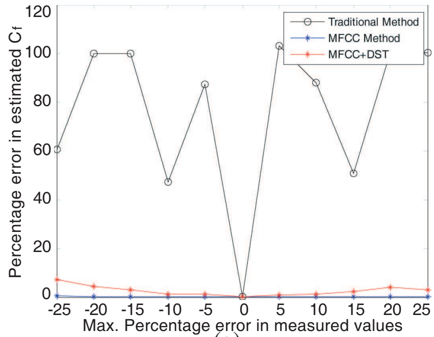


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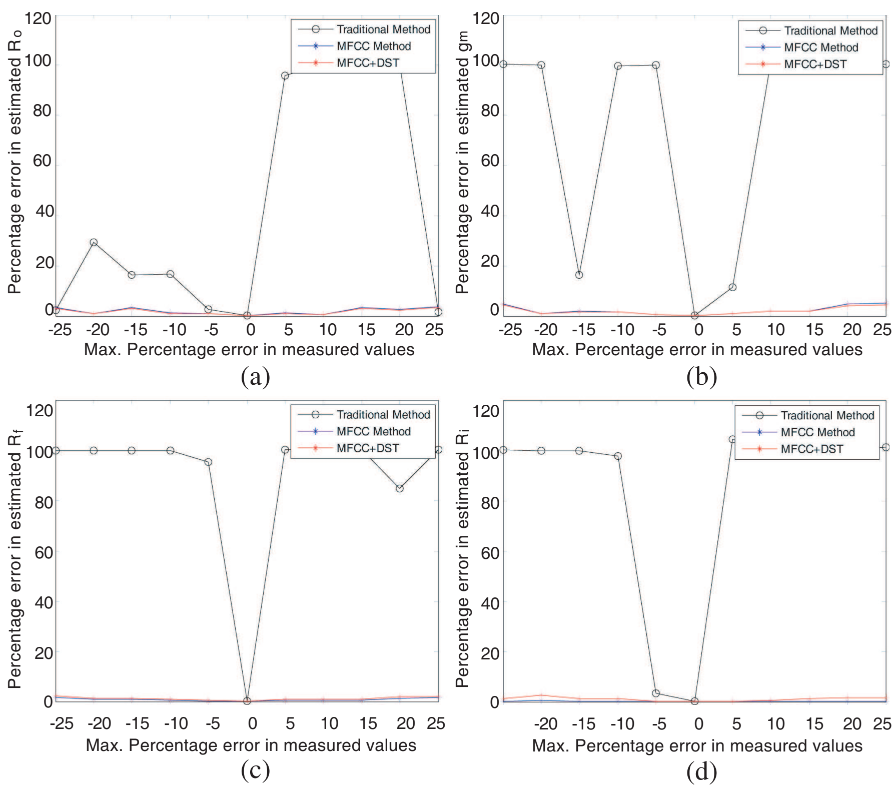
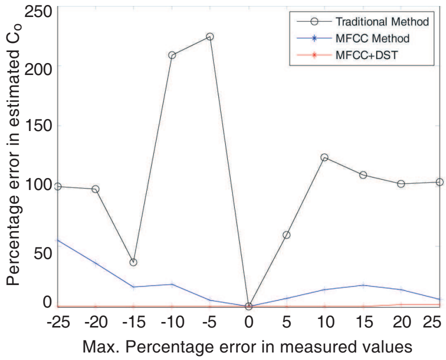
Figure 3. Estimation errors for the circuit elements of Vendelin model for random measurement errors in the case of single hidden layer neural networks.





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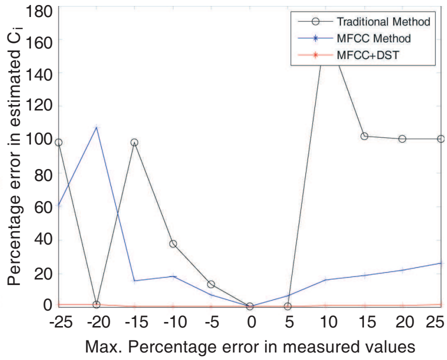

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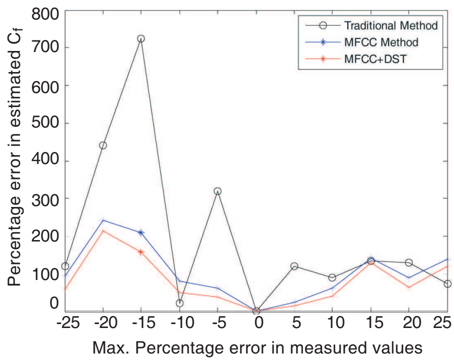

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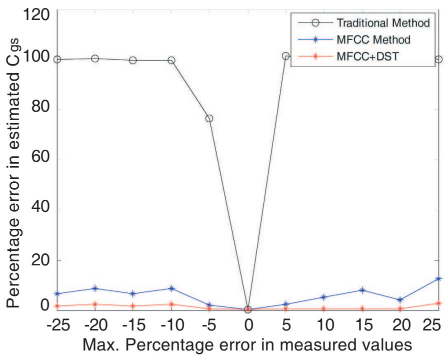
Figure 4. Estimation errors for the circuit elements of Vendelin model for random measurement errors in the case of two hidden layers neural networks.



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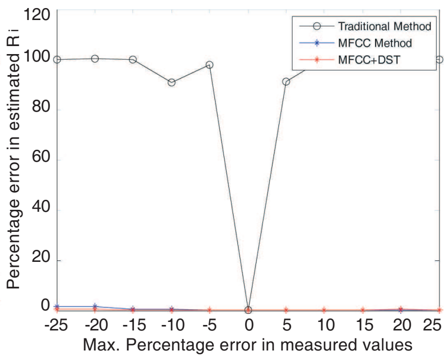

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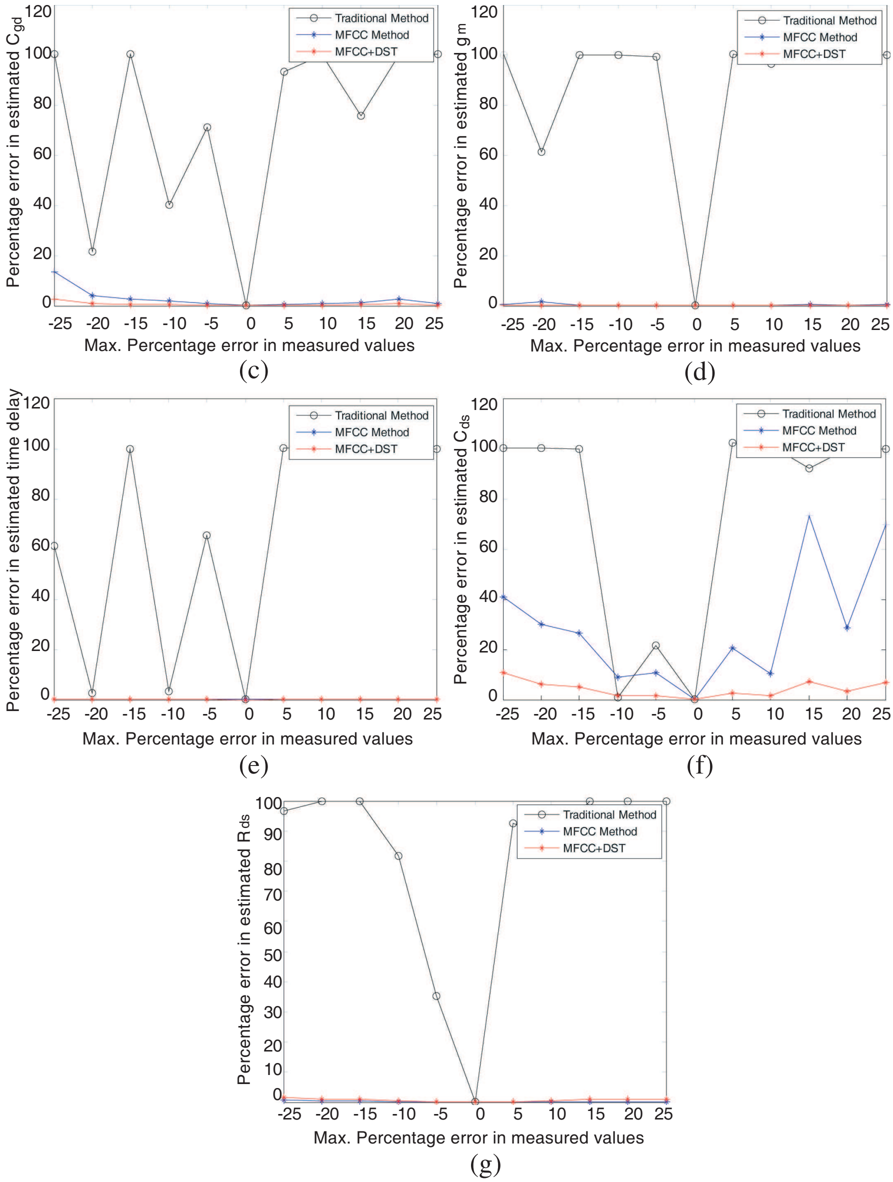


Figure 5. Estimation errors for the intrinsic circuit elements of CF001-01 MESFET for random measurement errors in the case of single hidden layer neural networks.

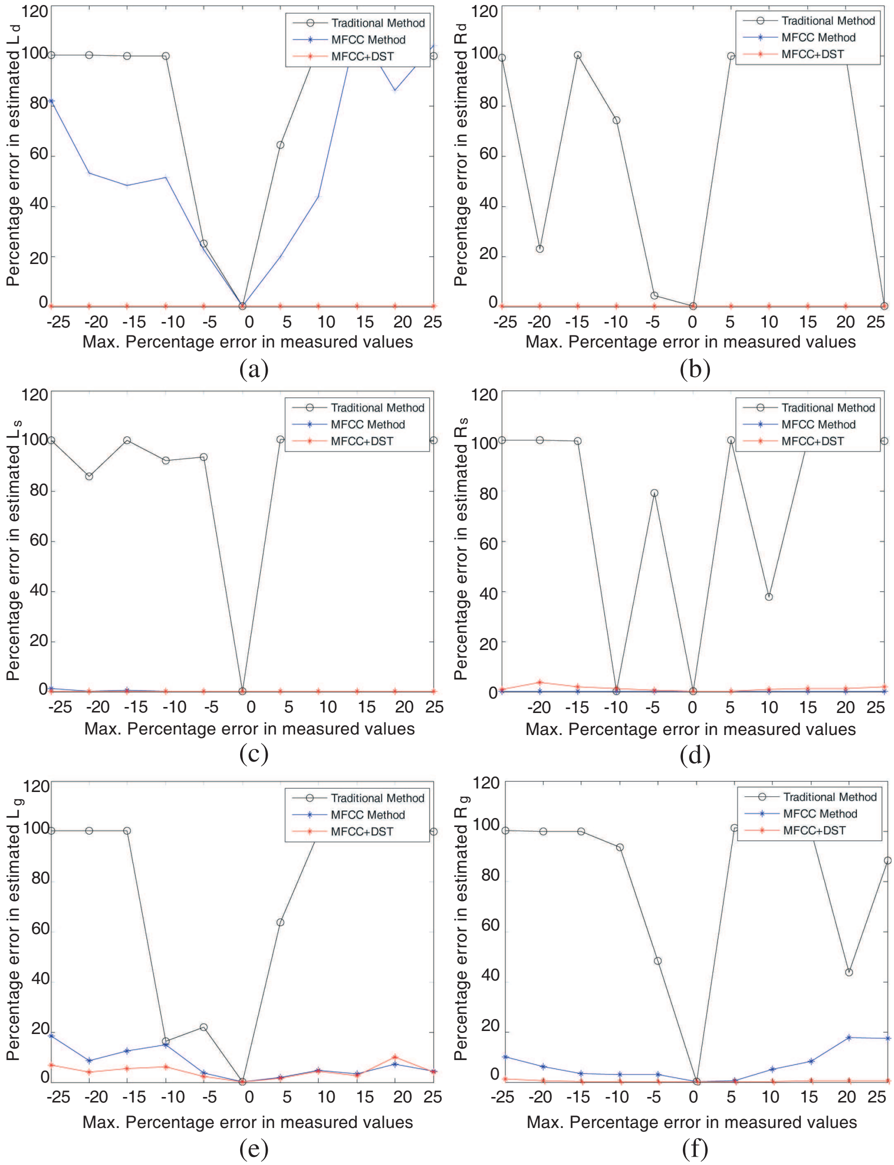
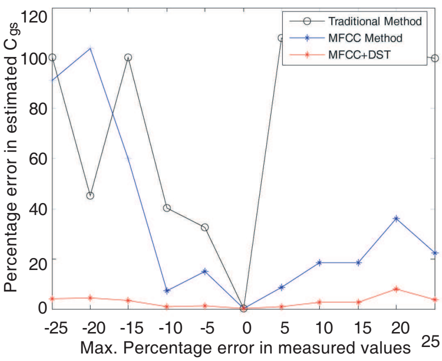


Figure 6. Estimation errors for the extrinsic circuit elements of CF001-01 MESFET for random measurement errors in the case of single hidden layer neural networks.

neural networks is lower for the two proposed methods than that for the traditional method in most cases, which reveals that the proposed methods are time saving.

In the testing phase, the neural networks are tested with input data subject to measurement errors. The measurement errors are



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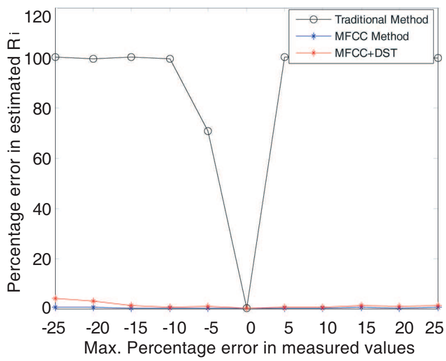

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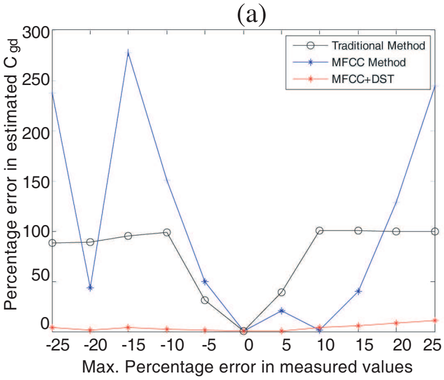

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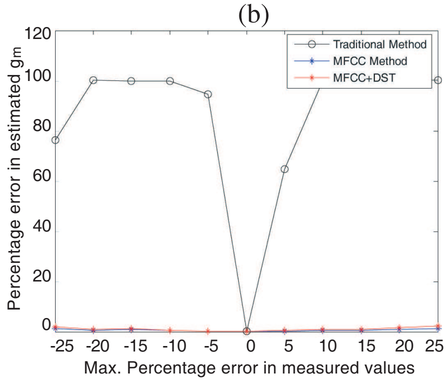

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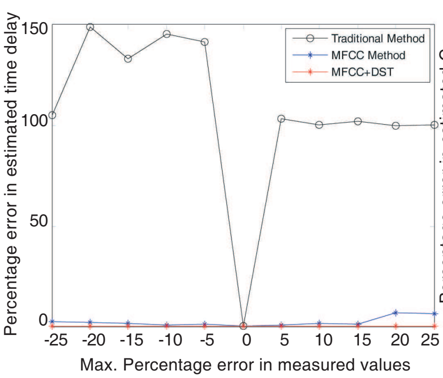

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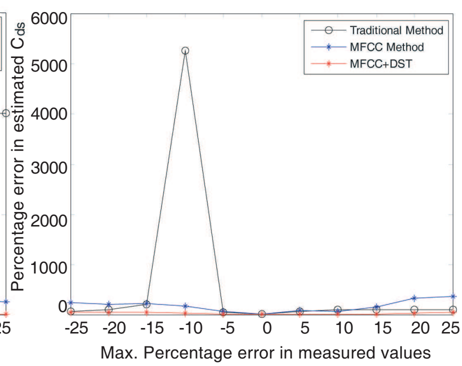

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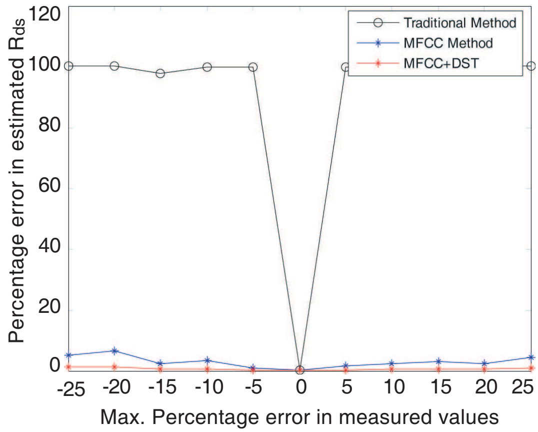

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Figure 7. Estimation errors for the intrinsic circuit elements of CF001-01 MESFET for random measurement errors in the case of two hidden layers neural networks.

simulated as uniformly distributed random errors added to the published data. A comparison study is held between the sensitivity of the three methods to the measurement errors in the published parameters. The results of this comparison study for all elements are given in Figs. 3 to 8. In these experiments, each circuit element is estimated using its created neural networks for all methods with errors having a uniform distribution added to the neural inputs. Since the errors in all neural inputs are not fixed, the maximum percentage error among the neural inputs is taken as the horizontal axis, and the percentage error in the estimated value of the circuit element is taken as the vertical axis.

Figures 3 to 8 show that the method based on the MFCCs of the inputs and MFCCs of DSTs of the inputs is more robust to measurement errors than the traditional method and in most cases better that using the MFCCs only based on the error pattern used. The studied cases for single and two hidden layers neural networks reveal that the use of two hidden layers does not add an advantage in the performance of the proposed method. So, single hidden layer neural networks are preferred for the task of small-signal modeling because of their simplicity.

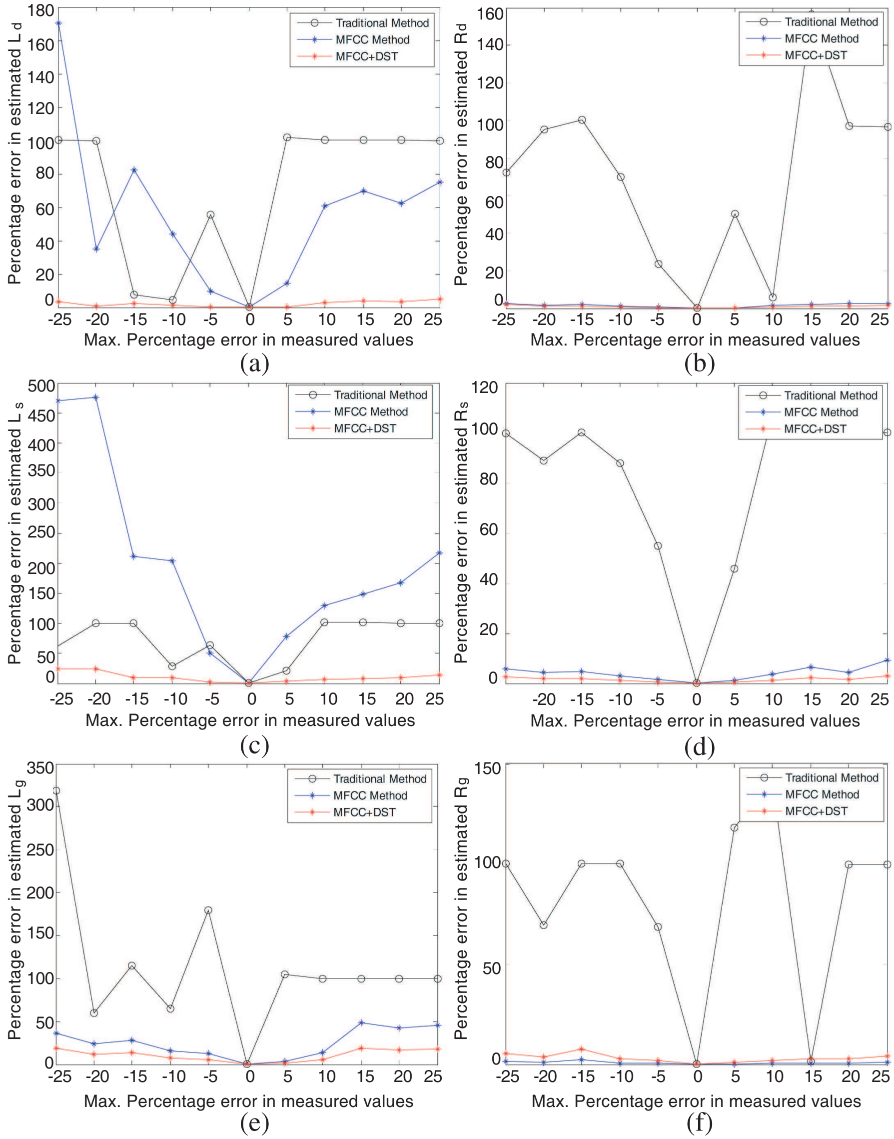

Figure 8. Estimation errors for the intrinsic circuit elements of CF001-01 MESFET for random measurement errors in the case of two hidden layers neural networks.

6. CONCLUSION

This paper has presented a new neural technique for small-signal modeling of FET transistors. This technique is based on estimating the MFCCs of the available data sets of S-parameters and frequencies and MFCCs of DSTs of these dataset. The advantages of this technique are the reduction in the neural networks size and storage capacity, a reduction in the training time and a large immunity to measurement errors in the testing phase. The proposed technique has been tested on published data and succeeded to avoid the effect of measurement errors on the estimated values of the circuit elements. Although two MESFET models have been used for the validation of the proposed technique, all circuit models proposed for FETs and HEMTs can also be used as the method is independent on the configuration of the small-signal circuit.

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