Piecewise Regression Model for Solenoid Embedded Inductors Based on the Quasi-newton Method

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This paper presents that the modeling to predict the characteristics with respect to the performance of solenoid embedded inductors manufactured by LTCC process via the nonlinear regression model based on the quasi-Newton method. In order to reduce the runs, the design of experiments (DOE) was used to generate the design space. The nonlinear process models were constructed by the piecewise regression model based on the quasi-Newton method for estimating the model coefficient with the break point on the statistical confidence intervals. Those models were verified by the model accuracy checking based on the assumption statistically.

Keywords : Embedded inductor, Factorial designs, Nonlinear regression, Piecewise regression, Quasi-newton method

1. INTRODUCTION

Recently, RF systems have the tendencies of miniaturization, low-cost, low-power consumption and high-performance due to the rapid growth of the wireless communication technologies. In order to satisfy those requirements of RF systems, technologies that are packaging integrated circuit in multi-chip module (MCM) are primary concern in the microelectronics. As a rule, passive elements have large portions in circuits, so that integration of passive elements is important in MCM application[1,2]. Especially in passive elements, inductor is an essential element in the communication circuits like a filter, a VCO, a LNA and a mixer[3]. Primary electronic characteristics of inductors related to the device operation and the properties are the self-resonance frequency (SRF), the inductance (L) and the quality factor (Q), which affect the performance of inductors. The value of SRF, L and Q largely depend on geometrical parameters of inductors[4-6]. Therefore, the characteristic prediction of inductors in terms of geometrical parameters is useful in manufacturing elements that have desired characteristics.

For those parameters and characteristics in the process, Ching Chuan Kuo *et al.* proposed the modeling of capacitors and nonlinear inductors using piecewise curve fitting technique[7]. Chi-Jui Wu *et al.* used to predict harmonic voltage and current growth trend from measurement data by using the applied regression model[8]. Danny M. P. Ng *et al.* proposed the varying regression methods in the communication application used to analyze the trend such as linear regression, exponential regression, power regression and additive regression[9]. Quasi-Newton algorithm in artificial neural network was also used to optimize the electromagnetic devices[10].

In this paper, the design is used to reduce the experiments runs and obtain the effectiveness for response prediction modeling. Those methodologies were based on the statistical inference. The piecewise regression based on the quasi-Newton method for estimating the parameter and the break point on the confidence interval for mean response on the nonlinear process were carried out. The model accuracy was then verified via the statistical methodology.

2. TEST STRUCTURE FABRICATION, MEASUREMENT AND PARAMETER EXTRACTION

The equivalent circuits of the inductors are used to determine the statistical model for solenoid inductors. The equivalent circuits for the inductors are constructed using actually fabricated test structures. Test structures are manufactured by using LTCC process[11]. Test structures consist with the top conductors and the bottom conductors those are connected through via stack for the realization of the solenoid pattern. 6 ceramic tapes are inserted between the top conductors and the bottom conductors. Ti and Au are deposited on 96 % alumina substrate that has a dielectric constant of 7.8. The width of metal lines is 10 mils and the diameter of via is 5.6 mils.

Test structures are measured by using standard network analysis through HP8510C network analyzer and Microtech probe station. Prior to measure the test structures, line-reflect-match (LRM) method was used for calibration. The 201 points of scattering parameter (S-parameter) were collected from range between 50 MHz and 5 GHz.

Test structures are classified by the spacing between coils, the shape, and the number of coils. The three types of spacing between coils, the three types of shape, and the two types of the number of the coils are designed.

After S-parameters for the test structures are measured, circuit models are extracted for the various building blocks. The building blocks are based on the partial element equivalent circuit (PEEC) method. Using these circuit model parameters, the optimization is performed. The optimization results are similar to the measured data. For the verification of parameters, predictive modeling is achieved for the different structure using extracted parameters. As expected, the predictive data are similar to measured data of manufactured structure. It confirms the validity of the optimized parameters.

With these optimized parameters, the building block equivalent circuits for the inductors used in statistical models are constructed. Total 27 equivalent circuits are defined by their geometrical parameters. The three geometrical parameters used in this work are the number of turns for coils, the spacing between coils, and the shape. The number of turns for coils is defined as the sequence (Seq) and the spacing between coils is defined as the spacing (Sp). The shapes are categorized by the straight-line shape and the serpentine-line shape. The serpentine inductors are constructed by the series connection of straight lines through the link block (Lk). The schematic diagram of 3-D solenoid inductor with 12-Seq, 30-Sp, and 2-Lk is illustrated in Fig. 1. The ranges of the three factors are summarized in Table 1. With the 27 equivalent circuits, the input admittance parameters are extracted using HSPICE circuit simulator. Then, the response factors are calculated using input admittance parameters.

The response factors of interest can be defined as [12,13]:

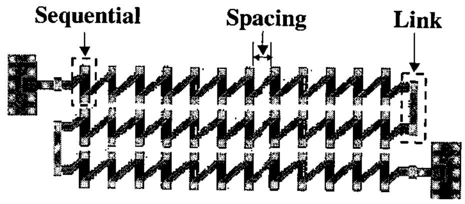

Fig. 1. Schematic diagram of the 3-D solenoid inductors.

Table 1. Summary of the process parameters.

Factor	Symbol	Unit	Level		
The number of sequence	Seq	EA	6	12	18
The number of link	Lk	EA	0	1	2
The spacing between sequences	Sp	mils	10	20	30

$$\text{Self-resonance frequency (SRF)} = \frac{1}{2\pi\sqrt{LC}} \quad (1)$$

$$\text{Inductance (L)} = \frac{imag(Z_{11})}{2\pi f} \quad (2)$$

$$\text{Quality factor (Q)} = \frac{imag(Z_{11})}{real(Z_{11})} \quad (3)$$

3. MODELING SCHEME

3.1 Statistical methodology

Initially, the design of experiments was carried out using 3-level factorial design in order to improve the model prediction range and accuracy for the characteristics. The design technique can cover all parameter effects and reduce the lack of the model points. The order in table was statistically randomized and the experimental design matrix in each run was summarized in Table 2.

The confidence intervals for mean response were then calculated to obtain the range of the mean on the significance level. The confidence intervals on the population mean are given by[14]:

$$\overline{X} - t_{\alpha/2}\left(\frac{S}{\sqrt{n}}\right) \le \mu \le \overline{X} + t_{\alpha/2}\left(\frac{S}{\sqrt{n}}\right) \quad (4)$$

where, $\overline{X}$ is the sample mean, S is the sample standard deviation, $t_{\alpha/2}$ is a value of random variables having a t-distribution with the degree of free-

Table 2. Design matrix.

Run	Seq [EA]	Lk [EA]	Sp [mils]
1	12	0	20
2	6	2	10
3	12	2	30
4	6	1	30
5	12	1	10
6	12	2	20
7	18	0	30
8	6	2	30
9	18	2	10
10	18	1	10
11	6	2	20
12	12	1	20
13	18	1	30
14	18	0	20
15	6	0	10
16	12	0	10
17	18	2	30
18	12	2	10
19	6	1	20
20	12	1	30
21	18	2	20
22	6	1	10
23	18	0	10
24	12	0	30
25	6	0	20
26	6	0	30
27	18	1	20

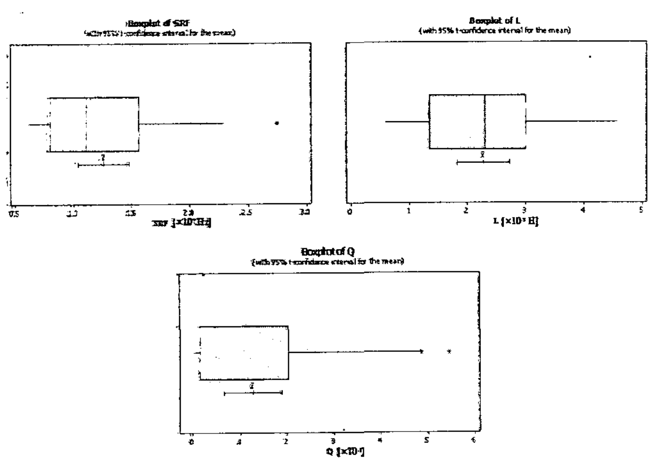

Fig. 2. Box plots of the response.

dom, $\nu = n-1$, α is the significance level, $t_{(\alpha/2=0.025, n-1=26)} = 2.056$.

The box plots of the response were illustrated in Fig. 2. The confidence intervals for mean response were summarized in Table 3.

Table 3. Summary of confidence intervals for mean response.

Response	Confidence intervals	
	-95 %	+ 95 %
SRF [$\times 10^9$]	1.039	1.478
L [$\times 10^{-8}$]	1.829	2.725
Q [$\times 10^{-1}$]	0.660	1.883

3.2 Piecewise regression model

The general form of a nonlinear regression model is expressed as follows[14]:

$$Y_i = f(\mathrm{X}_i, \gamma) + \varepsilon_i \tag{5}$$

where , $\underset{q\times 1}{\mathrm{X}_i} = \begin{bmatrix} X_{i1} \\ X_{i2} \\ \vdots \\ X_{iq} \end{bmatrix}$, $\underset{p\times 1}{\gamma_i} = \begin{bmatrix} \gamma_0 \\ \gamma_1 \\ \vdots \\ \gamma_{p-1} \end{bmatrix}$.

A piecewise regression is a form of the extended regression model. There is a certain point that separates the regression models where a different response function used for defining the each model. The form of piecewise regression in this study is defined by following[15]:

$$\begin{aligned} &\Phi_{Piecewise}(x_1, x_2, \cdots, x_i \mid \hat{y}) \\ &= f(x_1, x_2, \cdots, x_i \mid \hat{y} > \phi) + g(x_1, x_2, \cdots, x_i \mid \hat{y} < \phi) \end{aligned} \tag{6}$$

where, $x_1, x_2, \cdots, x_i$ are ith process factor. $\hat{y}$ is a response value, ϕ is a break point parameter.

The dimension-reduced model was achieved via piecewise regression model with the break point where the regression model changed. The break points to separate the regression models on the predicted model space have the increment on the confidence intervals for the mean response. Those increments were defined by the following:

$$Increment(\Delta) = \frac{Y_{\max} - Y_{\min}}{n} \tag{7}$$

where, $Y_{\max}$ is the maximum response value and $Y_{\min}$ is the minimum response value, n is the sample size.

The R-squared values obtained by the change of the increment on the confidence intervals of the mean response were summarized in the Table 4. As seen in the Table 4, SRF has the large R-squared value in which the break point is 1.339, L and Q are 1.984, 1.47, respec-

Table 4. R-squared value for the change of the break point.

	SRF [$\times 10^9$ Hz]	R-squared [%]	L [$\times 10^{-8}$ H]	R-squared [%]	Q [$\times 10^{-1}$]	R-squared [%]
Increment = Δ	0.079		0.1448		0.2	
-2Δ	1.102	88.93	1.984	96.62	0.87	97.97
-Δ	1.181	88.20	2.132	96.46	1.07	97.98
Mean	1.260	90.68	2.280	94.46	1.27	98.77
+Δ	1.339	92.56	2.428	94.19	1.47	98.94
+2Δ	1.418	90.89	2.576	93.65	1.67	98.93

tively. From the results, these accuracy models that can predict the response on the confidence intervals for the mean response were obtained.

The quasi-Newton algorithm was used in the regression model in order to estimate the model coefficient parameters. The least square method, the loss function, was used to estimate for parameter coefficients that minimize the residual variance[16,17].

3.3 Modeling procedure

The general regression models were not suitable for the predicted model due to the complexity of nonlinear on the process, the nonlinear regression model was proposed, the confidence intervals for mean response were calculated and then the increment for each characteristic was also calculated. Those values determined the model accuracy region and the break point for the response, respectively. The R-squared values were calculated to verify the explanation of the model fitness. The statistical verification methodologies were carried out to validate the model. The proposed modeling procedure in this study was illustrated in Fig. 3.

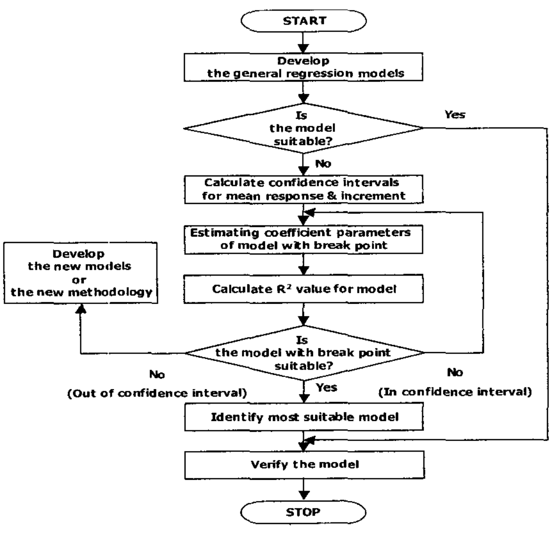

Fig. 3. Block diagram of modeling procedure.

4. RESULTS AND DISCUSSION

The correlations for between input variables and output variables are summarized in Table 5. The correlation coefficient value ranges is generally between –1 and 1. The p-value means that the correlation coefficient is significantly different form zero. The negative effects were appeared to several parameter relationships significantly. In case of the number of the spacing, having the negative effect for SRF and Q but revealed the positive effect for L. In other characteristic factors, only one factor has the positive effect, respectively. From the correlation coefficients, whether which factor significantly increase or decrease can be assumed as a certain factor changed. The statistical significance level is 0.05 (α =0.05) in this study.

The piecewise regression models with the break point for the characteristics (SRF, L and Q) were written as:

$$\hat{SRF} = \begin{cases} 1.2728 + (-0.0237)Seq + (-0.1152)Lk + (0.0042)Sp \ , & \hat{SRF} \le 1.339 \\ 2.5064 + (-0.0562)Seq + (-0.1587)Lk + (0.0009)Sp \ , & \hat{SRF} > 1.339 \end{cases} \quad (8)$$

$$\hat{L} = \begin{cases} 0.4617 + (0.0258)Seq + (-0.4106)Lk + (0.0405)Sp \ , & \hat{L} \le 1.984 \\ 1.6553 + (0.1231)Seq + (-0.1814)Lk + (0.0024)Sp \ , & \hat{L} < 1.984 \end{cases} \quad (9)$$

$$\hat{Q} = \begin{cases} 1.1339 + (0.0249)Seq + (-0.3153)Lk + (-0.0289)Sp \ , & \hat{Q} \le 1.47 \\ 5.241 + (-0.2781)Seq + (0.1)Lk + (0.054)Sp \ , & \hat{Q} > 1.47 \end{cases} \quad (10)$$

Table 5. Summary of correlation coefficients and P-values.

	SRF		L		Q	
	CC	SL	CC	SL	CC	SL
Seq	-0.521	0.005	0.524	0.005	-0.230	0.248
Lk	-0.478	0.012	-0.009	0.965	-0.760	0.000
Sp	-0.072	0.720	0.142	0.479	-0.022	0.915

CC : Correlation coefficient
SL : Significance level

Table 6. Summary of R-squared values between general regression models and piecewise regression models.

	General regression	Piecewise regression
SRF	44.1 %	92.56 %
L	20.3 %	96.62 %
Q	58.3 %	98.94 %

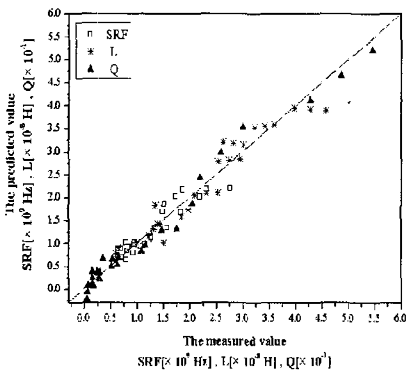

Fig. 4. The measured response vs. the predicted response.

The comparison between the general regression model and the piecewise regression model is summarized in Table 6. The R-squared value indicates how this model can explain the comprehensive process statistically. As shown in Table 6., all R-squared values for the regression models were much less than the piecewise regression model indicating that the piecewise regression model can improve the process explanation.

The modeling outputs for all characteristics were illustrated in Fig. 4. The symbols represent the linear relationship between the predicted and the measured for the characteristics of LTCC.

One of the assumptions of this analysis is that the residuals are both normally and randomly distributed[14]. In order to verify the assumption, the residual plots for models are illustrated in Fig. 5. The residuals are randomly scattered about zero. There are no patterns in the plot. The normal probability plots for the residuals of models are illustrated in Fig. 6. It is observed that the residuals are approximately normally distributed. It means that the prediction model is satisfied with the assumptions of the residuals. The straight and dashed lines represent the minimum and the maximum of 95 % confidence region for residuals, respectively. In order to detect the outlier of the data, the standardized residuals were calculated[14]:

$$d_i = \frac{e_i}{\hat{\sigma}}, \quad i = 1,2,\cdots,n. \tag{11}$$

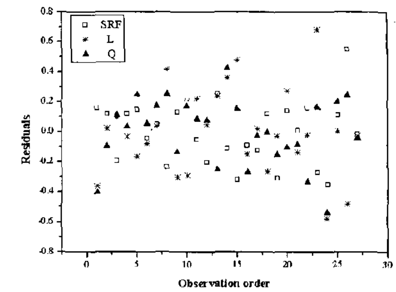

Fig. 5. Residual plots.

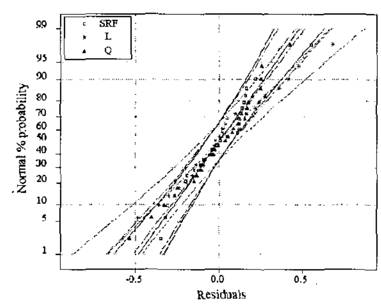

Fig. 6. Normal probability plots of residuals.

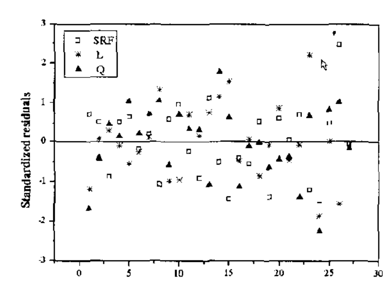

Fig. 7. Standardized residual plots.

where, e_i is residual , $\hat{\sigma}$ is $\sqrt{MSE}$, MSE is error mean square.

Generally, the standardized residuals should be in the interval $-3 \le d_i \le 3$, any standardized residual with out of those range is potentially unusual data for model to be fitted. The calculated standardized residuals were plotted in the Fig. 7. As shown in Fig. 7., the standardized residual for the models are distributed between –3 and 3. There are no special patterns and features.

5. CONCLUSION

This paper has presented that the modeling to predict the characteristics with respect to the performance for the solenoid embedded inductors manufactured by LTCC process via the nonlinear regression model based on the quasi-Newton method. The design of experiments used to reduce the run and reside on the statistically significant region. The confidence intervals for mean response are suggested to find the break point in the piecewise regression model. The proposed piecewise regression model with the break point on the confidence interval for mean response was better than the general regression model. Therefore, this methodology can allow us to predict the device characteristics and can also improve the model accuracy for the semiconductor manufacturing.

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