POWER ADDED EFFICIENCY MODEL FOR MESFET CLASS E POWER AMPLIFIER USING JACKKNIFE RESAMPLING

Fouziah Md. Yassin[1*], Noraini Abdullah[2], Zainodin H. J[2]., & Saturi Baco[1]

[1]Physics with Electronics Programme,
[2]Mathematics with Economics Programme
School of Sciences and Technology,
Universiti Malaysia Sabah, Jalan UMS, 88400 Kota Kinabalu, Sabah, Malaysia
Email*: fouziahy@ums.edu.my

ABSTRACT. *There are several types of amplifier classes, and this includes the class E amplifier. The class E can achieve its efficiency up to 100%. This paper thus aims on getting the best model in estimating the power added efficiency of Class E power amplifier circuit using Silicon Carbide MESFET. Twelve models are obtained from three independent variables; DC current (I_{dc}), drain voltage (V_{dc}), and power out (P_{out}). The original data set of 7 is generated to become 105 data samples (21 sets x 5 observations where each set with two missing observations) using the Jackknife sampling technique at the first stage ($^7C_2$). The power added efficiency model employs the Multiple Regression (MR) technique up to the second order of interactions. The best model is based on the eight selection criteria (8SC). The best model is found to be model M12.5.0, chosen from the six selected model).Efficiency factors affect the power added efficiency estimation are found to be $X_3(I_{DC})$ and X_{12}(interaction between P_{out} and V_{DS}).*

KEYWORDS. Multiple Regression; Jackknife; interactions; Power Added Efficiency; Efficiency Factors.

INTRODUCTION

Amplifiers are categorized into several classes according to their operation and efficiency namely classes A, B, AB, C, D, E and F. Class E amplifier is switching type Power Amplifier (PA) that is widely used for RF and microwave applications. It has major improvement in comparison with the class-D configuration in term of efficiency. It provides high efficiency up to 100%. In class-E, power dissipation can be minimized especially during the switching transitions because the transistor operates as an on/off switch and the load network shapes the voltage and current waveforms to prevent simultaneous high voltage and high current in transistor (Soumya and P. Manikandan, 2012). The circuit is simple and consists of one active device such as Bipolar Junction Transistor (BJT), Heterojunction Bipolar transistor (HBT) and Metal Semiconductor Field Effect Transistor (MESFET) (Milosevic *et al*., 2002). The basic circuit of the class-E amplifier is shown in Figure 1. If power modulation techniques are applied, the power supply modulator pulls a high current to the power amplifier. Thus, the placement of the modulator in the high power path (in series with the RF choke (L_{dc})) makes efficiency the most important parameter (Soumya and P. Manikandan, 2012).

Silicon Carbide Metal Semiconductor Field Effect Transistor (SiC- MESFET) is one of wide-bandgap device that has been used in numerous power amplifiers. Previous study by Franco and Katz (2005) reported that maximum power added efficiency (PAE) of SiC MESFET Class E amplifier was 84.8% for simulated and 83.5% from experiment with power gain of 16 dB. Another study by Lee and Jeong (2007) reported that the maximum PAE of

SiC MESFET was 72.3% with power gain of 10.27 dB. PAE can be interpreted as the efficiency of the network to convert the input DC power into the amount of the output RF power that is left over after the direct contribution from the input RF power has been removed (Stepan, 1997). PAE can be expressed as:

$$\text{PAE}= [\ (P_{out} - P_{in}) / (I_{dc}V_{dc})] \times 100 \qquad (1)$$

where P_{out} is output power, P_{in} is for input power and I_{dc} is a DC current while the V_{dc} here is a drain voltage. Therefore, in this paper we will discuss the best model to identify variables that affect the power added efficiency (PAE) of Class E power amplifier circuit for Silicon Carbide MESFET based on Jackknife sampling and Multiple Regression method.

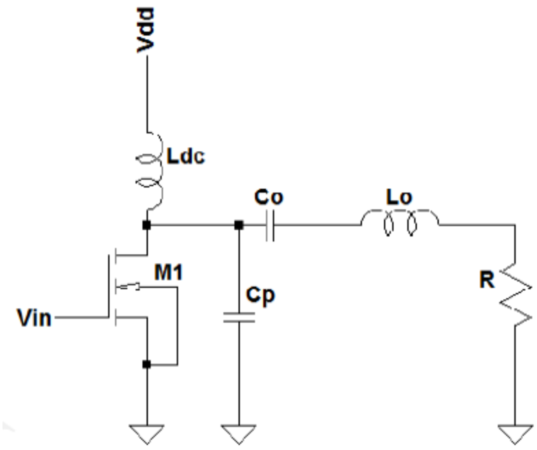

Figure 1: Basic class-E amplifier diagram (Bameri *et al.*, 2011)

MATERIALS AND METHOD

The dataset is a secondary data that investigate an alternative use in high efficiency, class-E RF power amplifiers in the VHF range with constant input power, 0.50119 Watt. The data was estimated from the graph of simulated result from the previous study by Franco and Katz (2005). Power added efficiency (PAE), DC current (I_{dc}), drain voltage (V_{ds}), and power out (P_{out}) as shown in Table 1 are the four variables that have been carried out the multiple regression technique. Power added efficiency (PAE) is the dependent variable, while DC current (I_{dc}), drain voltage (V_{ds}), and power out (P_{out}) are the independent variables in this study.

Table 1. The original data set of 7 with 4 variables.

PAE (%)	P_{out} (Watt)	V_{ds} (V)	I_{dc} (A)
30.833	0.625	6	0.0669
68.330	3.125	10	0.3839
78.330	4.500	14	0.3646
81.667	7.500	18	0.4761
83.334	11.500	22	0.5999
84.800	16.000	26	0.7029
84.800	21.500	30	0.8254

Since the size of samples is too small for model building, the Jackknife sampling technique is applied at the first stage to generate more samples. Next, there are four phases in the model building procedures of multiple regressions that is shown in details in Zainodin *et al*., 2011. Multiple regression (MR) analysis is a statistical technique that can be used to analyze the relationship between a single dependent (criterion) variable and several independent (predictor) variables (Aminatul Hawa *et al.*, 2012). The description of these variables involved can be seen in Table 2.

Table 2. Description of variables involved in model building.

Variable	Description
Y	Power added efficiency (PAE)
X_1	Output power (Pout)
X_2	Drain voltage (Vds)
X_3	Direct current (Idc)

When interaction effects are present, interpretation of the individual variables may be complete by stating specific MR model as follows:

$$Y_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \cdots + \beta_k X_{ki} + \varepsilon_i \quad (2)$$

where X_i is a random variable representing the ith value of Dependent Variable and $X_{1i}, X_{2i} \ldots X_{ki}$ are the ith value of the independent variable (Lind *et al.*, 2005). According to the model building procedures in Zainodin *et al.* (2011), twelve all possible models of phase 1 can be obtained from the three independent variables as shown in Table 2 (X_1, X_2 and X_3). All possible models, N can be calculated by using the following formula:

$$N= \sum_{j=1}^{q} j(C_j^q) \quad (3)$$

where, q is a number of single independent variables and j=1,2,…q (Aminatul Hawa *et.al*, 2012). For this study, q=3. Therefore, the possible models are:

$$N= 1(C_1^3) + 2(C_2^3) + 3(C_3^3) \quad (4)$$

The summary of all possible models is shown in Table 3. The twelve all possible models are made up of seven individual models are without interactions while the four models are up to the first order and one with a second order interaction.

Table 3. Summary of all possible models.

Number of Variables	**Individual**	**Interactions**		
		First Order	**Second Order**	**Total**
1	3			3
2	3	3		6
3	1	1	1	3
Total	7	4	1	12

The selected models of phase 2 can be obtained by carrying out the multicollinearity and coefficient tests. The existence of multicollinearity can be identified if the absolute correlation coefficient is greater than or equal to 0.95 ($|r| \geq 0.95$) (Zainodin *et al*., 2011). The higher are the correlation coefficient values will tend to increase the standard error of the beta coefficient, and this would produce a unique assessment of the role of each independent variable to the model. Hence, the model would result in difficult or impossible output (Aminatul Hawa *et al.*, 2012).

Next, the coefficient test is performed on the reduced model. It is an elimination procedure of any insignificant variable by using the backward elimination method. The variable is judged by the size of the highest p-value for eliminating the variable from the model. The variable that has the highest p-value greater than 0.05 ($p \geq 0.05$) would eliminated from the model one by one (Zainodin *et al.*, 2011 and Noraini et al., 2008). In phase 3, the selected models with the same independent variables are filtered out. The best model can only be obtained by carrying out the eight selection criteria (8SC) (Zainodin *et al.*, 2011). For the last phase that is, Phase 4, the randomness and normality tests are used to test the standardized residuals of the best model chosen (Noraini *et al.*, 2012).

RESULTS AND DISCUSSION

Jackknife Sampling Method for Data Generation

The Jackknife was invented by Quenouille in 1949 for the more limited purpose of correcting possible bias in ϕ_n for small sample sizes (Quenouille, 1949). Re-sampling is done by removing k observations. Total possible sets are determined by:

$$N = \sum {}^{n}C_k \tag{5}$$

where, N is the number of possible sets generated, n is the number of original data and k is the number of observations that will be removed.

For this study, n=7 and k=2 that generates one-hundred and five (105) samples. Table 4 shows twenty-one (21) sets of data for PAE. The highlighted data are the removed observations. The same procedures are applied on the other variables (Tichelaar & Ruff, 1989).

Table 4. Twenty-one sets of data for PAE.

Number of samples	Measurements						
	Set 1	Set 2	Set 3	Set 4	Set 5	Set 6	Set 7
1	30.833	30.833	30.833	30.833	30.833	30.833	30.833
2	68.33	68.33	68.33	68.33	68.33	68.33	68.33
3	78.33	78.33	78.33	78.33	78.33	78.33	78.33
4	81.667	81.667	81.667	81.667	81.667	81.667	81.667
5	83.334	83.334	83.334	83.334	83.334	83.334	83.334
6	84.8	84.8	84.8	84.8	84.8	84.8	84.8
7	84.8	84.8	84.8	84.8	84.8	84.8	84.8
Number of samples	**Measurements**						
	Set 8	**Set 9**	**Set 10**	**Set 11**	**Set 12**	**Set 13**	**Set 14**
1	30.833	30.833	30.833	30.833	30.833	30.833	30.833
2	68.33	68.33	68.33	68.33	68.33	68.33	68.33
3	78.33	78.33	78.33	78.33	78.33	78.33	78.33
4	81.667	81.667	81.667	81.667	81.667	81.667	81.667
5	83.334	83.334	83.334	83.334	83.334	83.334	83.334
6	84.8	84.8	84.8	84.8	84.8	84.8	84.8
7	84.8	84.8	84.8	84.8	84.8	84.8	84.8

Continue

Number of samples	Measurements						
	Set 15	Set 16	Set 17	Set 18	Set 19	Set 20	Set 21
1	30.833	30.833	30.833	30.833	30.833	30.833	30.833
2	68.33	68.33	68.33	68.33	68.33	68.33	68.33
3	78.33	78.33	78.33	78.33	78.33	78.33	78.33
4	81.667	81.667	81.667	81.667	81.667	81.667	81.667
5	83.334	83.334	83.334	83.334	83.334	83.334	83.334
6	84.8	84.8	84.8	84.8	84.8	84.8	84.8
7	84.8	84.8	84.8	84.8	84.8	84.8	84.8

The summary of sample variance for each variable can be seen in Table 5. Since the variance of 105 samples for all variables are less than the original data, the data can thus use for model building.

Table 5. Samples variance for all variables.

Number of Samples	Samples Variance			
	Y	**X_1**	**X_2**	**X_3**
7 (original)	381.4151	56.3697	74.6666	0.0627
105	330.0708	48.7815	64.6154	0.0542

The Best Model

In this section, model M12 is chosen for illustration purposes. In phase 2, the Pearson correlation analysis verifies that there is an existence of multicollinearity between the independent variables in model M12.the multicollinearity test is carried out as in Zainodin *et al*. (2011) and as a result, five variables (X_1, X_2, X_{13}, X_{23} and X_{123}) are eliminated from model M12.5. Only two variables (X_3 and X_{12}) remain in the model for the coefficient test as shown by Noraini *et al*. (2008). Since both variables show that the decision is to reject the null hypothesis when the p-value is less than 0.05 as shown in Table 6, there is no further variable elimination on model M12.5.0. Model M12.5.0 signifies M12 as the parent model, five multicollinearity source variables have been removed and zero insignificant variables present.

Table 6. Coefficient test on model M12.5.0.

	Coefficients	*Standard Error*	*t Stat*	*P-value*
Intercept	23.5938	1.4071	16.7666	4.476E-31
X_3	140.5840	4.5257	31.0634	8.346E-54
X_{12}	-0.0865	0.0047	-18.0285	1.737E-33

All the six selected models in Table 7 will then undergo phase 3 of the model-building phases as in Zainodin *et al*. (2011). Table 7 also shows the corresponding eight selection criteria values for each of the six selected models. The best model is chosen when it has majority of the criteria with the least value. It can be seen that model M12.5.0 has the majority of the least values of the eight selection criteria (8SC).

Table 7. The corresponding selection criteria values for each selected models.

Model	k+1	SSE	AIC	RICE	FPE	SCHWARZ	GCV	SGMASQ	HQ	SHIBATA
M1.0.0	2	18400.681	675.321	681.507	675.442	740.780	678.265	634.506	695.997	670.160
M2.0.0	2	12931.997	474.615	478.963	474.701	520.620	476.685	445.931	489.147	470.988
M3.0.0	2	9088.584	333.559	336.614	333.619	365.891	335.013	313.399	343.771	331.010
M5.0.0	2	2860.314	104.976	105.938	104.995	115.151	105.434	98.632	108.190	104.174
M8.1.0	3	4885.999	204.018	195.440	191.387	219.744	193.196	174.500	200.122	188.119
M12.5.0	3	2170.894	90.647	86.836	85.035	97.634	85.839	77.532	88.916	83.583

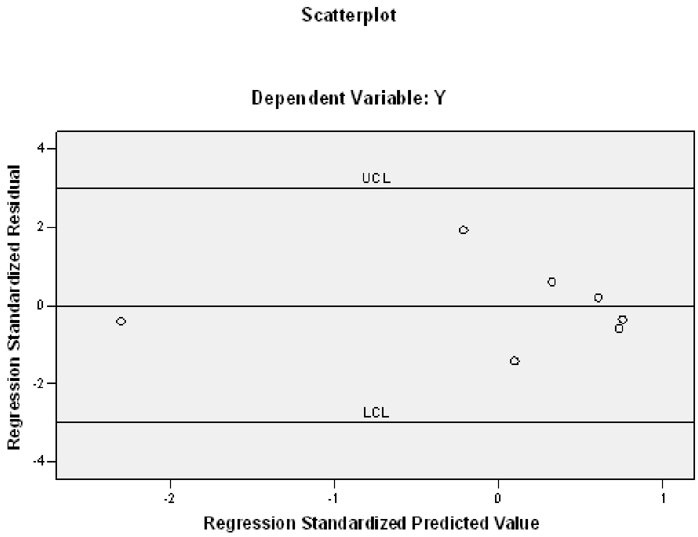

Figure 2. Scatter Plot of model M12.5.0.

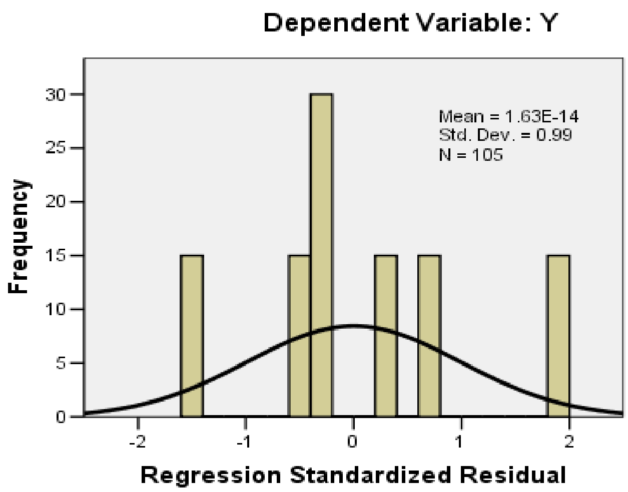

Figure 3. Normality plot of model M12.5.0.

Figure 2 and Figure 3 show the scatter plot of the randomness test and normality plot of the normality test of the best model M12.5.0.The scatter plot shows that standardized residuals are randomly distributed between ±3standard deviations from the line of origin. The normality plot of Figure 3 further shows that the standardized residuals are normally distributed. It can thus be said that the goodness-of-fit tests have met the assumptions of the regression analysis. Therefore, the best regression model is represented by:

$$Y = 23.594 + 140.584X_3 - 0.087X_{12} \tag{6}$$

Substituting back the defined variables into equation (6), the model then becomes:

$$PAE\ (\%) = 23.594 + 140.584\ (I_{dc}) - 0.087\ (P_{out})(V_{ds}) \tag{7}$$

Equation (7) shows that PAE has positive relationship with I_{dc} but has negative relationship with the interaction variable between P_{out} and V_{ds}.

CONCLUSION

For the small size of sample, Jackknife sampling techniques is useful to generate more data so that they can be used for model building. As a result, with 105 data, M12.5.0 is chosen as the best model. It can be used to predict the PAE result affected by DC current, output power and drain voltage with P_{in} is set as constant. It shows the DC current (I_{dc}) is found to play a major factor for the PAE. For experiment, it may be the most important parameters in getting the PAE result. The interaction variable between output power (P_{out}) and drain voltage (V_{ds}) has given a significant impact to the model meaning that output power and drain voltage are the limiting factors for the PAE.

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Appendix: All Possible Multiple Regression Models (3 variables)

	Models of the One Single Independent Variable
M1	$V_1 = \beta_0 + \beta_1 X_1 + \varepsilon_1$
M2	$V_2 = \beta_0 + \beta_2 X_2 + \varepsilon_2$
M3	$V_3 = \beta_0 + \beta_3 X_3 + \varepsilon_3$
	Models of the Two Single Independent Variables
M4	$V_4 = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \varepsilon_4$
M5	$V_5 = \beta_0 + \beta_1 X_1 + \beta_3 X_3 + \varepsilon_5$
M6	$V_6 = \beta_0 + \beta_2 X_2 + \beta_3 X_3 + \varepsilon_6$
	Models of the Three Single Independent Variables
M7	$V_7 = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \varepsilon_7$
	Models of the First Order Interactions
M8	$V_8 = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_{12} X_{12} + \varepsilon_8$
M9	$V_9 = \beta_0 + \beta_1 X_1 + \beta_3 X_3 + \beta_{13} X_{13} + \varepsilon_9$
M10	$V_{10} = \beta_0 + \beta_2 X_2 + \beta_3 X_3 + \beta_{23} X_{23} + \varepsilon_{10}$
M11	$V_{11} = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_{12} X_{12} + \beta_{13} X_{13} + \beta_{23} X_{23} + \varepsilon_{11}$
	Models of the Second Order Interactions
M12	$V_{12} = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_{12} X_{12} + \beta_{13} X_{13} + \beta_{23} X_{23} + \beta_{123} X_{123} + \varepsilon_{12}$