LNA Test: A Polynomial Coefficient Approach

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***Abstract*—Parametric fault testing of a low noise amplifier based on Taylor series expansion of input-output function is presented. We classify the circuit under test (CUT) as faulty or good based on a comparison of the polynomial coefficients of the CUT with those of the fault-free circuit. The method needs little augmentation of circuit as only a minimal set of output parameters is used for classification. We also extend this approach to fault diagnosis in conjunction with sensitivity of polynomial coefficients to circuit parameters. Experimental results show that all injected single parametric faults of sizes greater than 10% are detected and reliably diagnosed.**

I. Introduction

Non-linear circuit testing has been well studied and different methods have been proposed for finding parametric faults [1], [2], [3], [4], [5], [6], [7], [8]. Prominent among them in the industry is the I_{DDQ} based testing where current from the supply rail is monitored and sizable deviation from its quiescent value is reported. However this requires augmentation of the CUT. For example, in the simplest case a regulator supplying power to any sizable circuit has to be augmented with a current sensing resistor and an ADC (for digital output) and then there is subsequent analysis to be performed on sensed current. Further I_{DDQ} is suitable only for catastrophic faults as the current drawn from the supply is distinguishable only when there is some "big enough" fault so as to change the current drawn from the supply from its quiescent value to a region where it is distinguishable. For example with resistor R_2 being open in Figure 1, the current drawn from supply can change by 50% of its quiescent value. Such faults can typically be found by monitoring I_{DDQ} using a current sensor. However parametric deviations say lesser than 10% from its nominal value cannot be observed using this scheme, specially so in the deep submicron era where the leakage currents can be comparable with defect induced current [9]. The other approach for testing parametric faults that can be found in literature [10], [11], [12], [13], [14] is based on the use of neural networks. Neural network based approaches propose the use of circuit observer blocks to track the output for a set of input signals which is used for training the neurons. The trained set of neurons is then used to estimate variations in the output for a standard input stimulus. This method, however, suffers from large amounts of training required and the consequent increase in test application time that the scheme is prohibitive for even medium sized analog circuits at production. More recently, the use of Volterra series coefficients was proposed to estimate non-linear characteristics of the system. These coefficients are then used for testing the circuit with a pseudo random input stimulus [15], [16]. This method however suffers from the high computational requirement of estimation of Volterra series coeffcients for every circuit at production which can increase the test cost significantly. It is therefore interesting to develop a method to detect parametric faults with little circuit augmentation while keeping the test access mechanism simple and the test application time to a minimum.

To address the issue of parametric deviation, we would typically need more observables to have an idea about the parametric drift in circuit parameters. This would mean an increase in complexity of the sensing circuit. However, we would also want only little augmentation to tap any of the internal circuit nodes or currents. To overcome these seemingly contrasting requirements the method intended should have some way of "seeing through" the circuit with only the outputs and inputs at its disposal. References [17], [18] have accomplished this sort of a strategy for linear circuits in a different context as described next.

Savir and Guo describe a method [17] based on transfer function of a circuit under test (CUT). The transfer function, $H(s)$, of the CUT is expressed as:

$$H(s) = \frac{\sum_{i=0}^{M} a_i s^i}{\sum_{i=0}^{N} b_i s^i} \qquad (M < N) \tag{1}$$

Here, a_i and b_i are referred to as transfer function coefficients (TFCs). The CUT is subjected to frequency rich input signals and the output at these frequencies is observed. With these input-output pairs they estimate the TFCs of CUT. These coefficients are now compared with the ideal circuit TFCs, which are known a priori. The CUT is classified faulty if any of the estimated coefficients are beyond the tolerable range. This method necessarily needs the CUT to be linear, as transfer functions are possible only for LTI systems.

To extend the above idea to more general non-linear circuits we adopted a strategy in [19], [20], [21] where we expand the function of the circuit as a polynomial by the Taylor's series expansion about the input voltage v_{in} = 0 as follows:

$$v_{out} = f(v_{in}) = f(0) + \frac{f'(0)}{1!}v_{in} + \frac{f''(0)}{2!}v_{in}^2 + \frac{f'''(0)}{3!}v_{in}^3 + \cdots + \frac{f^{(n)}(0)}{n!}v_{in}^n + \cdots \tag{2}$$

where $f(x)$ is a real function of x. Ignoring the higher order terms in (2), we can expand v_{out} up to the n^{th} power of v_{in}, which gives the approximation,

$$v_{out} = a_0 + a_1 v_{in} + a_2 v_{in}^2 + \cdots + a_n v_{in}^n \tag{3}$$

where $a_0, a_1, a_2, \ldots, a_n$ are all real-valued functions of circuit parameters $p_k \, \forall \, k$. Further assume that normal parameter variations (normal drift) in a good circuit are within a fraction α of their nominal value, where $\alpha << 1$. This means that every parameter p_i is allowed to vary within the range $p_{k,nom}(1-\alpha) < p_k < p_{k,nom}(1+\alpha) \, \forall \, k$, where $p_{k,nom}$ is the nominal value of parameter p_k. Whenever one or more of the coefficient values slip outside its individual hypercube we get a different set of coefficients that reflects a detectable fault. Therefore, equation (4) describes a hypercube for all parameters that correspond to either good circuit values or undetectable parameter faults [2], [8], [17]:

$$a_{i,\min} < a_i < a_{i,\max} \, \forall \, a_i, \; 0 \leq i \leq n \tag{4}$$

This paper is organized as follows. Section II we state previously published results [19] on the polynomial expansion of function $f(v_{in})$ and notions of detectable fault sizes. In Section III we describe the problem at hand and discuss the proposed solution with an example. In Section IV we generalize the test solution to an arbitrarily large circuit. Section V outlines fault diagnosis. Section VI presents the simulation results for a standard Low noise amplifier. We conclude in Section VII.

II. Background

The coefficients $a_i \; \forall \; 0 \leq i \leq n$ are in general non-linear functions of circuit parameters $p_k \, \forall \, k$. The rationale in using these coefficients as metrics in classifying CUT as faulty or fault free is based on the premise of dependence of coefficients on circuit parameters. We now note some theorems that have been previously proved relating polynomial coefficients to circuit parameters [19].

Theorem 1. If coefficient a_i is a monotonic function of all parameters, then a_i takes its limit (maximum and minimum) values when at least one or more of the parameters are at the boundaries of their individual hypercube.

Lemma 1. If coefficient a_i is a non-monotonic function of one or more circuit parameters p_i, then a_i can take its limit values anywhere inside the hypercube enclosing the parameters.

By Theorem 1 and Lemma 1 it is clear that by exhaustively searching the space in the hypercube of each parameter we can get the maximum and minimum values of the polynomial coefficient. Typically this can be formulated as a non-linear optimization problem to find the maximum and minimum values of coefficient with constraints on parameters allowing only a normal drift.

Theorem 2. In polynomial expansion of Non-Linear Analog circuit there exists at least one coefficient that is a monotonic function of all the circuit parameters.

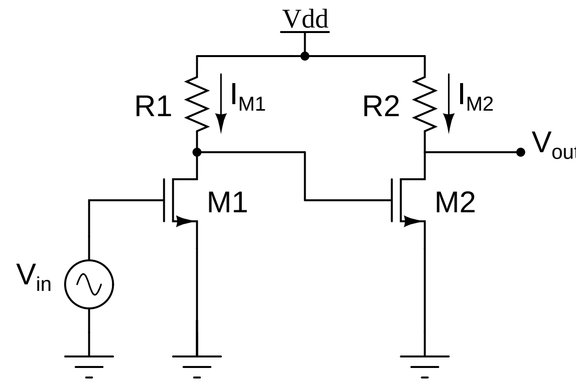

Fig. 1. Cascaded amplifier.

In conclusion, from Lemma 1 and Theorem 2, circuit parameter deviations have a bearing on coefficients and the monotonically varying coefficients can be used to detect parametric faults of the circuit parameters [19].

Definition: A minimum size detectable fault (MSDF) for a circuit parameter is defined as the minimum fractional deviation ρ in the nominal value of the parameter, which is detectable with all other parameters held at their nominal values. This fractional deviation can be positive or negative and is referred to as upside-MSDF (UMSDF) or downside-MSDF (DMSDF) accordingly.

If ψ is the set of all coefficient values spanned by the parameters while varying within their normal drifts, i.e.,

$$\psi = \{v_0, v_1, \cdots, v_n \, | v_0 \in A_0, v_1 \in A_1, \cdots, v_n \in A_n\}$$
$$\forall k \quad p_{k,nom}(1-\alpha) < p_k < p_{k,nom}(1+\alpha)$$

then by definitions of MSDF, ψ includes all possible values of coefficients that are not detectable. Any parametric fault inducing coefficient value outside the set ψ will result in a detectable fault.

III. Problem and Approach

We shall first illustrate with an example the calculation of limits of the polynomial coefficients for a simple circuit using MOS transistors. We shall follow this up with MSDF values for the circuit parameters.

Example 1. Two stage amplifier: Consider the cascaded amplifier shown in Figure 1. The output voltage V_{out} in terms of input voltage results in a fourth degree polynomial:

$$V_{out} = a_0 + a_1 v_{in} + a_2 v_{in}^2 + a_3 v_{in}^3 + a_4 v_{in}^4 \tag{5}$$

where constants a_0, a_1, a_2, a_3 are defined symbolically in (6) for transistors M1 and M2 operating in the saturation region. Nominal values of $V_{DD} = 1.2V$, $V_T = 400mV$, $\left(\frac{W}{L}\right)_1 = \frac{1}{2}\left(\frac{W}{L}\right)_2 = 20$, and $K = 100\mu A/V^2$ are used for this example.

$$a_0 = V_{DD} - R_2 K \left(\frac{W}{L}\right)_2 \left\{ \begin{array}{l} (V_{DD}-V_T)^2 + \\ R_1^2 K^2 \left(\frac{W}{L}\right)_1^2 V_T^4 - \\ 2(V_{DD}-V_T) R_1 \left(\frac{W}{L}\right)_1 V_T^2 \end{array} \right\}$$

$$a_1 = R_2 K \left(\frac{W}{L}\right)_2 \left\{ \begin{array}{l} 4R_1^2 K^2 \left(\frac{W}{L}\right)_1^2 V_T^3 \\ +2(V_{DD}-V_T) R_1 K \left(\frac{W}{L}\right)_1 V_T \end{array} \right\}$$

$$a_2 = R_2 K \left(\frac{W}{L}\right)_2 \left\{ \begin{array}{l} 2(V_{DD}-V_T) R_1 K \left(\frac{W}{L}\right)_1 \\ -6R_1^2 K^2 \left(\frac{W}{L}\right)_1^2 V_T^2 \end{array} \right\}$$

$$a_3 = 4V_T K^3 \left(\frac{W}{L}\right)_1^2 \left(\frac{W}{L}\right)_2^2 R_1^2 R_2$$

$$a_4 = -K^3 \left(\frac{W}{L}\right)_1^2 \left(\frac{W}{L}\right)_2^2 R_1^2 R_2 \tag{6}$$

To find the limit values of the coefficient a_0 we assume that parameters R_1 and R_2 deviate by fractions x and y from their nominal values, respectively. To maximize a_0 we have the objective function (7) subject to constraints (8) through (12). Note that here we have set out to find MSDF of R_1. Similar approach can be used to find the MSDF of R_2.

$$1.2 - R_{2,nom}(1+y) \left\{ \begin{array}{l} 2.56 \times 10^{-3} + \\ 1.024 \times 10^{-7} R_{1,nom}^2 (1+x)^2 \\ -5.12 \times 10^{-4} R_{1,nom}(1+x) \end{array} \right\} \tag{7}$$

$$\begin{array}{l} 4.096 \times 10^{-9} R_{1,nom}^2 (1+x)^2 R_{2,nom} \ (1+y) \\ +5.12 \times 10^{-6} R_{1,nom}(1+x) R_{2,nom}(1+y) \\ \quad = 4.096 \times 10^{-9} R_{1,nom}^2 (1+\rho)^2 R_{2,nom} \\ \quad + 5.12 \times 10^{-6} R_{1,nom}(1+\rho) R_{2,nom} \end{array} \tag{8}$$

$$\begin{array}{l} 1.28 \times 10^{-5} R_{1,nom}(1+x) R_{2,nom}(1+y) \\ -1.536 \times 10^{-8} R_{1,nom}^2 (1+x)^2 R_{2,nom} \ (1+y) \\ \quad = 1.28 \times 10^{-5} R_{1,nom}(1+\rho) R_{2,nom} \\ \quad - 1.536 \times 10^{-8} R_{1,nom}^2 (1+\rho)^2 R_{2,nom} \end{array} \tag{9}$$

$$\begin{array}{l} 2.56 \times 10^{-8} R_{1,nom}^2 (1+x)^2 R_{2,nom}(1+y) \\ \quad = 2.56 \times 10^{-8} R_{1,nom}^2 (1+\rho)^2 R_{2,nom} \end{array} \tag{10}$$

$$\begin{array}{l} 1.6 \times 10^{-8} R_{1,nom}^2 (1+x)^2 R_{2,nom}(1+y) \\ \quad = 1.6 \times 10^{-8} R_{1,nom}^2 (1+\rho)^2 R_{2,nom} \end{array} \tag{11}$$

$$-\alpha \leq x, y \leq \alpha \tag{12}$$

The extreme values for x and y are obtained by solving the set of equations (7-12). We get $x = -\alpha$ and $y = -\alpha$ and this gives the MSDF for R_1, as

$$\rho = (1-\alpha)^{1.5} - 1 \approx 1.5\alpha - 0.375\alpha^2 \tag{13}$$

Table I gives the MSDF for R_1 and R_2 based on the above calculation.

TABLE I
MSDF FOR CASCADED AMPLIFIER OF FIGURE 1 WITH $\alpha = 0.05$.

Circuit parameter	%upside MSDF	%downside MSDF
Resistor R_1	10.3	7.4
Resistor R_2	12.3	8.5

IV. GENERALIZATION

The computation of the previous section is too complex for arbitrarily large circuits. Such circuits are handled by first obtaining a nominal numeric polynomial expansion for them. This is done by sweeping the input voltage across all possible values and noting the corresponding output voltages. A generalized test setup for this is shown in figure 3. The output voltage is plotted against the input voltage. A polynomial is fitted to this curve and the coefficients of this polynomial are taken to be the nominal coefficients for the desired polynomial. The circuit is simulated for different drifts in the parameter values at equally spaced points from inside the hypercube enclosing each circuit parameter, spaced ϵ apart. Polynomial coefficients are obtained for each of these simulations. The maximum and minimum values of coefficient in this search are taken as the limiting values for that coefficient. Once the limiting values for all coefficients have been determined the CUT is subjected to a input sweep at the input at frequencies of interest and the output response is curve-fitted using a polynomial of the same order as that used for the fault free circuit. If there are any coefficients that lay outside the limiting values of the corresponding coefficients of the fault free circuit, we conclude that CUT is faulty. The converse need not be true as there could be other specifications, the circuit needs to meet, which are not captured by polynomial based test. Flowchart I in Figure 2 summarizes the process of numerically finding the polynomial coefficients and their bounds. Flowchart II in Figure 2 outlines a procedure to test CUT using the polynomial coefficients.

V. FAULT DIAGNOSIS

Fault diagnosis involves the location of likely fault sites in a CUT given that the CUT has failed an applied test giving a particular response. Fault diagnosis using sensitivity of output to circuit parameters has been investigated [22]. We have extended this approach of diagnosis exploiting the sensitivity of polynomial coefficients to circuit parameters. The advantage of this approach is improved fault diagnosis without circuit augmentation. Sensitivity of i^{th} coefficient C_i to k^{th} parameter p_k is represented by $S_{p_k}^{C_i}$ and is expressed as,

$$S_{Pk}^{Ci} = \frac{p_k}{C_i} \frac{\partial C_i}{\partial p_k} \tag{14}$$

A. Computation of Sensitivities

Numerical computation of sensitivities given by 14 is accomplished by introducing fractional drifts $(= \alpha)$ in each component $(p_k \ \forall \, k)$; simulating the circuit and measuring the fractional drift in each coefficient of the polynomial resulting from curve fitting operation. This way the numerical

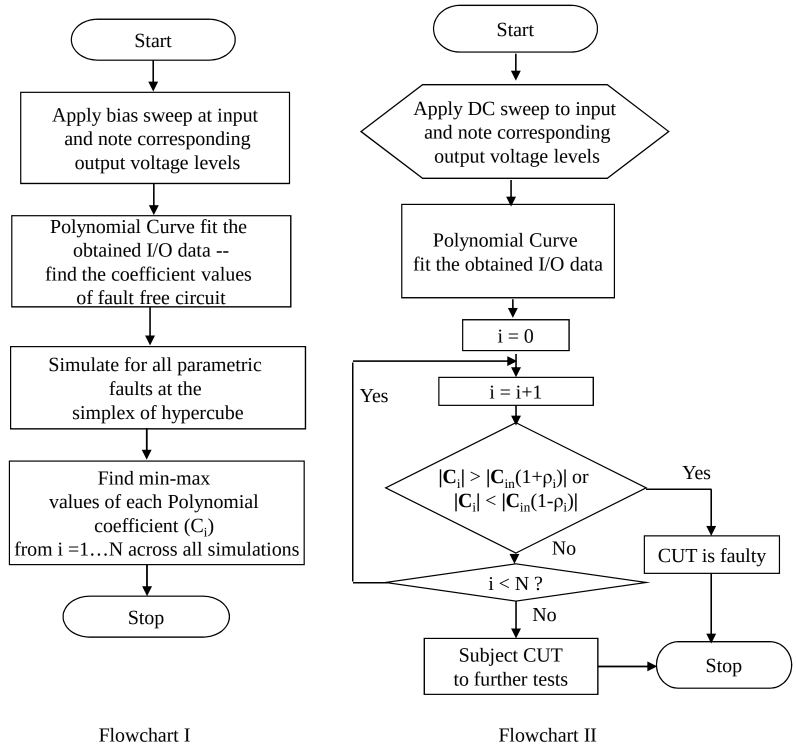

Fig. 2. Fault simulation process and bounding of coefficients (Flowchart I), and complete test procedure (Flowchart II).

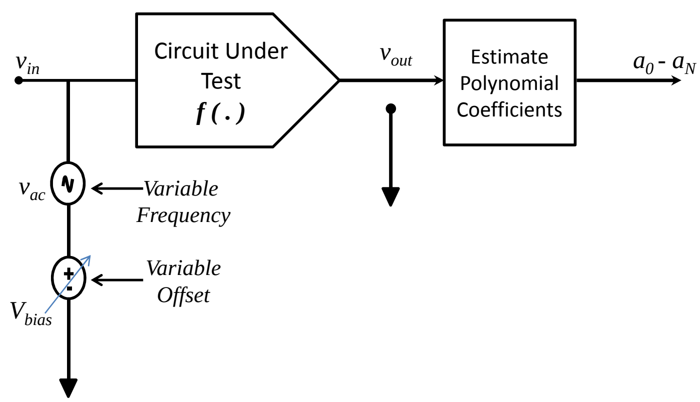

Fig. 3. Test setup for polynomial coefficient based testing.

sensitivities are computed and a dictionary is maintained for sensitivities. The order of complexity in computation of sensitivities is linear in the number of circuit parameters (N), i.e., $O(N)$.

B. Diagnosing Parametric Faults

Restricting to single parametric faults, we find the descending order of sensitivities of all coefficients to parameters, depending on the coefficients that have exceeded their limit values. The parameter with highest sensitivity is said to be at fault with a probability $\mathrm{P}(\delta \mathrm{p_k} | \delta \mathrm{C_i})$ which can be interpreted as the confidence in diagnosing the fault, given by:

$$\mathrm{P}(\delta \mathrm{p_k} | \delta \mathrm{C_i}) = \phi \left(\frac{S_{p_k}^{C_i} \delta p_k}{\delta C_i} \right) \tag{15}$$

where δp_k is the suspected drift in parameter p_k and δC_i is the measured drift in coefficient. Note that ϕ in (15) is a probability measure[23], dependent on $\delta p_k, \delta C_i$ and $S_{p_k}^{C_i}$. For example, if sensitivity of some coefficient, say C_1 to parameter p_1 is 5%, measured drift in coefficient value is 10% and we suspect that the parameter drift is 10% then the probability of this being true, by assuming ϕ to be an exponential probability

TABLE II
LNA SPECIFICATION.

Performance Parameter	Nominal Value
Gain (dB)	16
IIP_3 (dBm)	-18
Noise figure (dB)	9.1
S_{11} (dB)	-16.5

measure, is $e^{\frac{-.05\times.1}{.1}} = .95$. Single parametric faults in the LNA of Figure 4 were diagnosable with up to 95% confidence level. The results are tabulated in Table V for several injected single parametric faults.

VI. SIMULATION RESULTS

We simulated an Low noise amplifier shown in Figure 4 for polynomial coefficient based test. Notice that the bias current $\mathrm{I_{bias}}$ shown in the figure is derived from a current mirror powered by band-gap reference circuitry (not shown). The circuit parameter values were chosen to meet performance specifications tabulated in table II. We used parametric faults of sizes α = 5% from their nominal value to find min-max values of coefficients. Figure 5 shows the simulated response at four different frequencies, namely, $f = 1\mathrm{GHz},\ 10\mathrm{GHz},\ 15\mathrm{GHz},$ and $35\mathrm{GHz}$ and the estimated polynomials obtained by curve fitting a fifth order polynomial are given by equations 16 through 19, respectively. Figure 6 compares the I/O response of the LNA for three different value of the load resistance R_L.

$$v_{out} = \big(2.5 - 1.498v_{in} - 1.2688v_{in}^2 + 1.139v_{in}^3 - 0.88514v_{in}^4 + 0.039463v_{in}^5\big) \times 10^{-3} \tag{16}$$

$$v_{out} = \big(2.36 - 1.348v_{in} - 1.3268v_{in}^2 + 1.049v_{in}^3 - 0.63614v_{in}^4 + 0.04443v_{in}^5\big) \times 10^{-3} \tag{17}$$

$$v_{out} = \big(2.12 - 1.267v_{in} - 1.1285v_{in}^2 - 1.016v_{in}^3 + 0.88516v_{in}^4 - 0.052876v_{in}^5\big) \times 10^{-3} \tag{18}$$

$$v_{out} = \big(1.95 - 1.068v_{in} + .9268v_{in}^2 + 0.786v_{in}^3 - 0.77324v_{in}^4 + 0.042v_{in}^5\big) \times 10^{-3} \tag{19}$$

The combinations of parameter values leading to limits on the coefficients are as shown in Tables III and IV. Some of the circuit parameters are not shown in the table because they do not appear in any of the coefficients and are kept at their nominal values. Further, results on pass/fail detectability of few injected faults are tabulated in Table V. Last column in table V shows the diagnosed results of a few injected faults using sensitivity of polynomial coefficients to circuit parameters as described in Section V.

TABLE III
PARAMETER COMBINATIONS LEADING TO MAXIMUM VALUES OF COEFFICIENTS WITH $\alpha = 0.05$.

Component (ohm, nH, fF)	a_0	a_1	a_2	a_3	a_4	a_5
$\mathrm{R_{bias}} = 10$	10	10	10.5	10.5	9.5	10.5
$\mathrm{L_C} = 1$	1	0.95	1.05	0.95	1.05	1
$\mathrm{C_{C1}} = 100$	95	95	95	95	95	105
$\mathrm{L_1} = 1.5$	1.425	1.5	1.5	1.425	1.575	1.425
$\mathrm{L_2} = 1.5$	1.5	1.425	1.425	1.575	1.5	1.5
$\mathrm{L_f} = 1$	1.05	1.05	1.05	1	1.05	1
$\mathrm{C_f} = 100$	105	95	95	105	95	95
$\mathrm{C_{C2}} = 100$	95	100	105	95	95	95
$\mathrm{R_{bias1}} = 100\mathrm{k}$	105k	105k	100k	105k	105k	95k
$\mathrm{R_{bias2}} = 100\mathrm{k}$	105k	95k	100k	95k	95k	95k
$\mathrm{R_L} = 100\mathrm{k}$	100k	95k	95k	100k	105k	100k

TABLE IV
PARAMETER COMBINATIONS LEADING TO MIN VALUES OF COEFFICIENTS WITH α = 0.05

Component (ohm, nH, fF)	a_0	a_1	a_2	a_3	a_4	a_5
$\mathrm{R_{bias}} = 10$	10	9.5	9.5	10	10	10
$\mathrm{L_C} = 1$	1.05	0.95	0.95	1	1	0.95
$\mathrm{C_{C1}} = 100$	100	105	95	100	95	105
$\mathrm{L_1} = 1.5$	1.425	1.5	1.575	1.575	1.575	1.575
$\mathrm{L_2} = 1.5$	1.5	1.575	1.5	1.425	1.425	1.5
$\mathrm{L_f} = 1$	1.05	1.05	0.95	0.95	1	0.95
$\mathrm{C_f} = 100$	105	95	95	105	105	105
$\mathrm{C_{C2}} = 100$	95	105	100	105	95	105
$\mathrm{R_{bias1}} = 100\mathrm{k}$	100k	95k	105k	105k	95k	100k
$\mathrm{R_{bias2}} = 100\mathrm{k}$	100k	105k	95k	95k	105k	95k
$\mathrm{R_L} = 100\mathrm{k}$	95k	100k	95k	100k	105k	95k

VII. CONCLUSION AND FUTURE WORK

We demonstrated a polynomial coefficient based test approach on a standard low noise amplifier. The method is general in that it can be potentially used for any non-linear circuit. The minimum size of detectable faults for some parameters in the circuit are as low as 10%, which implies an impressive fault coverage. The method has been extended to sensitivity based fault diagnosis with probabilistic confidence levels in parameter drifts. Next, in order to increase the sensitivity of polynomial coefficient to circuit parameters we wish to investigate the use of exponential transforms. In the future, we will also consider the implementation of this scheme as built in self test by storing the fault free polynomial coefficients along with the permissible intervals in memory and then comparing these with the coefficient values of the circuit under test. Yet another interesting extension to this problem is to consider testing of the circuit under process parameter variation of different components. The importance of solving this problem lies in the fact that distinguishing structural defect induced faults from process parameter variation induced faults will help us fix the manufacturing defects (which manifest as parametric faults) and hence improve the yield for a given process.

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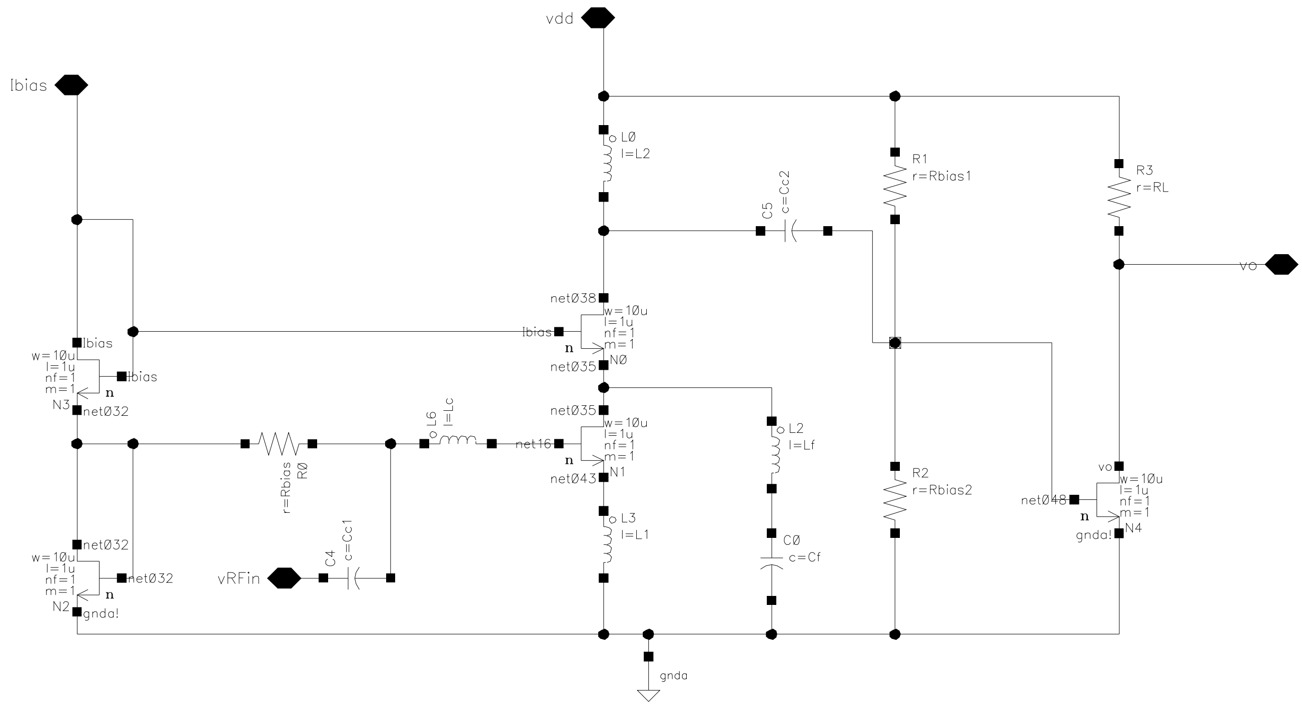

Fig. 4. Low noise amplifier schematic.

TABLE V
RESULTS OF TEST AND DIAGNOSIS OF SOME INJECTED FAULTS FOR LNA.

Circuit Parameter	Coefficients out of bounds	Detected	Diagnosed fault sites
$\mathrm{R_{bias}}$ down 25%	$a_0 - a_4$	Yes	$\mathrm{R_{bias}}$
$\mathrm{L_C}$ down 15%	a_2, a_5	Yes	$\mathrm{L_C}$ or $\mathrm{C_{C1}}$
$\mathrm{C_{C1}}$ up 10%	a_1, a_2, a_3	Yes	$\mathrm{C_{C1}}$ or $\mathrm{L_C}$
$\mathrm{L_1}$ down 25%	$a_0 - a_4$	Yes	$\mathrm{L_1}$
$\mathrm{L_2}$ up 15%	a_0, a_4	Yes	$\mathrm{L_2}$
$\mathrm{L_f}$ up 10%	a_1, a_2	Yes	$\mathrm{L_f}$ or $\mathrm{C_f}$
$\mathrm{C_f}$ up 10%	a_4, a_5	Yes	$\mathrm{L_f}$
$\mathrm{C_{C2}}$ down 10%	a_4, a_5	Yes	$\mathrm{C_{C2}}$

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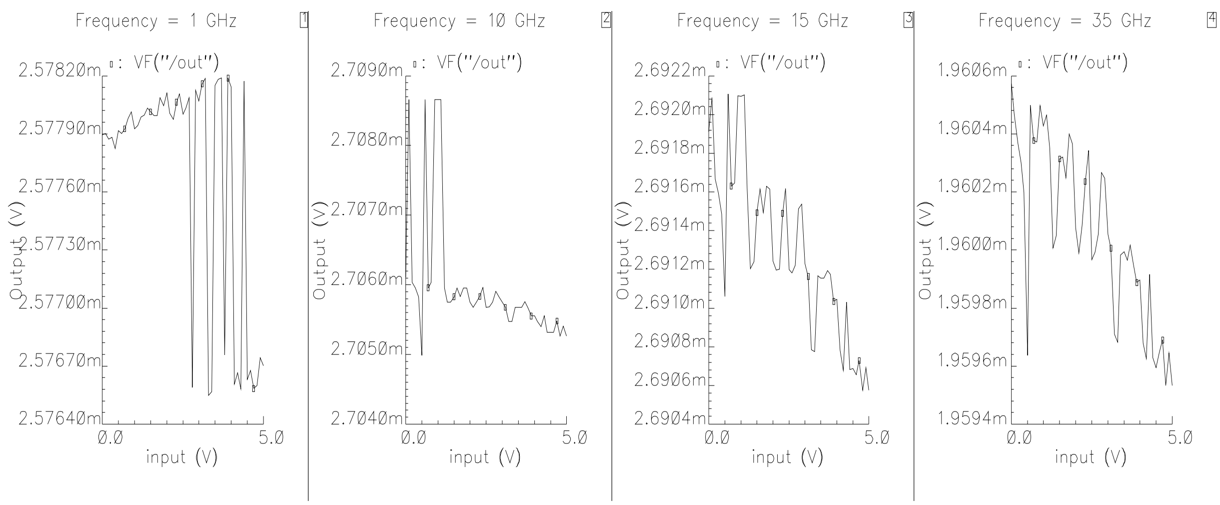

Fig. 5. I/O response of LNA at four frequencies.

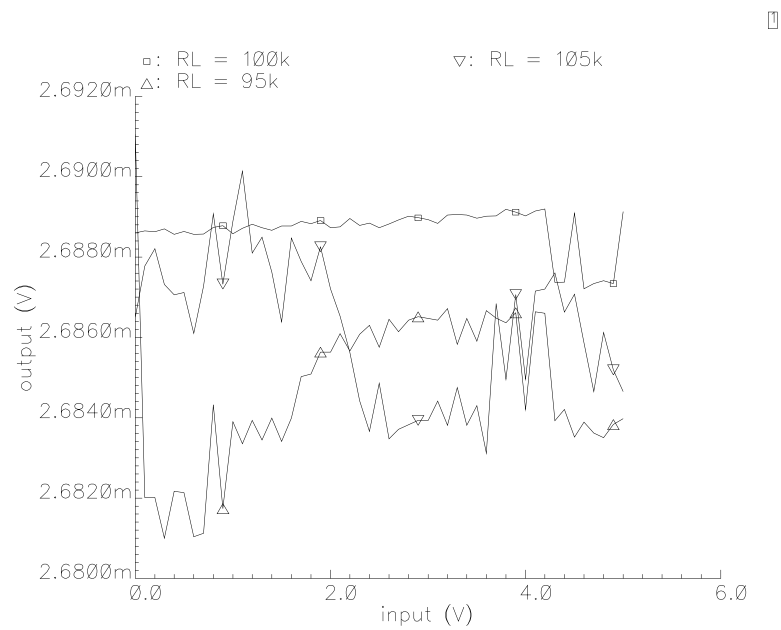

Fig. 6. Comparison of I/O plots of LNA at 3 different values of load resistance R_L = 95kΩ, 100kΩ (nominal), 105kΩ.

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