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Novel Design of Lower Arm Vehicle Using Finite Element Analysis and Statistical Method

Hemin M. M[1,a], Rahman M. M[2] and Omar R.M[3].

[1] Faculty of Mechanical Engineering, Universiti Malaysia Pahang,Malaysia

[2] Automotive Engineering Centre, Universiti Malaysia Pahang, , Malaysia

[3] Universiti Tenaga Nasional, Malaysia

[a]hemin_hm@yahoo.com

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ABSTRACT

The aim of this study is to investigate the influencing factors of the Lower suspension arm by integrating the finite element technique with response surface methodology (RSM). Response surface methodology has been widely used to predict Stress von Mises on Lower arm systems models. Aluminum alloys (AA7075-T6) are selected as a suspension arm material. The structural model of the suspension arm was developed utilizing the Solid works. The finite element model and analysis were performed utilizing the finite element analysis code. The finite element model is correlated with design of experiments (DOE) modal test. Influences of the various factors namely; Mesh Size, Loads are investigated using RSM. A mathematical prediction model has been developed based on the most influencing factors, and the validation simulation analysis proved its adequacy. RSM was used to design the experiments and analyzed the results obtained. RSM aimed towards prediction stress on Lower arm through the various factors of the suspension arm geometrical construction.

Keyword: **Robust design; RSM; FEA; suspension arm**

1. Introduction

The use of statistical design of experiment (DOE) techniques combined with finite element analysis (FEA) provides the engineering community with valuable tools for forecasting the behavior of a system or process. With the use of orthogonal polynomial expansion techniques, experimental results can be effectively transformed into mathematical equations based on the strength of the various factors and associated interactions. Conle and Mousseau (1991) used the vehicle simulation and finite element result to generate the fatigue life contours for the chassis component using automotive proving ground load history result combine with the computational techniques.

They concluded that the combination of the dynamics modeling, finite element analysis is the practical techniques for the fatigue design of the automotive component. Kim et al. (2002) was studied a method for simulating vehicles dynamic loads, but they add durability. Nadot and Denier (2003) have been studied fatigue phenomena for nodular cast iron automotive suspension arms. The authors found that the major parameter influencing fatigue failure of casting components are casting defects. (Rahman et al. 2007) were used finite element analysis to predict the fatigue life and discussed identify the critical locations of two- stroke free piston linear engine component using variable amplitude loading. The linear static finite element analysis was performed using MSC. NASTRAN. Finally, the author showing the contour plots of the fatigue life histogram and damage histogram at the most critical location.

The DOE and FEA combination allows the engineer to study a range of boundary conditions for numerous design factors and to analyze the impact and associated response for each factor and interaction within the system (Larry, 1996).

Hu et al. (1999) found that the optimal design was one that used the original finger length, the vertical slot, the chamfer pad, the 28mm thickness of disc, and the 10mm thickness of friction material based on the DOE analysis. CCD is one of the most important experimental designs used for optimizing parameters. CCD is far more efficient than running 3K factorial design with quantitative factors (Montgomery, 2005).

RSM is an important methodology used in developing new processes, optimizing their performance, and improving the design and/or formulation of new products. It is often an important concurrent engineering tool in which product design, process development, quality, manufacturing engineering, and operations personnel often work together in a team environment to apply RSM. It is a dynamic and foremost important tool of design of experiment (DOE), wherein the relationship between responses of a process with its input decision variables is mapped to achieve the objective of maximization or minimization of the response properties (Raymond & Douglas 2002).

In this paper, the RSM has been applied to develop a mathematical model to predict the stress for lower arm vehicle by integrating the FE analyses with structured DOE. Finite element techniques have been used as a tool to model the mechanical properties of the suspension arm. Three-dimensional linear tetrahedron solid elements (TET10) used for the initial analysis based on the loading conditions and it was subsequently validated using finite element analysis. The accuracy of the model has been tested using the analysis of variance (ANOVA) with the aid of a statistical design of experiment software called Design-Expert version 6.0. Knowledge of tool life will help the process planner or operator in selecting the optimum parameters to minimize the stress.

2. Response Surface Methodology

RSM is a collection of mathematical and statistical techniques that are useful for modelling and analyzing the problems in which response of interest is influenced by several variables and the objective is to optimize this response (Montgomery, 2001). RSM also quantifies relationships among one or more measured responses and the vital input factors (DOE, 2010).

2.1 Test for significance of the regression model

This test is performed as an ANOVA procedure by calculating the *F*-ratio, which is the ratio between the regression mean square and the mean square error. The *F*-ratio, also called the variance ratio, is the ratio of variance due to the effect of a factor (in this case the model) and variance due to the error term.

This ratio is used to measure the significance of the model under investigation with respect to the variance of all the terms included in the error term at the desired significance level, a significant model is desired.

2.2 Test for significance on individual model coefficients

This test forms the basis for model optimization by adding or deleting coefficients through backward elimination, forward addition or stepwise elimination/addition/exchange. It involves the determination of the *P*-value or probability value, usually relating the risk of falsely rejecting a given hypothesis. For example, a "Prob. > *F*" value on an *F*-test tells the proportion of time you would expect to get the stated *F*-value if no factor effects are significant. The "Prob. > *F*" value determined can be compared with the desired probability. In general, the lowest order polynomial would be chosen to adequately describe the system.

2.3 Test for lack-of-fit

As replicate measurements are available, a test indicating the significance of the replicate error in comparison to the model dependent error can be performed. This test splits the residual or error sum of squares into two portions, one which is due to pure error which is based on the replicate measurements and the other due to lack-of-fit based on the model performance. The test statistic for lack-of-fit is the ratio between the lack-of-fit mean square and the pure error mean square. As previously, this *F*-test statistic can be used to determine as to whether the lack-of-fit error is significant or otherwise at the desired significance level. Insignificant lack-of-fit is desired as significant lack-of-fit indicates that there might be contributions in the regressor–response relationship that are not accounted for by the model.

The checks performed here include determining the various coefficient of determination, R^2. These R^2 coefficients have values between 0 and 1. In addition to the above, the adequacy of the model is also investigated by the examination of residuals (Montgomery, 1997). The residuals, which are the difference between the respective, observe responses and the predicted responses are examined using the normal probability plots of the residuals and the plots of the residuals

3. Mechanical Properties

Material model and material properties play an important role in the result of FE method. The material properties are one of the major inputs, which is definition of how the material behaves under the cyclic loading conditions. The materials parameters required depend on the analysis methodology being used. The mechanical properties of 7075-T6 aluminum alloy are shown in Table 1. AA7075-T6 has been choose the for lower suspension arm because of his advantage like Excellent joining characteristics, good workability, high resistance to corrosion and lightweight.

Table 1: Mechanical properties of aluminum alloy 7075-T6

Material	Young's Modulus (GPa)	Poisson's ratio	Tensile strength (MPa)	Yield strength (MPa)
Aluminum alloy AA7075-T6	72	0.33	570	490

4. Finite Element Modeling And Analysis

The suspension arm was modeled using, MSC Nastran, Finite element analysis software. The premise was to model a lower arm structure and verify that the two techniques, theoretical and computer provided the same answer. Stress analyses considering the ultimate load condition applied to the parts during the driving were performed. Table 2 shows the five ultimate load conditions of the lower arm.

Table 2: Load conditions of lower arm

Case	**Conditions**		**Load(N)**	
		X	**Y**	**Z**
1	Pothole brake limit load	−5688.2	−4801.2	−60.4
2	Oblique kerb limit load	9579.7	2382.1	238.3
3	Pothole corner limit load	−1107.0	1108.3	197.6
4	Lateral kerb strike limit load	−549.7	12218.3	845.9
5	Ultimate vertical limit load	−573.7	−3408.9	-66.7

The Pothole brake limit load is the condition applied to the lower arm in the case of simultaneous falling into a pit and braking; the oblique kerb limit load is the condition in the case of traversing the inclined curve road; the Pothole corner limit load is the condition in the case of driving the corner of a pit; the lateral kerb strike limit load is the condition in the case of turning along a side curve; the ultimate vertical limit load is the maximum vertical load condition applied to the lower arm. A simple three-dimensional model of suspension arm was developed using Solidworks software as shown in Fig. 1. The three-dimensional FE model, loading and constraints of suspension arm is shown in Fig. 2. The boundary conditions as shown in Fig. 2 and the mechanical properties of the material for the lower arm were input into MSC. Patran and 10 node tetrahedral element (TET10) was used for the solid mesh.

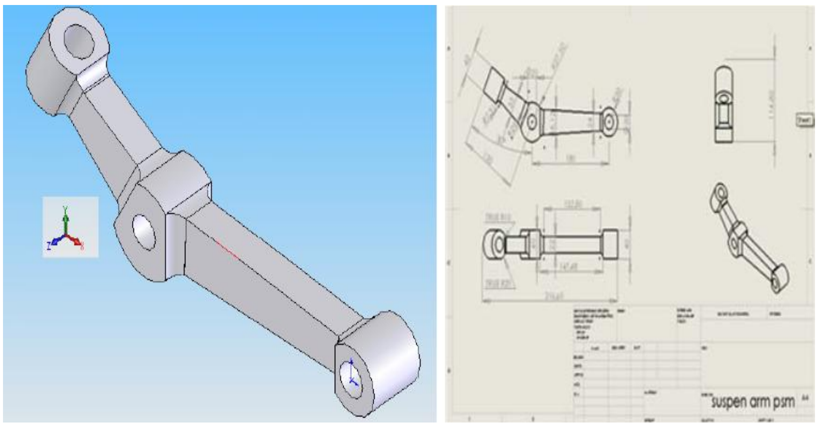


Fig.1.Structural model and overall dimension of suspension arm

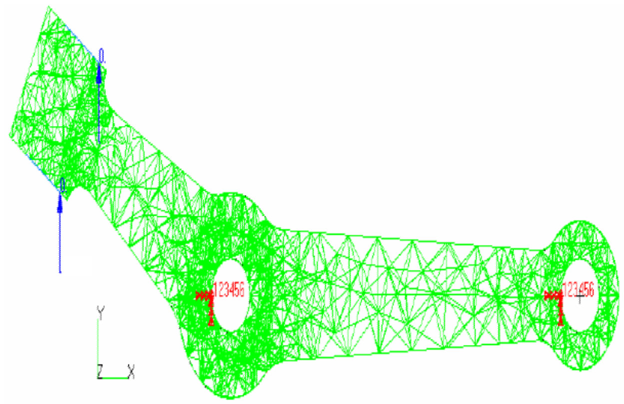


Fig.2.Boundary conditions of lower arm

5. Methodology

Human made products or processes can be treated like a system, if it produces a set of responses for a given set of inputs. Suspension system can also be treated like a system as shown in Fig. 3. Some systems like suspension system produce unwanted outputs namely squeal for a set of inputs parameters. The present study was aimed at establishing the input-output relationships for prediction of lower suspension arm. Suspension system has numerous variables. In order to arrive at the most influential variables and its effects a phase strategies were proposed. CCD based Response surface methodology (RSM) was deployed to develop a linear model for prediction of Lower arm.

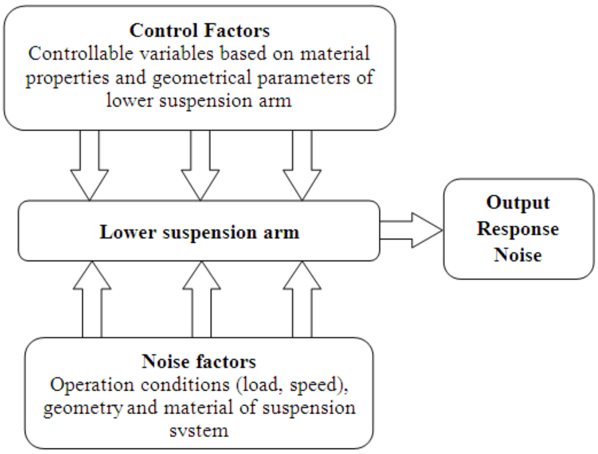


Fig.3. Suspension system

6. Experimental Results And Analysis Using CCD

This section discusses about the two phases of experiments, its results, developed mathematical models of the system and its adequacy. In light of the screening experiments, a decision was taken to study the effects of the top four factors, namely; Mesh size, Load X, Y, Z. The variables and their levels are listed in Table 3.

Table 3: Coded levels of variable and actual values for CCD

Factor			Level	
Coded	**Uncoded**	**Units**	**Low**	**High**
A	Mesh size		5	7
B	Load X	N	-5688.2	9579.7
C	Load Y	N	-4801.2	12218.3
D	Load Z	N	-66.7	845.9

Different terms used in the Table 4 are as follows. The term 'DF' means degrees of freedom. The DF refers to the number of terms that will contribute to the error prediction. The term 'Seq SS' represents the sum of squares for each term, which measures the variability in the data contributed by the term. The Model F-value of 5.65 implies the model is significant. There is only a 0.10% chance that a "Model F-Value" this large could occur due to noise. Values of "Prob > F" less than 0.0500 indicate model terms are significant. In this case; C, B^2,and C^2 are significant model terms.

Values greater than 0.1000 indicate the model terms are not significant. Moreover, the design showed insignificant lack of fit (F-value =0.34), which is desirable, related to the pure error and this means there is a 9.292 % chance that lake of fit could have occurred due to noise.

Table 4: Analysis of variance by ANOVA for response surface model

Source	**DF**	**Sum of Square**	***F* value**	***Prob>F***	
Model	14	1487000	5.65	0.0010	significant
A- Mesh size	1	5547.56	0.3	0.5949	
B-Load x	1	1200.50	0.064	0.8039	
C-Load y	1	407100	21.66	0.0003	
D-Load z	1	8149.39	0.43	0.5202	
AB	1	7482.25	0.4	0.5375	
AC	1	22952.25	1.22	0.2865	
AD	1	44944.00	2.39	0.1428	
BC	1	2401.00	0.13	0.7257	
BD	1	20592.25	1.1	0.3118	
CD	1	44732.25	2.38	0.1437	
A^2	1	46693.07	2.48	0.1358	
B^2	1	163600	8.7	0.0099	
C^2	1	247800	13.19	0.0025	
D^2	1	26821.53	1.43	0.2508	
Residual Error	15	281900			
Lack-of-Fit	10	114800	0.34	0.09292	not significant
Pure Error	5	167100			

**p<0.05indicate the term is significant*

The response equation for von Mises in coded form is given under:

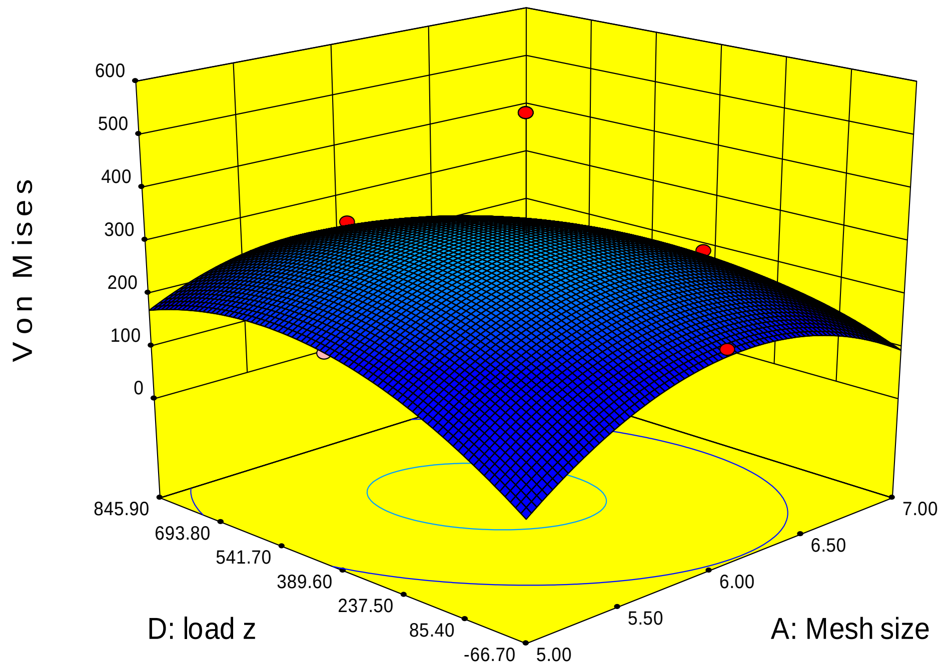
$$\begin{aligned} von.Mises &= 317.12 - 17.56*A - 8.17*B + 150.39*C + 21.28*D + 21.63*A*B \\ &+ 37.88*A*C - 53.00*A*D + 12.25*B*C - 35.78*B*D - \\ &52.88*C*D - 134.25*A^2 + 251.25*B^2 + 309.25*C^2 - 101.75*D^2 \end{aligned} \quad (1)$$

Where: the amount of von Mises in term a function of Mesh size (A), Load x (B), Load y (C), and Load z (D). The coefficient with one factor represents the effect of the particular factor, while the coefficient with two factors or more represents the interaction between these factors. The positive sign in front of the terms indicates synergistic effect, while negative sign indicates antagonistic effect.

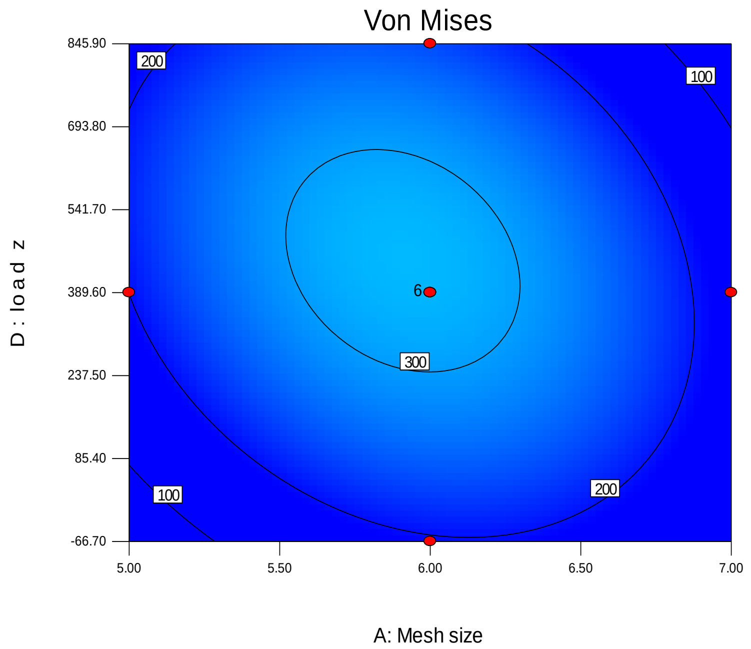
The graphical representations of the model (equation 1) facilitate an examination of the effects of the experimental factors on the response. 3D response surface is a representation of the fitted response function, and they were obtained using the Design -Expert software.

The effects of mesh size and load *z* dose interaction on Mises are presented in Fig. 4 by 3D and 2D plots. It can be observed that the maximum von Mises of 300 MPa and the minimum von Mises of 200 MPa occur at 5 -6 of reaction mesh size and -66.7 N -845.9 N of load z, respectively.

The effect of load *x* and load *y* dose interaction on von Mises are presented in Fig. 5 by 3D and 2D plots. It can be observed that the maximum von Mises of 780 MPa and the minimum von Mises of 500 MPa occur at 1945.75 -9579.70 N of reaction load *x* and -4801.20 -12218.30 N of load y, respectively.

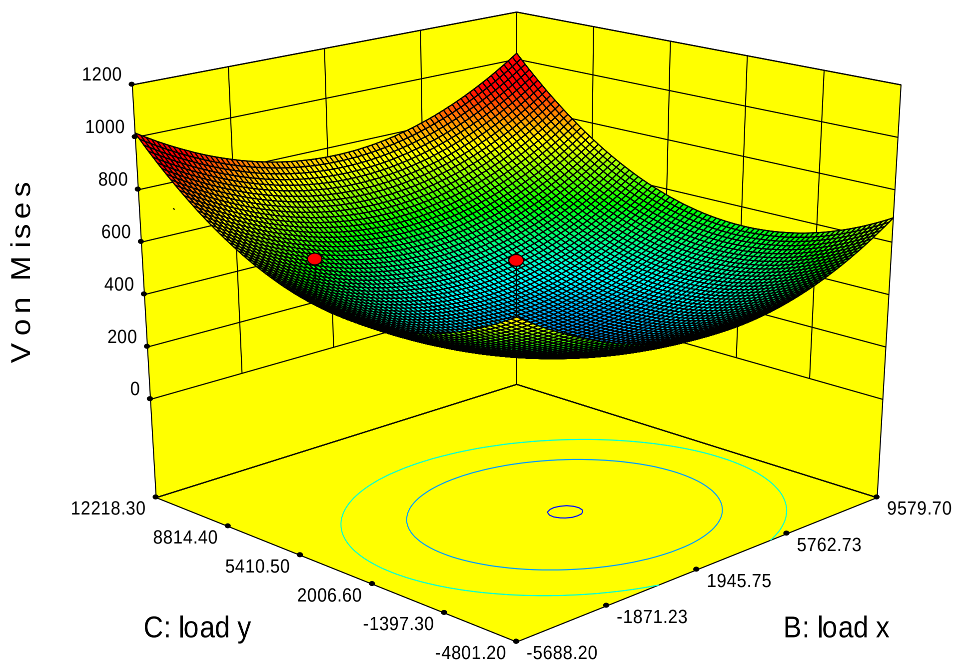


(a) 3 Dimension

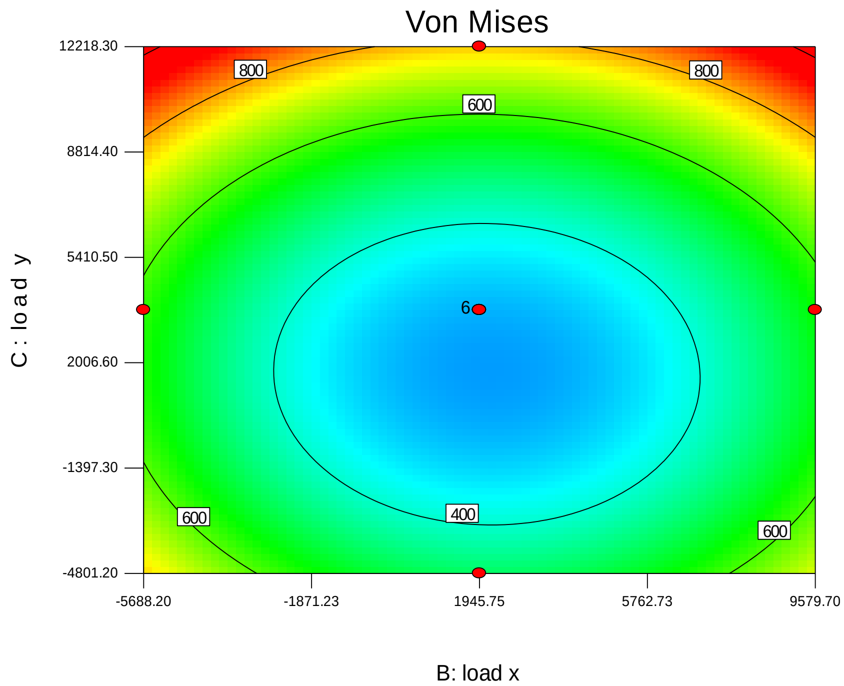


(b) 2 Dimension

Fig.4. The interaction between mesh size and reaction load z on von Mises



(a) 2 Dimension



(b) 3 Dimension

Fig.5. The interaction between load x and reaction load y on von Mises

The following observations can be made from the surface plots:

a. Fig. 6 shows the normal probability plot of residuals. It shows that there is no abnormality in the methodology adopted (R^2 =0.8406).
b. The R^2 analysis is tabulated in Table 5. The "Pred R-Squared" of 0.5120 is in reasonable agreement with the "Adj R-Squared" of 0.6919. "Adeq Precision" measures the signal to noise ratio.
c. A ratio greater than 4 is desirable; Model's ratio of 8.183 indicates an adequate signal. In fact, when the value of correlation coefficient R is close to 1, it means the response correlation FEA result and predicted values are better.
d. The statistical analysis shows that, the developed linear model based on central composite design is statistically adequate and can be used to navigate the design space.

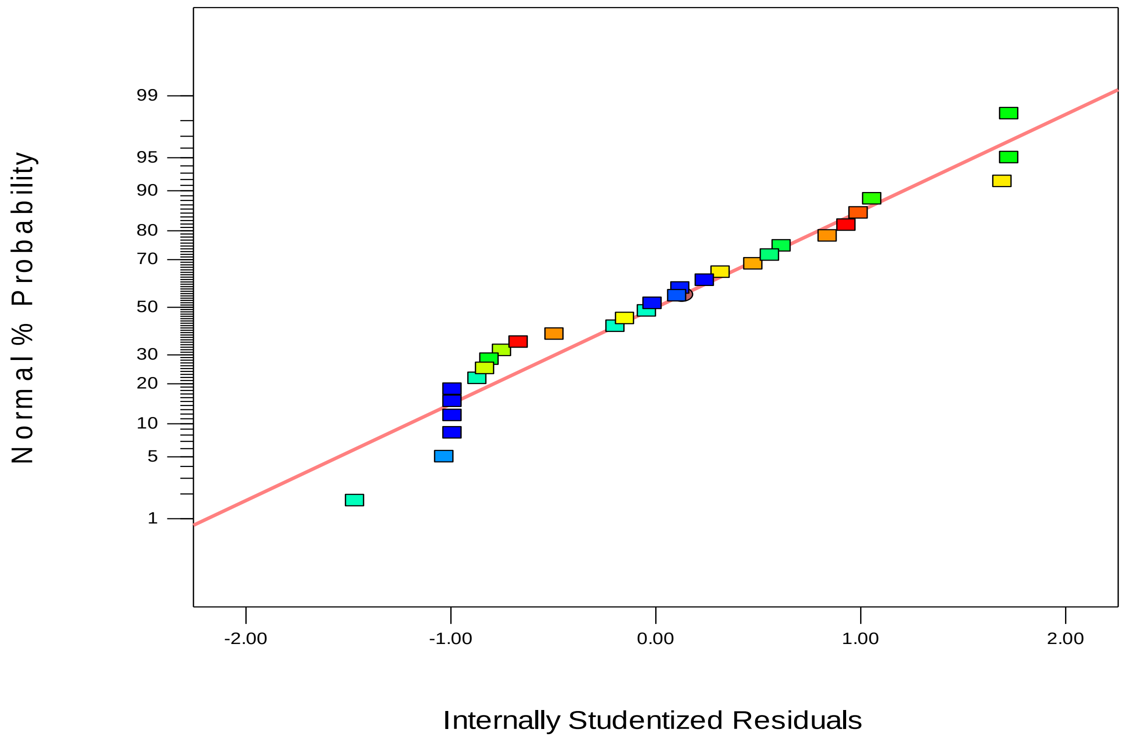


Fig.6. Normal probability plot for residuals

Table 5: R^2 analysis

Std. Dev.	137.09
Mean	511.83
C.V. %	26.78
PRESS	863300
R-Squared	0.8406
Adj R-Squared	0.6919
Pred R-Squared	0.5120
Adeq Precision	8.183

Fig. 7 is the predicted versus actual plot shows how the model predicts over the range of data. Plot should exhibit random scatter about 45 degree line and the clusters indicate problems of over or under predicting. The best fit line plot (Fig. 7) of the 30 points (table 6) was found to be close to the ideal Y = X line; predicted responses show good agreement with actual results; The scatter shows the bowling scores can be predicted very precisely. Table 6 lists the Comparison between predicted versus actual simulation and gives the factor settings, predicted responses, measured von Mises and percentage deviation for each run, a total number of thirty trials were conducted and a set of data was collected as per the structure of CCD of experiments.

Table 6: Comparison between predicted versus actual simulation

No. Run	A: Mesh size	B: Load X	C: Load Y	D: Load Z	Actual FEA	Predicted DOE	Residual	% deviation
1	6.00	9579.70	3708.55	389.60	410.00	425.70	-15.70	-3.65
2	6.00	1945.75	3708.55	-66.70	295.00	277.58	-82.58	5.9
3	7.00	-5688.2	-4801.2	-66.70	410.00	413.36	-3.36	-0.82
4	6.00	1945.75	-4801.2	389.60	501.00	451.75	49.25	9.83
5	7.00	-5688.2	12218.3	845.90	672.00	731.97	-59.97	-8.9
6	6.00	1945.75	3708.55	389.60	910.00	835.36	74.64	8.2
7	6.00	1945.75	12218.3	389.60	848.00	768.64	79.36	9.35
8	5.00	1945.75	3708.55	389.60	905.00	958.53	-53.53	-0.59
9	5.00	-5688.2	-4801.2	-66.70	790.00	751.75	38.25	4.84
10	6.00	1945.75	3708.55	845.90	422.00	491.64	-69.64	-16.5
11	6.00	1945.75	3708.55	389.60	531.00	595.92	-64.92	-12.22
12	5.00	9579.70	12218.3	845.90	467.00	422.31	44.69	9.56
13	7.00	9579.70	12218.3	-66.70	807.00	846.53	-39.53	-4.89
14	6.00	1945.75	3708.55	389.60	726.00	737.92	-11.92	-1.64
15	5.00	9579.70	12218.3	-66.70	807.00	739.70	67.30	8.3
16	7.00	-5688.2	-4801.2	845.90	743.00	717.58	25.42	3.42
17	5.00	-5688.2	12218.3	845.90	199.00	200.43	-1.43	-0.71
18	7.00	9579.70	-4801.2	-66.70	189.00	165.32	23.68	12.52
19	6.00	-5688.2	3708.55	389.60	743.00	576.54	166.46	22.4
20	7.00	-5688.2	12218.3	-66.70	416.00	460.21	-144.21	-10.62
21	7.00	1945.75	3708.55	389.60	580.00	475.99	104.01	17.93
22	5.00	-5688.2	12218.3	-66.70	695.00	776.77	-81.77	-11.76
23	7.00	9579.70	12218.3	845.90	206.00	194.10	11.90	5.77
24	5.00	-5688.2	-4801.2	845.90	247.00	236.65	10.35	4.1
25	6.00	1945.75	3708.55	389.60	188.00	207.12	-129.12	-10.17
26	6.00	1945.75	3708.55	389.60	542.00	517.12	224.88	4.59
27	5.00	9579.70	-4801.2	-66.70	542.00	517.12	224.88	4.59
28	6.00	1945.75	3708.55	389.60	188.00	217.12	-129.12	-15.48
29	5.00	9579.70	-4801.2	845.90	188.00	217.12	-129.12	-15.48
30	7.00	9579.70	-4801.2	845.90	188.00	217.12	-129.12	-15.48

% Deviation = [(actual value – predicted value)/ actual value] × 100

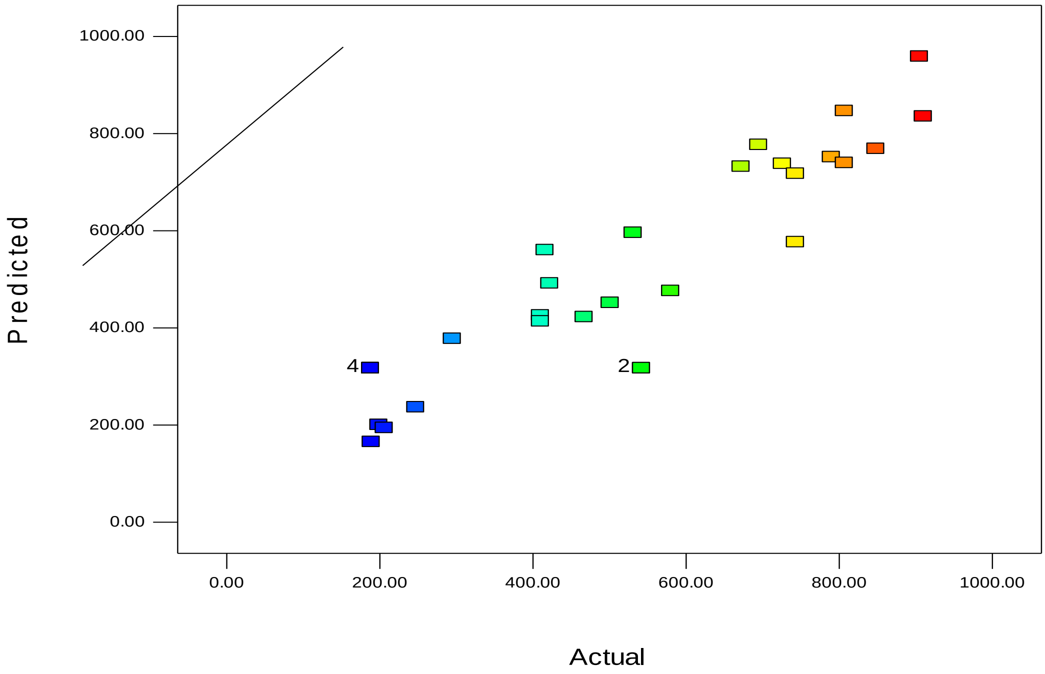


Fig.7. The best fit line plot

Fig. 8 shows the percentage deviation plot, actual results varied between -16.5 % and 22.4 % from predicted responses. This indicates that designed model space can be navigated for prediction.

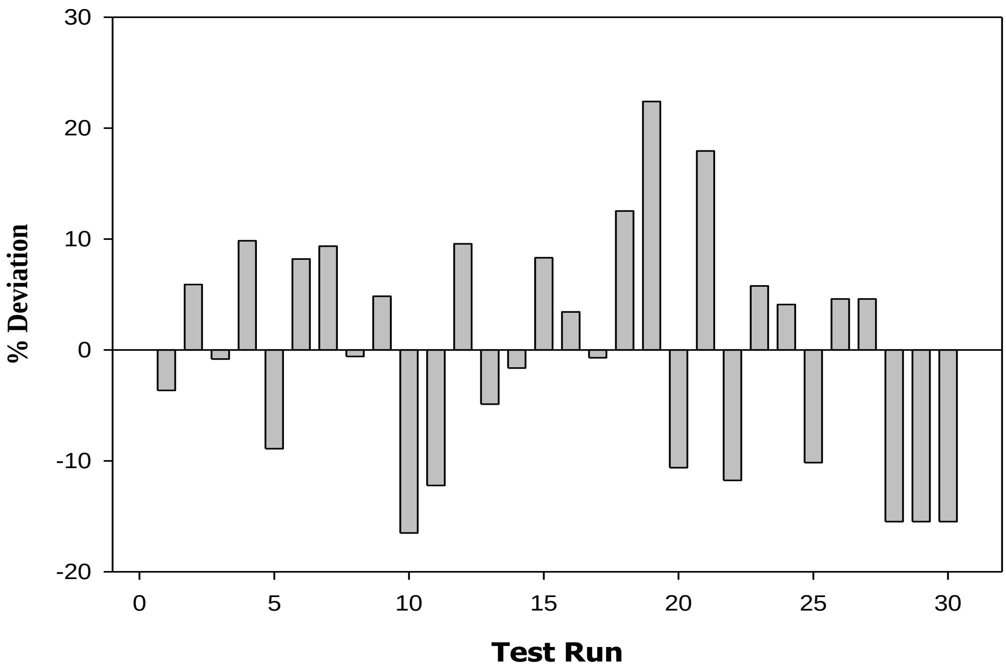


Fig.8. Percentage deviation of FEA results

7. Conclusion

Statistical techniques together with good engineering knowledge and common sense will usually lead to sound conclusions. Linear model for the Lower arm based on Central composite design of experiments was successfully developed, statistically adequate and can be used to navigate the design space. To validate the model, randomly generated twenty one test cases were examined. Continued research in this direction can bring about more comprehensive and appropriate guide lines for designers .The combined approach of modeling lower arm using CEA and DOE is found to be statistically adequate through verification trials.

References

Conle, F.A and Mousseau C.W. (1991). Using vehicle dynamic simulation and finite element result to generate fatigue life contours for chassis component. *International Journal of Fatigue*, 13(3): 195 - 205.

(DOE) Design-Expert Software, Version 8.0.4.1. (2010). User's Guide, Technical Manual, Stat-Ease Inc., Minneapolis

Hu, Y., Mahajan, S., and Zhang, K. (1999), Brake squeal DOE using nonlinear transient analysis. SAE Paper 1999-01-1737.

Kim, H.S, Yim, H.J and Kim, C.M. (2002), Computational durability prediction of body structure in prototype vehicles. International Journal of Automotive Technology, 3(4): 129-136.

Larry W. Nye. (1996), K-Factor Test-Board Design Impact on Thermal-Impedance Measurements. Texas Instruments Incorporated

Montgomery, D.C. (2005), Design and analysis of experiments. 5th edition. Wiley, Singapore.

Montgomery, D. C. (2001), Design and Analysis of Experiments, 5th edition, John Wiley and Sons, Inc. New York

Montgomery, D.C. (1997), Design and Analysis of Experiments, 4th edition. Wiley, New York.

Nadot, Y. and Denier, V. (2003). Fatigue failure of suspension arm: experimental analysis and multiaxial criterion. International Journal of Fatigue, 11(4): 485-499.

Rahman, M.M., Ariffin, A.K., Abdullah, S. and Jamaludin, N. (2007). Finite element based durability assessment of a free piston linear engine component. SDHM, 3 (1): 1-13

Raymond, H. Myers & Douglas, C. Montgomery. (2002). Response surface methodology: Process and product optimization using designed experiments, 2nd edition, John Wiley & Sons, USA.