

A Robust Integrated Multibias Parameter-Extraction Method for MESFET and HEMT Models

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Abstract—An integrated multibias extraction technique for MESFET and high electron-mobility transistor (HEMT) models is presented in this paper. The technique uses s -parameters measured at various bias points in the active region to construct one optimization problem, of which the vector of unknowns contains a set of bias-dependent elements for each bias point and one set of bias-independent elements. This problem is solved by an extremely robust decomposition-based optimizer, which splits the problem into n subproblems, n being the number of unknowns. The optimizer consistently converges to the same solution from a wide range of randomly chosen starting values. No assumptions are made concerning the layout of the device or the bias dependencies of the intrinsic model elements. It is shown that there is a convergence in the values of the model elements and a decrease in the extraction uncertainty as the number of bias points in the extraction is increased. Robustness tests using 100 extractions, each using a different set of random starting values, are performed on measured s -parameters of a MESFET and pseudomorphic HEMT device. Results indicate that the extracted parameters typically vary by less than 1%. Extractions with up to 48 bias points were performed successfully, leading to the simultaneous determination of 342 model elements.

Index Terms—Decomposition, HEMT, linear, MESFET, modeling, multibias, optimization, parameter extraction.

I. INTRODUCTION

THE extraction of MESFET and high electron-mobility transistor (HEMT) small-signal equivalent circuits from measured s -parameters at various bias points is a crucial step in the construction of nonlinear models. Unfortunately, extracting a physically sound small-signal model that provides an accurate description of both the device packaging and the intrinsic model elements becomes virtually impossible when the s -parameters measured at different bias points are used independently to extract a small-signal model for each bias point. The extraction problem is especially problematic for larger devices with more complex parasitic networks or devices operating at higher frequencies where the effects of the parasitic elements surrounding the device become more pronounced [1].

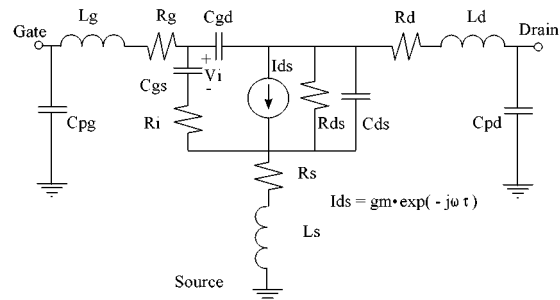


Fig. 1. Small-signal model of an MESFET/HEMT transistor.

A. Single Bias Extractions

The two main techniques used for determining small-signal models from measurements are direct extraction and optimizer-based extraction. Direct-extraction techniques rely on two sets of cold s -parameter measurements ($V_{ds} = 0$) made with the gate at both pinchoff and at a suitable forward bias. This data, together with simplifications in the model, are used to calculate the extrinsic bias-independent elements of the FET model shown in Fig. 1. The intrinsic elements are calculated after deembedding the extrinsic elements using the equations in [2]. The direct extraction method provides good approximate values for the more dominant model elements such as the intrinsic capacitors C_{gs} , C_{gd} , and C_{ds} , and it has the advantages of being fast and simple to implement. However, the technique cannot determine all the extrinsic elements uniquely. The parasitic capacitance C_{pd} is normally determined by either assuming that the device is symmetrical in terms of its gate and drain networks, and that C_{pd} , therefore, equals C_{pg} , or by using additional device structures [3]. Not all devices are symmetrical in layout, and when working with packaged commercial devices, this information will, in general, not be available to the user. The use of additional device structures increases the cost of obtaining a model, and it is not a viable alternative when a standard commercial device has to be modeled. A certain amount of experience is also needed for choosing suitable cold biases and the frequency range over which the extrinsic elements are to be calculated. Errors made in determining the extrinsic elements influences the calculation of the intrinsic element values and can result in nonphysical values for the less dominant intrinsic elements, such as R_i and τ [4]. In the case of very noisy measurements, the extracted

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values of these elements form a very erratic function of the bias, making the bias-dependent model meaningless.

Optimization-based parameter extraction is computationally more intensive and has traditionally been sensitive to the choice of optimization starting values. While several promising optimization-based extraction methods that are insensitive to starting values have recently been published [5]–[7], it still remains difficult to determine all the model elements with a high degree of certainty when s -parameters measured at a single bias point are used [5], [7]. This is especially true for the parasitic resistances R_g , R_d , and R_s , and the channel charging resistance R_i . The phenomenon is independent of the optimization method used and is due to the small influence that these elements have on the measured data. Their values are, therefore, easily influenced by measurement uncertainties and small errors made in the determination of the other model elements. These effects cause traditional multidimensional optimizers to be numerically ill conditioned.

One of the popular attempts to overcome this problem uses cold s -parameters measured with the gate held below the pinch-off voltage and an optimizer to extract a cold FET model. This model requires fewer intrinsic elements, but still represents an ill-conditioned optimization problem. Although having fewer model elements to extract, the cold FET measurements generate less data for use in the extraction since it behaves as a passive circuit. This form of extraction does not overcome the problem of uncertainty in the extracted values of insensitive elements [8] since the extrinsic elements are only determined from one set of data. The element values will, therefore, reflect the measurement errors for the specific bias point. If dominant extrinsic elements are held constant in subsequent optimizations, there can be a propagation of errors.

B. Multibias Extraction Techniques

Due to the ill-conditioned nature of the FET model extraction problem, single bias extractions cannot determine all the model elements. To overcome this problem, several solutions that make use of data measured at different bias points have been suggested [5], [9]–[13]. Most of these procedures exploit the fact that the extrinsic elements are bias independent, while some also introduce relationships between the intrinsic model elements that are derived from the device physics [10], [13].

Current multibias extraction algorithms normally make use of multidimensional gradient optimizers [9]–[13] or random optimizers [12]. Bandler *et al.* [9] described a multibias extraction that uses the l_1 norm. No assumptions were made concerning the bias dependencies of elements and any bias independent behavior was reinforced with the aid of penalty functions. The technique relies heavily on the theoretical property of the l_1 norm to ignore large deviations. Lee [10] implemented a multibias extractor for heterojunction bipolar transistor (HBT) devices using a commercial frequency-domain circuit simulator/optimizer. Two sets of s -parameters measured in the active mode of the device, and one set of s -parameters measured with the device biased in the cutoff mode, were used. The extrinsic elements were taken to be bias independent and the current dependent elements in the active bias circuits

were linked to each other by the ratio of their currents. Cai *et al.* [11] also implemented a multibias extraction technique for HBT's and made use of direct extraction techniques and a Levenberg–Marquardt optimizer. Patterson *et al.* [13] proposed a multibias algorithm that relies on the physics-based equivalent-circuit model proposed by Ladbroke [14]. This model is better conditioned than the normal equivalent-circuit small-signal model, but it is not valid for bias points outside the saturated region of the V_{DS} – I_{DS} curves. It also needs process parameter values, which is normally difficult to obtain for commercial devices. Patterson also made use of a principal components analysis and orthogonal transformations to further improve the conditioning of his optimization procedure. Lin and Kompa [5] proposed a technique in which the extrinsic elements were optimized, and the intrinsic elements calculated using a new set of robust closed-form equations. By extending this approach to multibias data, they showed that the uncertainty in the extraction of problematic elements such as R_g and R_i can be reduced greatly. Ghazinour [12] described a multibias extraction algorithm for MESFET's and HEMT's that makes use of a hybrid evolutionary/conjugate gradient optimization approach. As random-based searches become very inefficient for large problems, Ghazinour reduced the number of variables in the problem by taking elements such as R_i , τ , and C_{ds} , which have a weak bias dependency in the active region, to be bias independent. The values of the remaining intrinsic elements were calculated as a function of the extrinsic elements.

All of these approaches optimize one global error function. This is inherently a difficult problem, as the number of local minima rises as the number of unknowns increase. To overcome problems related to the number of variables, current algorithms for solving the multibias extraction problem follow two distinct paths, namely: 1) reducing the number of variables in the optimization problem by representing the intrinsic elements as functions of the extrinsic elements with the aid of analytic expressions [5], [6], [12] or developing more robust optimization methods that are suited to high-dimensional problems [7], [9], [15], [16].

This paper proposes a new multibias extraction algorithm, which combines s -parameter measurements from different bias points into an integrated extraction procedure. The performance of the proposed technique is evaluated using measured multibias s -parameter data for an MESFET and a pseudomorphic high electron-mobility transistor (pHEMT) device. The new extraction algorithm is built around a robust decomposition-based optimizer [7], [17]. The sensitivity of the optimizer with respect to the optimization starting values is tested by performing a large number of extractions, using random starting values chosen over a very wide range. Results indicate that the extracted parameters typically vary by less than 1%. Extractions with up to 48 bias points were performed successfully, leading to the simultaneous determination of 342 model elements. The results presented here also graphically illustrate, for the first time, how the extraction accuracy increases with the use of more bias points in the multibias extraction.

The technique has the following advantages.

- The decomposition-based optimizer does not make use of one global error function, making it more immune to local

minima and the ill-conditioned nature of the problem than other methods.

- Procedures that calculate certain elements with analytical equations [5], [6], [12] place a limit on the modeling fit that can be achieved since these element values cannot be varied individually. The danger also exist of the analytical equations failing due to a few bad measurement points. The proposed procedure determines all the elements with optimization and has proven itself to be resistant to the effect of measurement errors [18].
- Unlike [12], no assumptions are made concerning the bias dependencies of the intrinsic elements, and there is nothing in the algorithm that will suppress weak bias-dependent behavior in intrinsic elements [9].
- Since no assumptions are made concerning the device layout, the algorithm is suitable for modeling commercial devices about which very little additional information is known.

The method has the same starting value independence as random searches, but it is far more efficient than a random-based search. It only requires the user to provide optimization boundaries, and as will be shown, the allowed optimization search space can be made very large.

II. METHOD DESCRIPTION

The new integrated multibias parameter-extraction method uses a decomposition-based optimization algorithm, summarized as follows [7]:

“Decomposition is defined as a process by which a function that is to be optimized is broken up into several subfunctions. The independent variables of the function is partitioned into groups according to their influence on a particular subfunction. Should the i th variable have its largest influence on the j th subfunction, it is assigned to that function. The subfunctions are optimized in a specific order, and only with respect to the variables assigned to them. This order is repeated until the whole problem has converged to its final value.”

Kondoh [15] first applied decomposition-based optimization to the MESFET model extraction problem and he determined his subfunction/variable associations and the order in which they are optimized by experimentation. Bandler [16] presented a more adaptive system in which the order of optimization was calculated using a voting system based on the size of the error made by the subfunction and the number of variables associated with it. Van Niekerk and Meyer [17] showed that a sequence of optimization can be calculated using the principal components sensitivity analysis. The sensitivity analysis is used to arrange the model elements from those having the largest effect on the function to be minimized to those having the least effect, and the subfunctions are optimized using this sequence. Van Niekerk and Meyer applied the maximum amount of decomposition possible to the extraction problem by dividing the problem into one dimensional suboptimization problems. For a more detailed description of the optimization method, the reader is referred to [7] and [17].

The multibias extraction algorithm combines all the measured data into one optimization problem. A new global error

function, which includes all the bias points that are considered in the extraction, is defined. This error function is then broken up into suitable subfunctions for use in the decomposition-based optimizer. The extrinsic elements of the model are bias independent and their effect will be common to all the measurement points. The multibias data, therefore, contains redundant information that can be used to define the extraction problem more uniquely. Special subfunctions are created for the bias-independent elements that make use of this information redundancy.

The new global error function for the multibias extractor is defined as

$$F(\bar{x}) = \sum_{i=1}^N \alpha_i(\bar{x})^2 \quad (1)$$

where

$$\alpha_i(\bar{x}) = \sum_{t=1}^M \sum_{j=1}^2 \sum_{k=1}^2 \frac{1}{\sigma_{jk}(t)} |R_{jk}(\bar{x}_{\text{ind}}, \bar{x}_t, \omega_i) - S_{jk}(t, \omega_i)| \quad (2)$$

and

$$\sigma_{jk}(t) = |S_{jk}(t, \omega_i)|_{\text{MAX}}. \quad (3)$$

Equation (1) is the sum of errors made at the different frequencies and (2) is the modeling error made at all the bias points for all four s -parameters at a specific frequency. R_{jk} are the model predicted s -parameters and S_{jk} are the measured s -parameters at bias point t and frequency ω_i , M is the total number of bias points considered in the extraction, N is the number of frequencies at which s -parameters are measured, j and k are the indexes of the four s -parameters, $\sigma_{jk}(t)$ is a normalization constant, \bar{x}_{ind} is the vector containing the bias-independent model elements, and \bar{x}_t is the vector containing the bias-dependent model elements describing bias point number t . The vector \bar{x} contains all the model elements for the multibias problem and is defined as

$$\bar{x} = [\bar{x}_{\text{ind}} \quad \bar{x}_1 \quad \bar{x}_2 \cdots \bar{x}_{M-1} \quad \bar{x}_M]. \quad (4)$$

For the bias-dependent model elements, each element is associated with the error made in modeling a specific s -parameter at one bias point across the frequency band, and an error subfunction is defined for each element as

$$f_l(x_l) = \sum_{i=1}^N |R_{jk}(x_l, \bar{x}_R, \omega_i) - S_{jk}(\omega_i)|^2 \quad (5)$$

where x_l is the model element being optimized and \bar{x}_R contains the other model elements.

The bias-independent model elements do not only influence a certain s -parameter at a specific bias point, but have an effect on that s -parameter at all the bias points. The definition of the error subfunction for a bias independent element is, therefore,

$$f_l(x_l) = \sum_{i=1}^N \left(\sum_{t=1}^M \frac{1}{\sigma_{jk}(t)} |R_{jk}(x_l, \bar{x}_{\text{ind}}, \bar{x}_t, \omega_i) - S_{jk}(t, \omega_i)| \right)^2. \quad (6)$$

TABLE I
MODEL ELEMENT/SUBFUNCTION ASSOCIATIONS USED FOR THE 15-ELEMENT MESFET AND HEMT MODEL IN THE MULTIBIAS EXTRACTION

	Model Element	Bias Dependent	Subfunction to be Minimized
1.	C _{gs} , R _i	Yes	S11 at specific bias point
2.	C _{gd}	Yes	S12 at specific bias point
3.	g _m , τ	Yes	S21 at specific bias point
4.	C _{ds} , R _{ds}	Yes	S22 at specific bias point
5.	C _{pg} , R _g , L _g	No	S11 at all the bias points considered
6.	C _{pd} , R _d , L _d	No	S22 at all the bias points considered
7.	R _s , L _s	No	S12 at all the bias points considered

The vector \bar{x}_{ind}'' contains the extrinsic model elements, with the exception of element x_L . Equation (6) represents the modeling error made in s -parameter S_{jk} over all the bias points and frequencies considered in the extraction. The use of (6) for optimizing the bias-independent elements creates four additional subfunctions that can be used in the decomposition process, one for each s -parameter. Table I provides a summary of the multi-bias error function/model element associations that were used. The validity of these associations have been confirmed using the sensitivity analysis proposed in [16].

The biggest advantage of the decomposition-based optimizer is that it is not adversely affected by the increase in the problem dimensions when using more bias points. Since the extraction procedure does not depend on the minimization of one global error function, it is not as sensitive to the increase in the number of local minima, as would be the case with a more conventional optimizer. The extraction algorithm is applied to s -parameters measured in the active region of the device's I - V curves. This ensures that the device acts as a nonreciprocal two port, thus providing the maximum amount of information possible for determining the model elements.

Once a multibias extraction using a suitably large number of bias points have been performed, the extrinsic model elements can be deembedded from the s -parameters measured at bias points over the complete I - V curve of the device, and the equations found in [5] can be used to calculate the intrinsic model elements at other bias points not considered in the initial extraction. The equations in [5] are preferred to those in [2] since they have been found to be more resistant to the propagation of calculation errors. The calculated element values are then used as the starting values for an expanded multibias extraction using an optimizer that employs a reduced level of decomposition. This second phase of optimization allows very large problems to be handled more efficiently.

III. RESULTS

Tests were performed using s -parameter data from an un-packaged Texas Instruments Incorporated $0.25 \mu\text{m} \times 300 \mu\text{m}$ low-noise MESFET and a $0.2 \mu\text{m} \times 100 \mu\text{m}$ GaAs pHEMT

[19]. Small-signal s -parameters were measured over the whole of the device I - V curves from a frequency of 1–26.5 GHz for the MESFET and 25 GHz for the pHEMT.

Both devices were modeled with 13 element models. The parasitic elements C_{pg} and C_{pd} were not included in the model because, due to the small values of the series inductances L_g and L_d , the highest measurement frequency was still too low to reliably separate the effect of these elements from the intrinsic capacitors C_{gs} and C_{ds} . In the case of the MESFET, no model containing parasitic capacitances could be found that resulted in smaller modeling errors than those given by the 13-element model. The 13- and 15-element pHEMT models provided comparable modeling errors, but the inclusion of C_{pg} and C_{pd} in the model destroyed the physically sound bias-dependent behavior of C_{gs} and C_{ds} and made it impossible to consistently converge to a unique solution. The pHEMT model can also be expanded with the addition of a resistor R_j in series with C_{gd} [3], [20]. Experiments were performed with such a model, but it was once again not possible to converge to a unique solution for all the model elements. This is not unexpected since R_j will only have a pronounced effect at very high frequencies. While the larger FET models are physically more correct, they are of little use if they cannot be consistently extracted from the available measured data. Experiments performed using simulated s -parameter data did confirm that the decomposition-based optimizer can extract more complex models from wide-band data [18].

To illustrate the advantages of the multibias approach, a number of single bias extractions were first performed for various bias points. Each extraction was repeated 100 times using random starting values picked from a search space defined in Table II. A uniform distribution was used. Fig. 2 shows a plot of the extracted values of the extrinsic element R_g as a function of V_{ds} for the MESFET. The one curve depicts the element value that corresponds with the lowest modeling error made, while the other curve shows the average R_g value. It is clear that there is a variation in the element value that is physically inconsistent. The differences between the two curves show that the parameter is sensitive to the optimization starting values used in the extraction. The values and sensitivity toward optimization starting values of the less sensitive elements, such as the parasitic resistances, are very much dependent on the

TABLE II
EXTRACTION RESULTS FOR THE MULTIBIAS ROBUSTNESS TEST FOR THE TWO DIFFERENT DEVICES CONSIDERED

	MESFET				GaAs pHEMT			
	Search Space		Results		Search Space		Results	
	Min. Value	Max. Value	Mean Value	Δ	Min. Value	Max. Value	Mean Value	Δ
Cgs (fF)	3.5E-2	1750	558.311	8.248	1.9E-2	950	66.132	0.0481
Cgd (fF)	4.4E-2	220	15.55	0.261	3.09E-3	154.5	36.698	0.0158
Cds (fF)	9.0E-3	450	71.306	0.327	1.28E-2	640.5	29.789	0.0628
gm (mS)	5.4E-3	270	66.185	1.074	5.0E-3	250	4.095	0.0027
τ (psec)	6.0E-4	30	3.852	0.0013	1.0E-4	5	0.864	0.0156
Ri (Ω)	1.5E-4	7.5	2.262	0.746	5.0E-4	25	1.37	0.246
Rds (k Ω)	2.56E-5	1.28	0.496	0.0081	1.0E-4	5	2.223	0.0317
Lg (pH)	9.0E-3	450	31.171	0.048	5.1E-3	255	43.546	0.156
Ld (pH)	9.0E-3	450	40.679	1.007	4.0E-3	200	17.326	0.677
Ls (pH)	2.0E-3	100	4.785	0.112	1.5E-4	7.5	0.1882	0.322 ⁽²⁾
Rg (Ω) ⁽¹⁾	1.5E-4	7.5	1.702	0.59	1.5E-4	7.5	5.743	0.123
Rd (Ω)	4.4E-4	22	4.4E-4	0 ⁽²⁾	3.0E-4	15	4.483	0.252
Rs (Ω)	2.9E-4	14.5	1.179	0.239	2.0E-4	10	2.0E-4	0 ⁽²⁾

- (1) If one of the random extractions for the MESFET is discarded, then the Δ value for Rg changes to 0.1605 Ω
- (2) See text

bias point used in the extraction. This leads to high uncertainty in the extracted values of these elements.

In contrast, the new multibias technique is independent of starting values and produce more consistent results for the non-dominant model elements. This is shown by performing a robustness test consisting of a multibias search using five bias points, and repeated 100 times using randomly chosen starting values. The random starting values were chosen inside the large search space defined in Table II using a uniform distribution. Table II summarizes the results of these tests for the MESFET and GaAs pHEMT. The table shows the mean extracted value of each element. An uncertainty factor Δ is defined as the difference between the maximum and minimum extracted element value. Due to space constraints, only the intrinsic elements for the bias point that had the largest modeling error are listed in Table II. It is clear from Table II that most of the model elements consistently converge to a very small range of values. This is also true for the traditionally insensitive elements such as R_g , R_i , and τ . The extracted R_d value for the MESFET, and the R_s value for the pHEMT, always tended to the lowest optimization boundary, regardless of the starting values used. In the MESFET, it was found that R_d exhibited a large bias dependence, with R_d wanting to assume negative values at high V_{ds} values. While physical reasons for the existence of a negative resistance in the high field region between the gate and drain

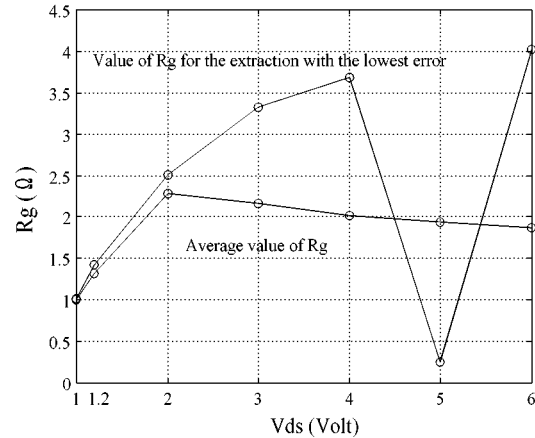


Fig. 2. Variation of the bias-independent parasitic resistance R_g with V_{ds} when single bias parameter extractions are used. Each of the single bias extractions were repeated 100 times using random starting values. The two curves show the mean value of R_g and the value of R_g that corresponds with the extraction that had the smallest error. The difference between the two curves illustrates the sensitivity of some of the parameters to optimization starting values.

has been advanced [14], [22], much debate concerning such an element still exist [23]. From an extraction point-of-view, a

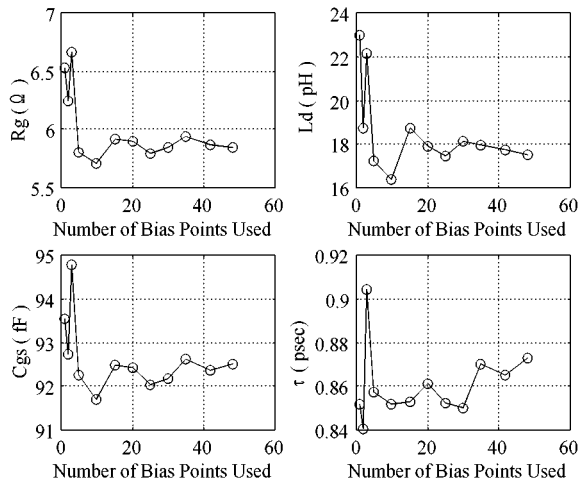


Fig. 3. Extracted values of two extrinsic bias-independent and two intrinsic bias-dependent elements for the HEMT are plotted as a function of the number of bias points used in the multibias extraction. The bias-dependent elements are shown for the bias point $V_{gs} = 0.0$ V and $V_{ds} = 1.5$ V.

negative resistance is undesirable since it acts as a new source of energy. This causes the other model elements to assume physically unrealistic values. The pHEMT source resistance R_s did not exhibit a dependence on bias, but its value is probably influenced by measurement imperfections (resonances) in the data. The pHEMT source inductance L_s exhibited similar behavior, with the variation in L_s being much larger than normally found in a dominant model element. The value of L_s is, however, very small, decreasing the influence that it has on the measured data, and making it more susceptible to measurement imperfections. Ultimately, the extraction results will depend on the quality of the measured data.

With the multibias approach, the use of more sets of data causes convergence in the extracted values of the model elements and a reduction of extraction uncertainty. It is, however, to be expected that there will be a point at which no more accuracy is gained from the inclusion of more bias points in the multibias extraction. Fig. 3 shows the values of four different elements (two extrinsic and two intrinsic) as a function of the number of bias points used when extracting the GaAs pHEMT model. Fig. 4 contains a similar plot showing the uncertainty in the model elements as a function of the number of bias points used. Due to the long executions times needed to perform a full robustness test with a large number of bias points, only results with up to ten bias points are shown in Fig. 4. A convergence in the values of the elements and the extraction uncertainty is discernable as the number of bias points used are increased. Similar results were obtained for the MESFET. From the different devices that were studied, it would appear that five or more well-distributed bias points are needed to perform a reliable multibias extraction.

Figs. 3 and 4 indicate that the model elements are becoming less dependent on the measurement uncertainties associated with the different bias points. The use of more bias points allows the extrinsic elements to be determined more accurately, which, in turn, decreases the correlation that exist between some intrinsic and extrinsic elements. For instance, R_i and R_g

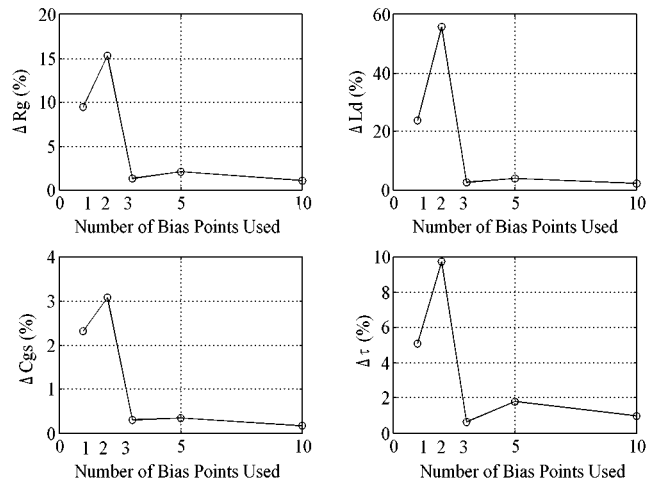


Fig. 4. Uncertainty in two of the extrinsic bias-independent elements and two of the intrinsic elements is plotted as a function of the number of bias points used in the multibias extraction. The uncertainty factor Δ shown in the figure is expressed as a percentage of the mean element value.

have a high correlation due to their positions in the model and because they look electrically the same [13]. The multibias algorithm can separate their values because they behave differently with changes in the bias, something which is not possible with a single bias algorithm.

Figs. 5 and 6 show a comparison of the measured and modeled s -parameters for the MESFET and pHEMT device that were obtained during the robustness test. The data represents the random extraction and bias point that resulted in the largest modeling error. Table III contains the average and maximum amplitude and phase errors across the full frequency range for each of the s -parameters shown in Figs. 5 and 6. A very good fit of measured and modeled data is obtained with the new extraction algorithm for each of the s -parameters at all of the bias points that were used.

IV. COMPARING THE DECOMPOSITION-BASED OPTIMIZER TO OTHER METHODS

The new multibias algorithm was compared to other methods in terms of its robustness, speed, and accuracy by using published and experimental results.

Various robust extraction methods have been proposed that rely on guided random searches such as tree annealing [23] or evolutionary strategies [12]. When the results presented in Table II are compared to those published in [12] and [23], it becomes clear that the new algorithm has a starting value independence comparable to the random searches. The allowed search space defined in Table II is larger than the search space that was used in [23], and it is comparable in size to the search space that was defined in [12].

While being robust, the random-based searches are inefficient, especially when a large number of unknowns have to be determined [23]. This either places a restriction on the size of the extraction problem that can be handled or make it necessary to make assumptions concerning the bias-dependent behavior of some model elements in order to reduce the number of

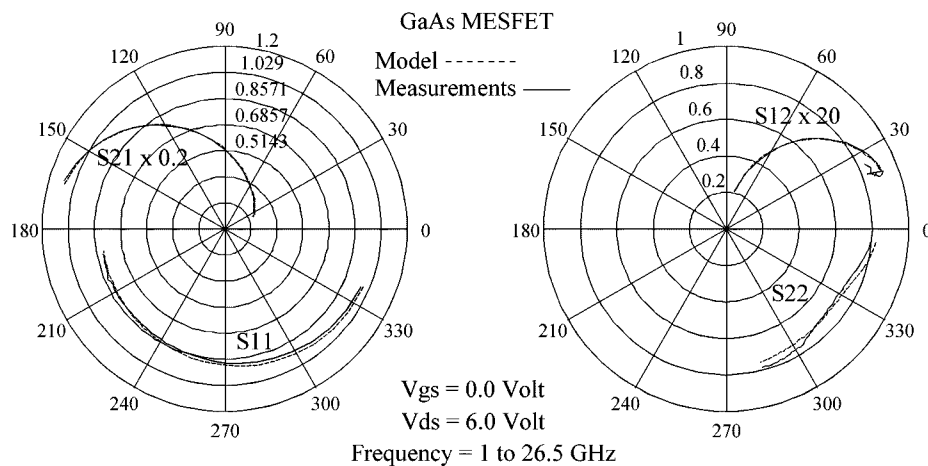


Fig. 5. Modeled and measured s -parameters for the GaAs MESFET are compared. The model elements used in the model describe the bias point and random extraction that resulted in the largest modeling error. The average and maximum errors made in modeling the amplitude and phase of the s -parameters are listed in Table III. S_{21} and S_{12} are scaled with the factors shown next to them in order to allow them to be clearly shown on the same polar plots as S_{11} and S_{22} .

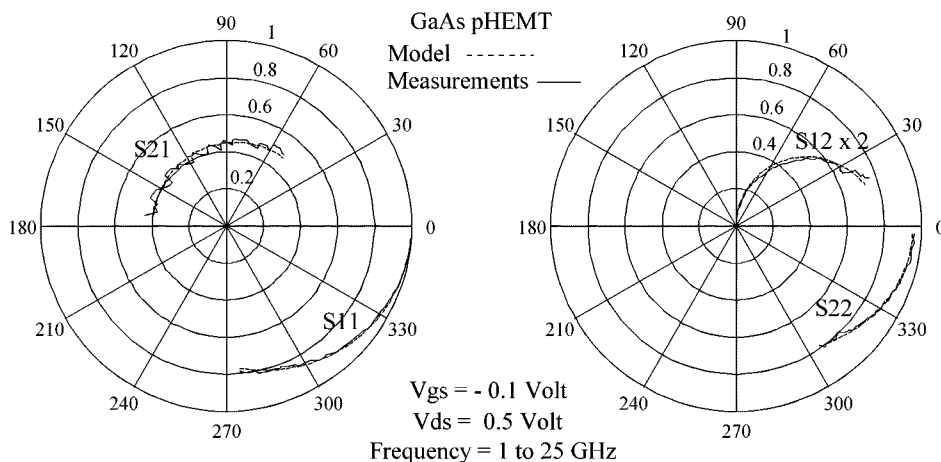


Fig. 6. Modeled and measured s -parameters for the GaAs pHEMT are compared. The model elements used in the model describe the bias point and random extraction that resulted in the largest modeling error. The average and maximum errors made in modeling the amplitude and phase of the s -parameters are listed in Table III. S_{12} is scaled by a factor of two in order to clearly show it on the same polar plot as S_{22} . It should be noted that S_{21} is not scaled, but that the bias point used is close to the cutoff region of the device.

unknowns [12]. The new multibias algorithm uses a decomposition-based optimizer that is suited to high-dimensional problems, and it is, therefore, not bound by the same restrictions as the random-based searches. A typical extraction, using ten bias points, took on average of 18.5 min of system time on a Silicon Graphics Workstation using an R10000 processor running at 180 MHz. This represents about 370 iterations of the optimizer. The termination condition of the optimizer were taken to

be a change of less than 0.01% in the value of all the model elements for more than two consecutive iterations. If a less strict condition, i.e., the percentage change in the global error function was used, the optimization procedure typically only needed 50–100 iterations, but larger inaccuracies were encountered in the values of the nondominant model elements. These elements are poorly represented by the changes in the value of the global error function, and the decomposition-based search spends most

TABLE III
COMPARISON OF MEASURED AND MODELED s -PARAMETERS (SEE FIGS. 5 AND 6)

	GaAs MESFET				GaAs pHEMT			
	Average	Average	Maximum	Maximum	Average	Average	Average	Average
	Amplitude	Phase	Amplitude	Phase	Amplitude	Phase	Amplitude	Phase
	Error	Error	Error	Error	Error	Error	Error	Error
S_{11}	0.0100	0.3482°	0.0198	0.9823°	0.0070	0.3832°	0.0193	1.7089°
S_{21}	0.0221	0.5089°	0.0438	1.2349°	0.0174	1.2383°	0.0397	3.468°
S_{12}	0.0009	1.0996°	0.0036	2.6479°	0.0041	1.7250°	0.0155	3.1465°
S_{22}	0.0215	0.4087°	0.0385	1.5355°	0.0080	0.4916°	0.0288	1.478°

TABLE IV
COMPARISON OF THE EXTRACTION RESULTS OBTAINED WITH A DIRECT EXTRACTION METHOD [24] AND THE NEW MULTIBIAS DECOMPOSITION-BASED OPTIMIZER USING THE MESFET AND pHEMT MEASURED DATA

	MESFET				pHEMT			
	Bias Point for Intrinsic Elements				Bias Point for Intrinsic Elements			
	Vgs = -0.6 Volt Vds = 3.0 Volt				Vgs = 0.0 Volt Vds = 1.5 Volt			
	Direct Extraction		Decomposition-Based Optimizer		Direct Extraction		Decomposition-Based Optimizer	
	Avg	Δ	Avg	Δ	Avg	Δ	Avg	Δ
Cgs (fF)	328.672	11.27	354.304	5.8	104.044	8.771	92.158	0.319
Cgd (fF)	32.904	1.607	31.21	0.329	31.698	3.205	33.004	0.028
Cds (fF)	67.997	3.113	74.546	0.54	36.854	8.252	26.287	0.186
gm (mS)	60.52	1.538	65.439	0.001	40.55	1.564	35.214	0.026
τ (psec)	1.965	0.132	2.236	0.01	0.303	0.371	0.850	0.015
Ri (Ω)	4.002	0.888	2.183	0.883	3.876	3.489	1.296	0.333
Rds (Ω)	293.868	53,008	220.793	3.017	410.1	135.98	420.706	0.295
Lg (pH)	30.272	7.242	31.171	0.048	43.274	44.119	43.564	0.156
Ld (pH)	55.044	7.398	40.679	1.007	37.919	11.07	17.326	0.677
Ls (pH)	5.101	0.836	4.785	0.112	6.814	5.537	0.188	0.322
Rg (Ω)	0.757	0.56	1.702	0.59	1.752	1.565	5.743	0.123
Rd (Ω)	1.390	2.061	4.4E-4	0	5.996	3.046	4.484	0.252
Rs (Ω)	0.0257	2.075	1.179	0.239	3.822	3.385	2.0E-4	0
Cpg (fF)	-1.249	—	—	—	15.27	2.662	—	—
Cpd+Cds (fF)	69.381	1.709	—	—	33.917	3.485	—	—

of its time moving these elements through the shallow region of the global objective function landscape that surrounds the solution.

The decomposition-based search was also compared to a multibias algorithm based on the systematic multidimensional optimizers described by Patterson [13], as well as one using a conventional damped Gauss–Newton optimizer. These proce-

dures optimized all the extrinsic elements together, using one error function based on the S_{11} , S_{12} , and S_{22} data for all the bias points considered in the extraction. The different sets of intrinsic elements were optimized with respect to all the s -parameters describing their particular bias point. The optimizers based on the work in [13] were found to be far superior to the conventional damped Gauss–Newton algorithm, and could

reduce the global error function to a low value from a wide range of starting values. It was, however, unable to produce the same consistently small distributions in the extracted values of the model elements as the full decomposition-based search. The multidimensional optimizers, when started from accurate initial element values, produced distributions that were a factor of 3–10 larger for dominant elements such as C_{gs} and L_g . The values of nondominant elements such as R_i varied over an even larger range of values, with the extraction uncertainty in R_i being far larger than its average value.

Direct parameter-extraction methods use data from different cold and hot bias points to determine the extrinsic and intrinsic model elements of the small-signal model. They can, therefore, be viewed as multibias algorithms. The procedure described by Tayrani [24] for extracting MESFET or HEMT extrinsic elements was implemented, and the equations of Berroth and Bosch [2] were used to calculate the intrinsic model elements. For the calculation of the parasitic inductors, resistors, and intrinsic elements, only measurements above 15 GHz were used, while for the parasitic capacitors, only frequencies below 10 GHz were used. These frequency ranges were chosen after plotting the calculated element values as a function of frequency, and resulted in a considerable reduction of the variation in their values. An extraction uncertainty Δ is defined as the difference between the largest and smallest calculated element values.

Table IV compares the average element values and their extraction uncertainty Δ obtained with the direct extraction procedure and the new multibias algorithm. The multibias extraction results were obtained from the five bias point robustness test described in the previous section and consistently produced more unique solutions than the direct extraction. The direct extraction procedure suffers from large extraction uncertainty when it comes to the determination of nondominant model elements such as the parasitic resistors and even more dominant elements such as the drain–source resistance R_{ds} . In the case of the MESFET, R_s also assumed nonphysical negative element values at a large number of frequency points.

While the direct extraction algorithm can calculate values for the parasitic capacitors C_{pg} and C_{pd} , only a 13-element model was used in the optimizer due to the reasons discussed before. The direct extraction procedure can only determine C_{pg} uniquely since the values of C_{ds} and C_{pd} cannot be separated. In the case of the MESFET, the C_{pg} calculations returned negative values, providing a further indication that these parasitic elements are negligible for the MESFET. Extractions performed with the approach described in [25] yielded a C_{pg} value of 3.98 fF, which is still very small when compared to the value of C_{gs} . For the pHEMT, the value of C_{pg} was found to be 15.27 fF, which is not negligible when compared to the value of C_{gs} . As was previously explained, the maximum measurement frequency is too low for the decomposition-based optimizer to accurately separate the values of these two capacitors.

It is clear that the multibias algorithm presented here is accurate, and has a robustness equal to that found in reported random extraction algorithms, but achieved with the efficiency of a gradient optimizer. The uniqueness of the extraction solutions that were produced with the new algorithm exceeds that which was

obtained with direct extraction procedures or the other multidimensional optimizers that were evaluated.

V. CONCLUSION

The formulation and extraction results of a robust multibias parameter extractor for MESFET and HEMT small-signal models have been presented. The extraction technique uses a decomposition-based optimizer that is insensitive to the choice of the optimization starting values used. It is shown that the inclusion of more bias points in the extraction increases the uniqueness of the extracted model elements. The new procedure was compared to other methods and published results. Its is shown to have a starting value independence equal to that of random optimizers.

The algorithms discussed in this paper are implemented in a FORTRAN 77 program that has been successfully compiled on a variety of platforms. The program is robust and requires no user intervention during extractions.

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