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Neural Approach for Temperature Dependent Modeling of GaN HEMTs

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ABSTRACT – Gallium nitride (GaN) high electron-mobility transistors (HEMTs) have gained a lot of interest for high-power and high-temperature applications at high frequencies. Therefore, there is a need to have the dependence on the temperature included in their models. To meet this challenge, the present study presents a neural approach for extracting a multi-bias model of a GaN HEMT including the dependence on the ambient temperature. Accuracy of the developed model is verified by comparing modeling results with measurements.

Keywords — Artificial neural networks, GaN technology, HEMT, microwave measurements, multi-bias, temperature.

I INTRODUCTION

Owing to its outstanding physical properties, the high electron-mobility transistor (HEMT) based on gallium nitride (GaN) technology is a suitable candidate for high-power and high-temperature applications at high frequencies [1–9]. As the ambient temperature may affect significantly the performance of a transistor and even its lifetime to failure, especially in case of high power devices, it is mandatory to study the device behavior with the change of the ambient temperature [8] and to develop appropriate models that should include the dependence on the temperature. It is well known that artificial neural networks (ANNs) represent a very efficient alternative to the conventional modeling techniques for microwave devices [10]-[31]. As constructed from measurements, neural models include all the effects contributing to the device behavior, which are usually not all taken into account in the standard equivalent circuit models, and therefore have the accuracy as good as in the case of the physical models, but without the need to know the physical mechanisms occurring in the device nor the number of the associated model parameters. Namely, ANNs have the capability to learn the relationship between two datasets. By using ANNs it is possible to develop models relating the device characteristics and the operating conditions of interest (e.g., bias condition, frequency, device geometry) and further express them in closed-form expressions. The purpose of the present paper is to use ANNs for constructing a temperature dependent model representing the small-signal scattering (S-) parameters of a GaN HEMT over a wide bias range and in a broad frequency range. Similar modeling approaches have been proposed over the years to model MESFETs and HEMTs realized in GaAs technology [11, 20]. Contrary to these previous studies, ANNs are applied in this work for temperature dependent modeling of the GaN HEMT technology, and moreover the neural approach is tailored to this specific case study. As will be discussed later, GaN HEMTs can reach very high values of the magnitude of S_{21} and hence, to make dynamics of the S_{21} magnitude smaller, the logarithmic scale was used for both S_{21} magnitude and frequency. The paper is organized in the following way: the developed neural approach for GaN HEMT modeling will be described in Section II.

Subsequently, in Section III, the obtained results will be presented and discussed. Finally, the concluding remarks will be given in Section IV.

II PROPOSED NEURAL APPROACH

In this work ANNs are applied for building a temperature dependent model of the S-parameters of GaN HEMT devices. In particular, it is proposed to train the ANNs to model the dependence of the S-parameters on the following operating conditions: ambient temperature, DC bias voltages (voltage between gate and source V_{gs} and voltage between drain and source V_{ds}), and frequency. Based on the previous experience in modeling S-parameters of different types of microwave transistors with respect to the bias condition [23, 26], a separate neural model is developed for each of the four S-parameters. Moreover, to achieve better accuracy, two separate ANNs are exploited for each of the S-parameters, one modeling the real part and the other for modeling the imaginary part (see Fig. 1). These two ANNs have each four neurons in the input layer, corresponding to the four above mentioned input parameters, and only one neuron in their output layer corresponding to the real or imaginary part of an S-parameter.

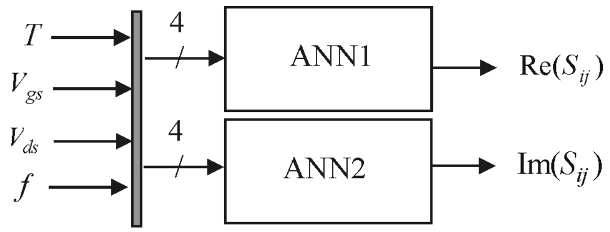

Fig. 1. Neural model for temperature-dependent S-parameters.

In the present case it has been found that for S_{21} it is more efficient and more accurate to use the magnitude/angle representation instead of the real/imaginary parts. Moreover, as will be discussed in the next section, the logarithmic representation for the frequency and S_{21} magnitude allows achieving better results than the linear representation. The final model used for S_{21} is shown in Fig. 2. Also in this case the two used ANNs are based on four input neurons and one output neuron.

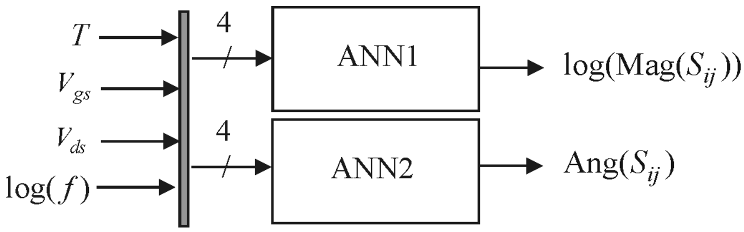

Fig. 2. Neural model for S_{21}.

The optimal number of neurons in the hidden layer(s) of an ANN cannot be determined prior to the model development. Therefore, ANNs with different numbers of hidden neurons were tested and validated to find an optimal structure for each ANN model and the best one was chosen as the final model.

The developed ANN model is simple to be implemented in standard microwave simulators. Namely, each ANNs is described by corresponding sets of mathematical expressions which are further implemented in a standard simulator to calculate the S-parameters to be assigned to a two-port symbolically defined device.

The approach can be straightforwardly applied to any device made in the considered technology. Nevertheless, the extraction of the model for different devices is out of the scope of the present study. However, the model can be extended to a class of the devices made in the same technology differing in geometry parameters or in physical parameters. In that case the ANNs should have more inputs corresponding to these parameters, as presented in [23] where a bias-dependent small signal model was developed for a class of on wafer HEMTs differing in the gate width. Development of the model for a class of devices requests measurements of several different devices to be used for building the training set.

III RESULTS AND DISCUSSION

A. Developed models

The device under test is an AlGaN/GaN HEMT on SiC substrate with a gate length of 0.7 µm and a gate width of 800 µm consisting of two fingers and each finger has a length of 400 µm. The measured S-parameters were used for model development and validation. The measurements were done from 0.3 GHz to 40 GHz with 198.5 MHz step for five different ambient temperatures: 20ºC, 35ºC, 50ºC, 65ºC, and 80ºC. The bias voltages were changed in the following range -6 V ≤ V_{gs} ≤ 0 V with 250 mV step and 0 V ≤ V_{ds} ≤ 28 V with 500 mV step. It should be noted that the measurements were not performed for the bias conditions at too high dissipated power condition to avoid device degradation.

At the beginning, ANNs were trained with a training set with uniform distribution of both frequency and bias points. The analysis of the results, especially for S_{21} and S_{22}, showed that the discrepancies are significantly larger in certain parts of the input space (i.e., low V_{ds} and in the transition region from the pinch-off to the maximum transconductance) and at low frequencies (i.e., up to 5 GHz). Therefore, a training set was built by using non-uniform distribution of the available data. The number of the samples was increased in the region of the input space where the errors were higher. It is worth noticing that the training sets referred to all available temperatures with exception of 65ºC. This is because the data at 65ºC were intended to be used for assessing the model generalization ability. Fig. 3 shows the distribution of training bias conditions for the temperature of 20ºC. For the other temperatures used for training, the same bias grid was used for building the training set, with the only difference in the bias conditions at which the maximum dissipated power was exceeded. As far as the frequency is concerned, more points were used in the low frequency range: up to 5 GHz all the available data and above one point every five.

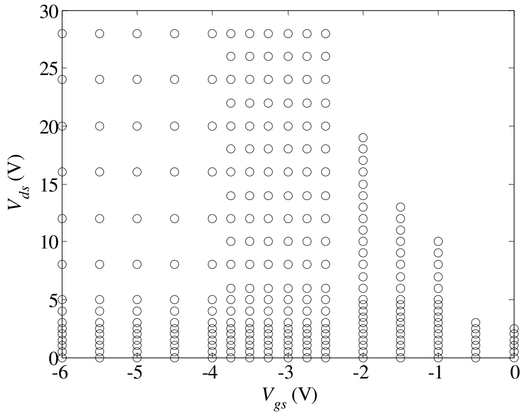

Fig. 3. Distribution of the bias points at T=20ºC used for the training set.

After training the ANNs with different numbers of hidden neurons and validating them, the ANNs listed in Table I were chosen as the final model. For S_{21} the ANNs for both representations real/imaginary parts (as shown in Fig. 1) and magnitude/angle (as shown in Fig. 2) are given. The used ANN naming convention is as follows: the ANN described as N-H1-H2-M has N neurons in the input layer, M neurons in the output layer, and H1 and H2 neurons in the first and second hidden layers.

Table I. The ANNs composing the final model

Parameter	Re	Im
S_{11}	4-24-22-1	4-25-25-1
S_{21}	4-22-21-1	4-24-24-1
S_{12}	4-25-25-1	4-24-24-1
S_{22}	4-24-22-1	4-25-25-1
Parameter	Log(Mag)	Ang
S_{21}	4-30-30-1	4-28-28-1

Training of each ANN depends on the computer configuration used and it takes not more than 15-20 min depending on the chosen number of hidden neurons (for Intel Core i7 processor and 8 GB RAM). The response of the developed model for any bias point (no matter if used or not in the training set) is of order of milliseconds.

To compare simulated and measured S-parameters at each bias point, the percentage errors E_{ij} were calculated as follows:

$$E_{ij} = \frac{1}{N_f} \sum 100 \left| \frac{S_{ijMEAS}(f) - S_{ijSIM}(f)}{S_{ijMEAS}(f)} \right| \tag{1}$$

where N_f represents the number of frequency points. Also for each considered temperature, the average and maximum E_{ij} values, $E_{ij\,avg}$ and $E_{ij\,\max}$, over the whole considered bias range were calculated:

$$E_{ij\,avg} = \frac{1}{N_b} \sum E_{ij} \tag{2}$$

$$E_{ij\,avg} = \max_{N_b} E_{ij} \tag{3}$$

where N_b is the total number of considered bias points.

Table II shows the average and maximum percentage errors for all five available temperatures. The reported results for s_{21} refer to magnitude/angle representation. The average percentage errors for the temperatures from the training set are lower than 3%, and the maximum values mostly lower than 6%. The errors are higher but still very acceptable in the case of the temperature of 65ºC, which was not used for the model development. This result definitely confirms the achieved good generalization of the model regarding the dependence on the temperature. As a further illustration, in Fig. 4 the bias dependent plots of the percentage errors referring to 65ºC are given. It can be observed that in most cases the errors are lower than 5%, except for E_{21}. Namely, for the bias points where S_{21} exhibits values close to zero, the percentage error has higher values but the absolute difference is really small, as discussed in [24]. The error plots for the temperatures used for the model development are very similar to the plots for 65ºC given in Fig. 4, but have smaller error values, as indicated in Table II. Having in mind that the error plots in Fig. 4 refer to the all available bias points (i.e., used for the training and not used for the training), relatively smooth error plot surfaces without significant deviations between adjacent bias points indicates that the developed models simulate the S-parameters for the training and test points with a similar accuracy.

In addition, Fig. 5 shows the S-parameters obtained by the neural model and compared with the corresponding measurements at 65ºC for the bias voltages V_{gs} = -2 V and V_{ds} = 19.5 V. To make the plot clear, S_{21} is divided by 20 and S_{12} is multiplied by 10. It should be noted again that these data were not used for the model development. A good agreement between the simulated S-parameters and the measurements is achieved. As can be observed, the developed model is capable to reproduce also the “kink” effect appearing in S_{22} [8, 32]. Moreover, a good agreement between maximum available gain (MAG) and maximum stable gain (MSG) as well as the stability factor μ, shown also in Fig. 5, which are calculated from the simulated and measured S-parameters, is achieved as well.

Table II. Calculated percentage errors for a GaN HEMT at five different ambient temperatures

Parameter	Temperature [ºC]	$E_{ij\,avg}$ [%]	$E_{ij\,\max}$ [%]
S_{11}	20	0.7	5.6
	35	1.7	5.1
	50	0.8	5.1
	65	3.8	12.0
	80	0.7	3.9
S_{21}	20	1.2	3.8
	35	1.1	4.6
	50	1.1	3.2
	65	3.6	14.4
	80	1.3	10.9
S_{12}	20	1.6	5.3
	35	1.5	6.0
	50	1.5	4.8
	65	2.5	6.9
	80	1.7	7.1
S_{22}	20	1.3	4.6
	35	1.1	5.1
	50	1.2	3.9
	65	2.8	7.8
	80	1.4	5.9

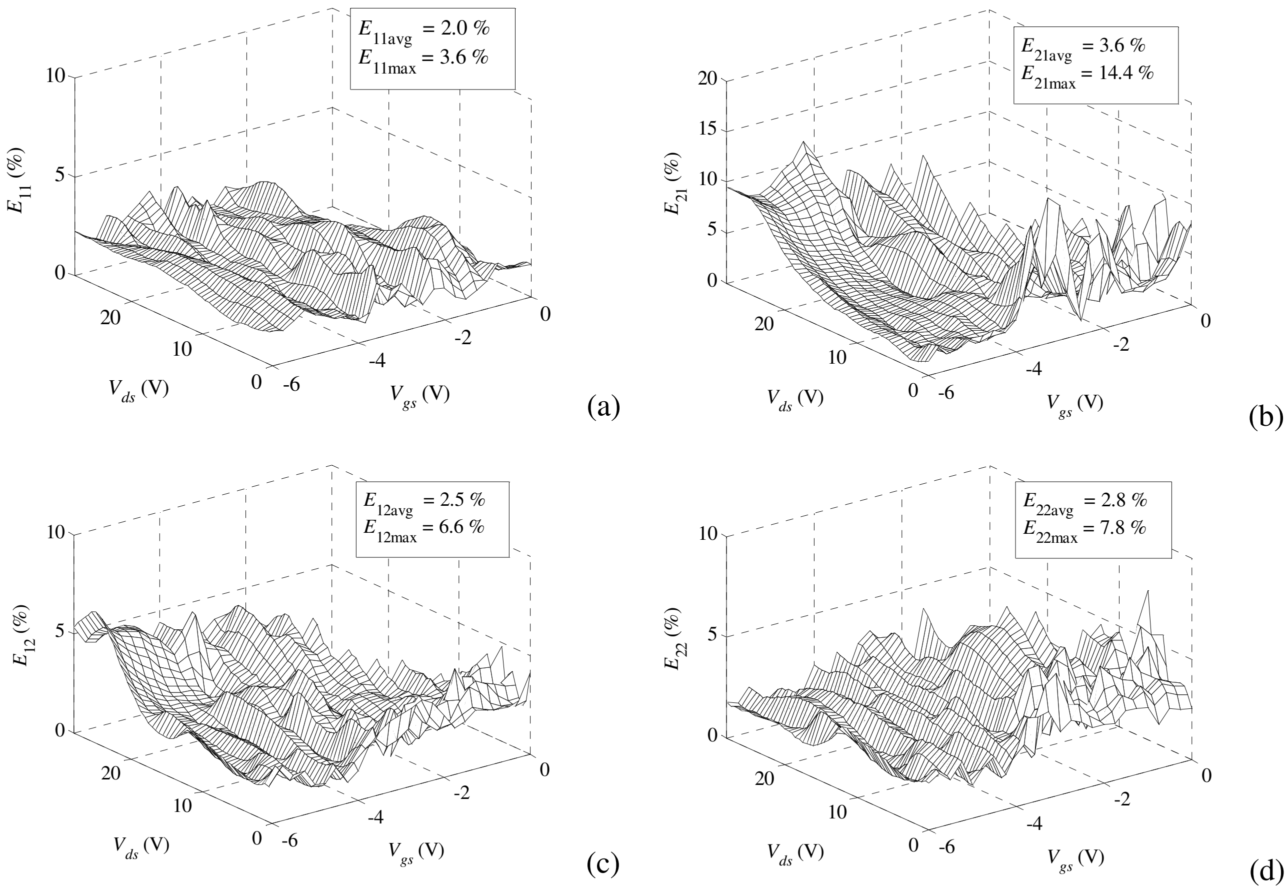

Fig. 4. Bias dependence of the percentage errors for a GaN HEMT with T = 65 °C: (a) E_{11}, (b) E_{21}, (c) E_{12}, and (d) E_{22}.

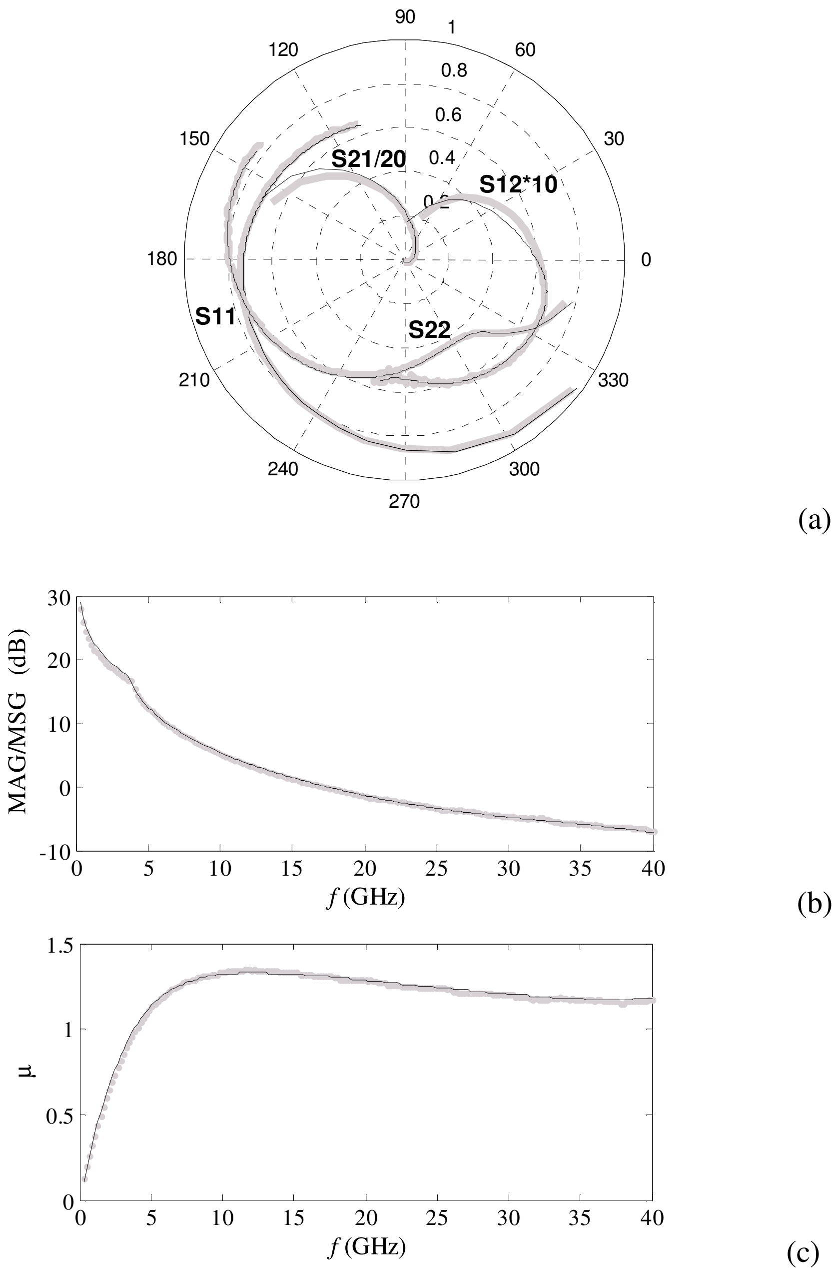

Fig. 5. Comparison between model (black thin lines) and measurements (grey thick lines in (a) or symbols in (b) and (c)) for a GaN HEMT with T = 65ºC, V_{gs} = -2 V, and V_{ds} = 19.5 V: (a) S-parameters (the corresponding percentage errors are: $E_{11} = 2.5\%$, $E_{21} = 3.3\%$, $E_{12} = 3.5\%$, and $E_{22} = 4.1\%$); (b) MAG (or MSG where MAG is undefined) and (c) the stability factor μ versus frequency.

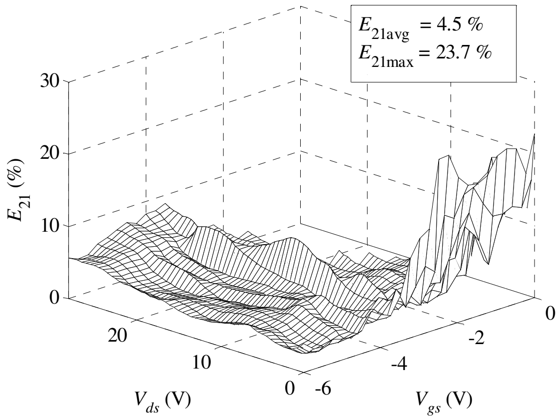

Fig. 6. Bias dependence of the percentage error E_{21} for ANN model of S_{21} represented by real and imaginary parts.

The high errors appeared not only for the temperature 65ºC but also for the temperatures used for the training set. Therefore, in order to solve this, the representation of S_{21} in the form of magnitude/phase was used. In particular, to make dynamics of the S_{21} magnitude smaller, the logarithmic scale was used for both S_{21} magnitude and frequency (see Fig. 2). By exploiting the logarithmically expressed magnitude and frequency, the “shape” of both magnitude and angle of S_{21}, especially at lower frequencies, was changed (see Fig. 7) yielding in more accurate modeling.

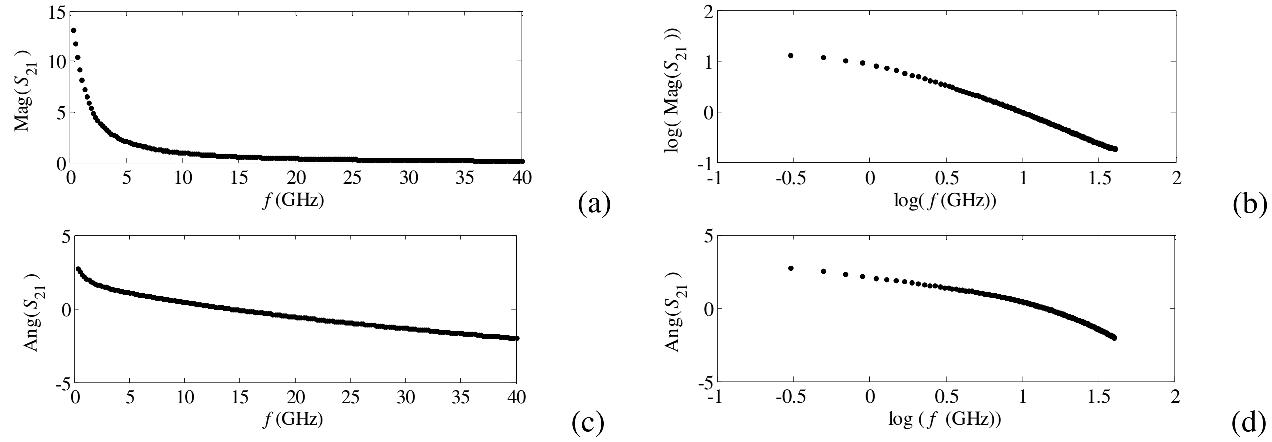

Fig. 7. The measured S_{21} versus frequency for a GaN HEMT with T=65ºC, V_{gs} = - 2 V, and V_{ds} = 19.5 V:
(a) magnitude and (b) phase of S_{21} with linear frequency representation;
(c) logarithmic magnitude and (d) phase of S_{21} with logarithmic frequency representation.

The final model exhibits not only good learning performance but also good generalization, as shown in Table I and in Fig. 4(b). In order to further illustrate this, Fig. 8 shows the comparison between measured and simulated S_{21} versus temperature at the bias condition V_{gs} = - 2 V and V_{ds} = 19.5 V and at the frequency of 1.094 GHz. The simulations were performed with a temperature step of 1ºC. It can be seen that although both models (with linear and logarithmic representation of frequency) show good agreement with measurements for the temperatures used in the training set, i.e., that both have learned the presented data very well, the model based on the logarithmic frequency representation clearly shows better generalization ability. If more of the temperature points are used for the training set, the discrepancies would be significantly smaller. To illustrate this, in Fig. 9, the plots referring to the same bias point as shown in Fig. 8 are given for the S_{21} models trained with the training set referring to all five available temperatures. The results refer to both models, with and without the logarithmic frequency representation. As far as the generalization regarding the temperature is considered, improvements can be observed in the both cases. Nevertheless, regarding the generalization referring for bias conditions, as in the case with the model developed with the data excluding the temperature of 65ºC, in the case of all temperatures included in the training set, the model with the logarithmic representation of frequency gives better test results than the model with the linear representation of frequency, as shown in Table III.

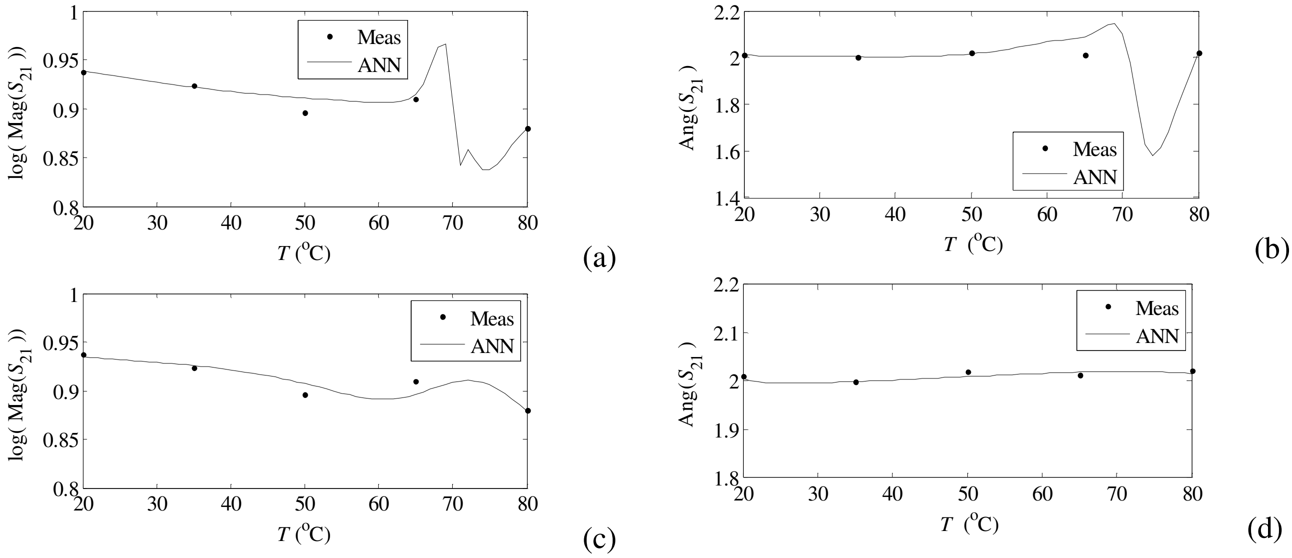

Fig. 8. Comparison between measured (symbols) and simulated (lines) S_{21} versus temperature for a GaN HEMT with V_{gs} = - 2 V, V_{ds} = 19.5 V, and f = 1.094 GHz:
(a) logarithmic magnitude and (b) phase of S_{21} with linear frequency representation;
(c) logarithmic magnitude and (d) phase of S_{21} with logarithmic frequency representation.

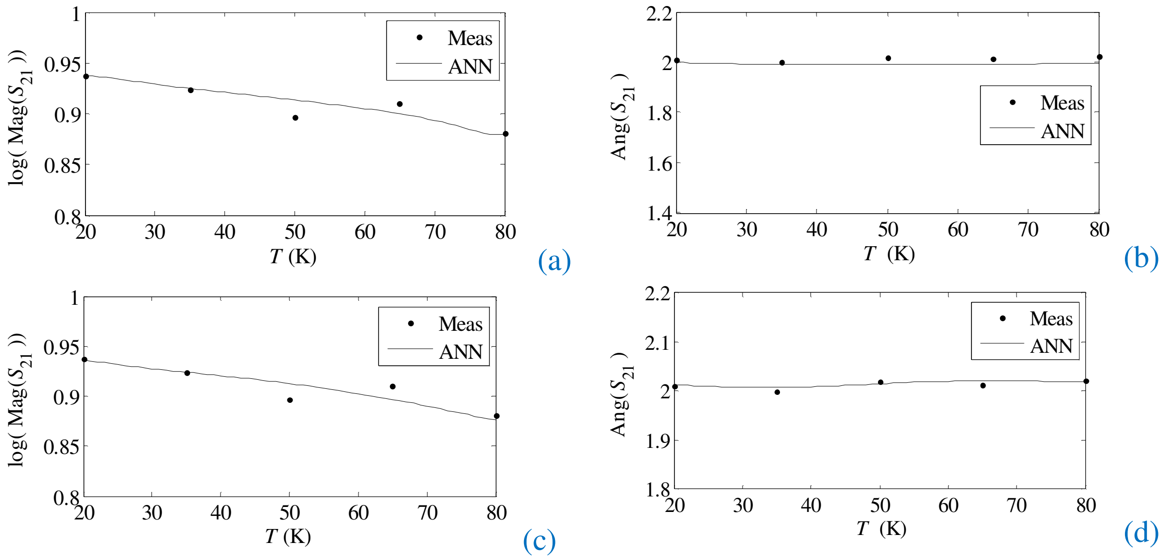

Fig. 9. Comparison between measured (symbols) and simulated (lines) S_{21} versus temperature for a GaN HEMT with V_{gs} = - 2 V, V_{ds} = 19.5 V, and f = 1.094 GHz for the model trained with the data referring to all five available temperatures:
(a) logarithmic magnitude and (b) phase of S_{21} with linear frequency representation;
(c) logarithmic magnitude and (d) phase of S_{21} with logarithmic frequency representation.

Table III. Calculated percentage errors for a GaN HEMT S_{21} at five different ambient temperatures for the models trained with the data referring to all five available temperatures

		linear frequency representation		logarithmic frequency representation	
Parameter	Temp [deg]	E_avg [%]	E_max [%]	E_avg [%]	E_max [%]
	20	2.1	6.7	1.6	6.2
	35	2.0	7.7	1.4	5.8
S_{21}	50	1.8	8.5	1.5	3.7
	65	1.8	10.5	1.4	3.7
	80	2.2	13.3	1.6	6.0

IV CONCLUSION

The present paper has been devoted to proposing a neural approach to extract a multi-bias model for a HEMT based on GaN technology. Particular attention has been paid to include the dependence on the ambient temperature. To achieve a successful model capable to reproduce the experimental data, ANNs have been trained with a training set with non-uniform distribution of the bias points and frequency. More points were used at low frequencies and in the strongly nonlinear bias region. Two separate ANNs have been used for each of the S-parameters, namely one modeling the real part and the other for modeling the imaginary part. In case of S_{21}, it has been found that it is more efficient and more accurate to use the magnitude/angle representation. In addition, the logarithmic function has been applied to its magnitude and the frequency. The accuracy of the developed technique has been confirmed by the good agreement between model simulations and measurements. Finally, it should be highlighted that the extracted model has been used to predict accurately the device behavior also for a temperature not used in the training process.

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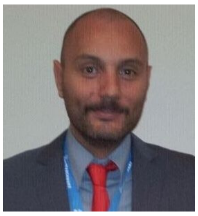

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