OPTIMIZATION OF WISHBONE SUSPENSION SYSTEM

Deepak K M[1], Chetan Kumar D S[2],
[1]M. Tech Scholar, Dept.of Mechanical Engineering, NHCE, Bangalore
[2] Sr.Asst Professor, Dept.of Mechanical Engineering, NHCE, Bangalore

Abstract*— The main objective of this paper is to optimize the present wishbone suspension system. The wishbone suspension system is one of the most used suspension systems of passenger cars. Double wishbone suspension system designed for life of car so it should not fail during service period. Its behaviour directly affects the safety and performance. However if the suspension system is not optimized, by which the weight of the suspension system is more, which adversely affect the performance of the vehicle. This project deals with the optimization of wishbone suspension system. The 3D model was modeled using Solid Edge ST10 is taken which is already used for analysis. Results of analysis like linear static and modal analysis, carried out using Ansys 14.5 is extracted for optimization. After getting the result from the Ansys, we focus on optimization of design. For optimizing design we primarily focus on reducing the thickness of upper and lower arm of the wishbone suspension system and while doing that we aim to accomplish factor of safety as 1.2, by which we can reduce the weight of the suspension and also keeping it safe from failing

Keywords: Wishbone, Ansys 14.5, Solid Edge ST10, Linear static, Modal Analysis, Lower arm, Upper Arm,

INTRODUCTION

In present days engineers search for optimized design through which the production cost can be lowered which also increases the demand due to increased competition. This gave rise to optimization methods through which the components such as chassis can be optimized to be both more proficient and affordable and to create imaginative methods to enhance the execution of current chassis. Therefore “Engineering Optimization” is said to be named a thorough numerical way to deal with distinguish through which best design/candidate can be selected as design alternatives. Any engineering problem can be solved by optimization. Due to advance softwares produced is several years, optimization is utilized in many industries such as aerospace, automobile, MEMS, chemical, electrical, and manufacturing industries in present time. With the improvement of PC innovation, multifaceted nature of issues being unravelled utilizing optimization methods is not any more an issue. Optimization methods combined with current instruments of PC helped configuration are additionally being utilized to improve the innovative procedure of theoretical and detailed design. There are more than one method or procedure for taking care of all optimization issues effectively. Therefore many optimization methods have been created for comprehending. Optimization might be characterized as the way toward augmenting or limiting a coveted target work while fulfilling the predominant constraints different types of optimization problems. The selection of method is entirely up to the engineer who selects the method and which is appropriate for his design.

I. DOUBLE WISHBONE SUSPENSION SYSTEM

This system comprises of one upper and one lower arm connected to a frame member which is connected to the chassis of the vehicle. These arms take after letter 'A' of the Roman letter set because of which these are likewise referred to as 'A' – arms. The coil springs receives the weight of the body through cross parts and the chassis of the vehicle, which is further transmitted to the lower wishbone arm. A safeguard is set inside the coil springs and is attached to the cross part and to bring down wishbone part.

Fig. 1 Present double wishbone suspension system.

II. Results of Linear Static Analysis

1. Stress Developed in Lower Arm

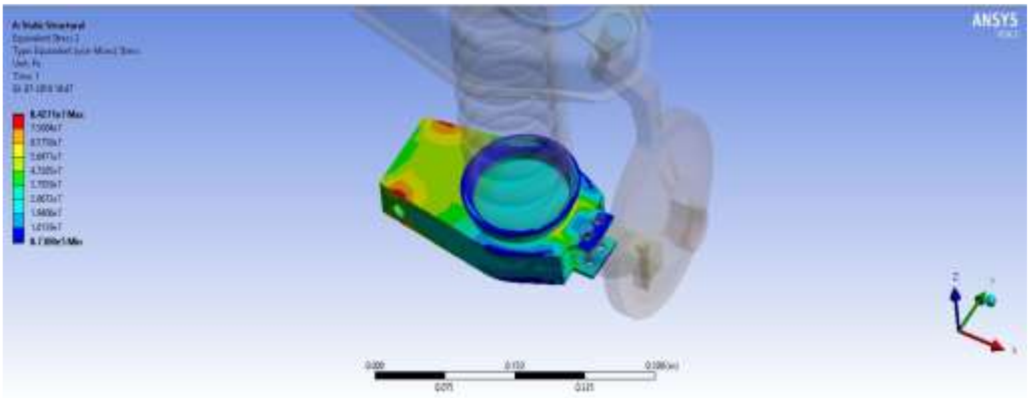


Fig. 2 Stress developed in Lower arm

The maximum stress acting in the lower arm of the suspension is 84.27Mpa.

2. Stress Developed in Upper Arm

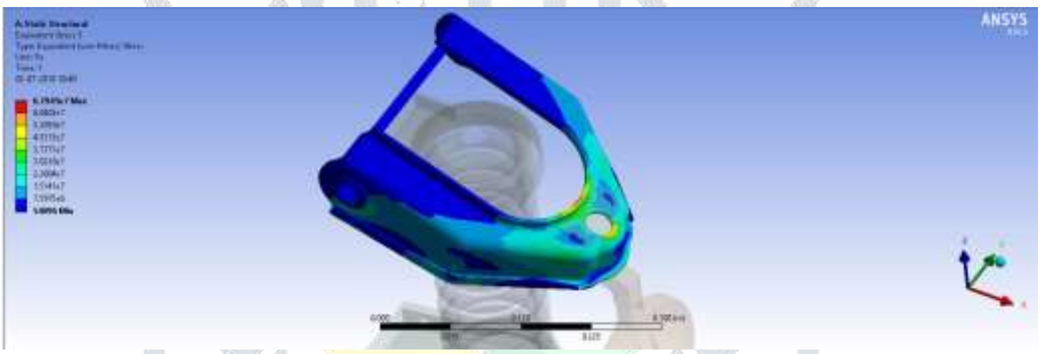


Fig. 3 Stress developed in Upper arm

The maximum stress acting in the upper arm of the suspension is 67.94Mpa.

III. Optimization

1. Design Of Experiments (DOE)

Optimization methods known as mathematical programming techniques are generally studied as a part of Operations Research. This is a branch in mathematics that employs logical methods and strategies to basic decision making issues with the point of setting up the best or ideal arrangements. Design of experiments (DOE) is one such well-defined area of operation research.

This technique empowers one to examine the test information and manufacture exact models to get the most precise portrayal of the physical circumstance. Consequently substitute techniques for work assessments, for example, design of experiments (DOE) and reaction surface demonstrating (RSM) are generally utilized in building design to limit the computational cost engaged with such analysis and simulation. The fundamental approach of such strategies is to develop an improved mathematical estimate of the computationally costly simulation and analysis code, which is then utilized as a part of place of the first code to encourage Multidisciplinary Optimization (MDO), reliability analysis, design space exploration etc.

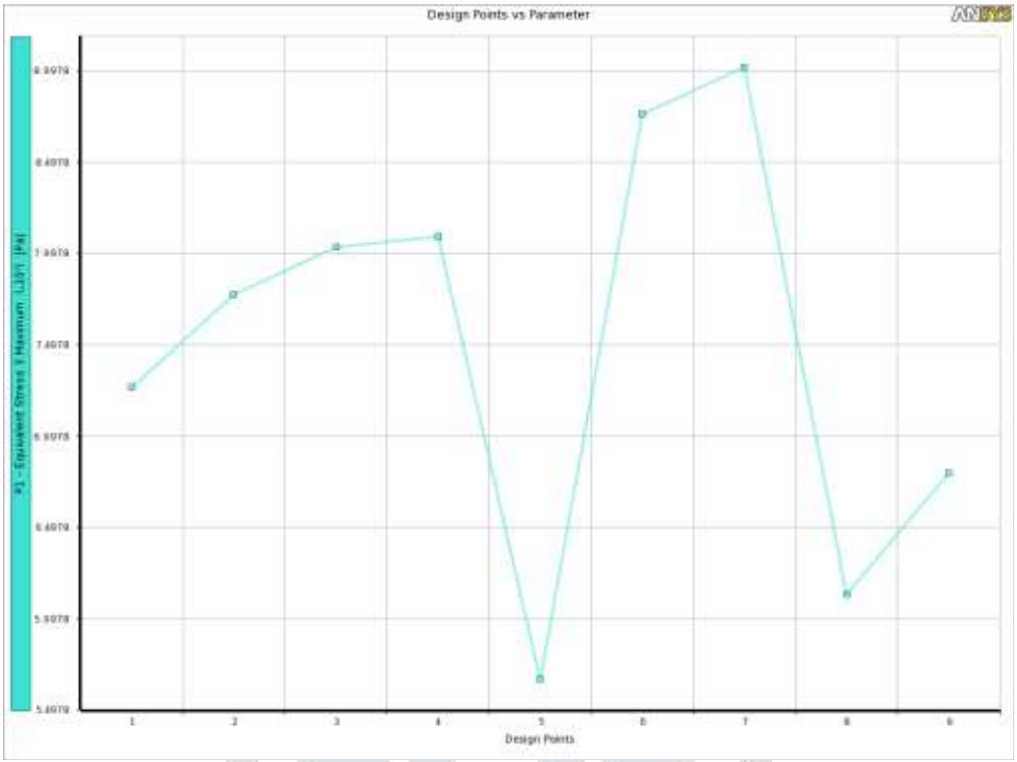
A variety of approximation models exist such as polynomial response surfaces, Kriging model, radial basis functions, neural networks and multivariate adaptive regression splines. In this research a classification of radial basis function known as Regulated Multiquadric Response Surface (MQR) model is employed to approximate the expensive simulation and analysis code

Design of experiments is opened and design points are created by giving upper bound and lower bound of the input variable parameter.

Once that is done the design of experiments is updated and we get 10 experiment points with varying input parameter within the range of upper bound and lower bound

Table 1: Design of experiments table

Design Points	Lower Bracket Thickness (mm)	Upper Bracket Thickness (mm)	Von Misses Stress in Upper Bracket (Pa)	Von Misses Stress in Lower Bracket (Pa)	Mass kg
1	4.75	4.25	7.2627E+07	2.5910E+08	22.180
2	4	4.25	7.7708E+07	2.6023E+08	21.799
3	5.5	4.25	8.0309E+07	8.5536E+07	22.553
4	4.75	3.5	8.0897E+07	2.6063E+08	21.776
5	4.75	5	5.6654E+07	2.3552E+08	22.582
6	4	3.5	8.7586E+07	2.5261E+08	21.395
7	5.5	3.5	9.0161E+07	9.5889E+07	22.149
8	4	5	6.1313E+07	2.6013E+08	22.200
9	5.5	5	6.7945E+07	8.4271E+07	22.955

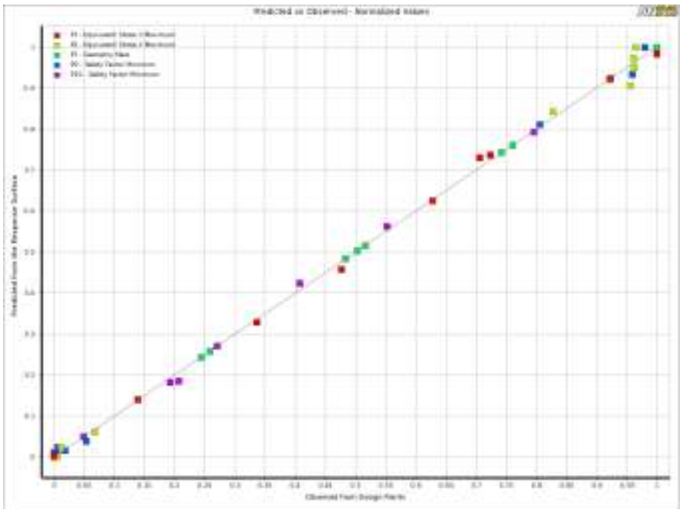


Graph. 1 Design point's graph

The graph represents design points that are tabulated above.

2. Goodness of Fit

The goodness of fit of a statistical model describes how well it fits a set of observations. Measures of goodness of fit commonly abridge the error between observed and the qualities expected under the model being referred to.

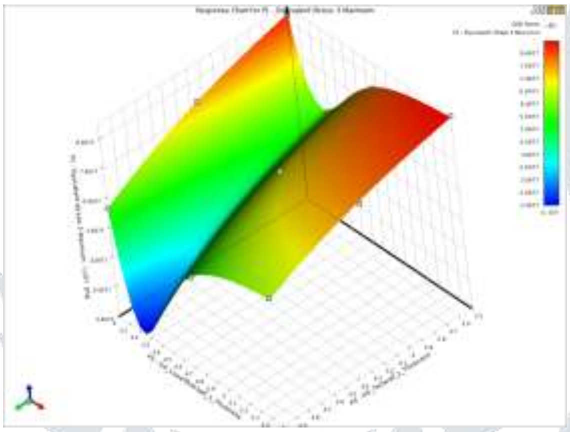


Graph 2: Goodness fit graph

For all response surface types, Goodness of Fit is calculated for learning focuses (the DOE focuses and refinement directs utilized toward create the response surface) and verification points.

3. Response surface- Maximum equivalent stress in Upper arm

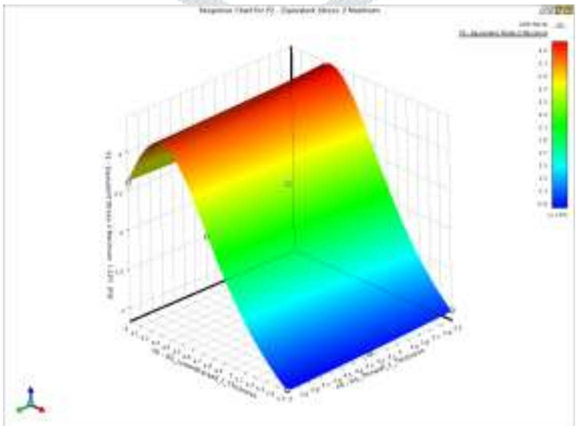
The plot shows the connections between maximum equivalent stress developed in upper arm relative to upper arm and lower arm thickness



Graph 3: Maximum equivalent stress in upper arm 3Dgraph

4. Response surface – Maximum equivalent stress in Lower arm

The plot shows the connection between maximum equivalent stress developed in lower arm relative to upper arm and lower arm thickness



Graph 4: Maximum equivalent stress in lower arm 3D graph

5. Response Surface Optimization

From results of response surface the response surface optimization generates candidate points. These Candidate Points results that are viewed in both table and chart, which enables to see various types of data about candidate points.

From which data of candidate points can be extracted by specifying one or more parameters. In the Chart view, the legend's colour coding empowers you to see and translate the examples, candidate focuses distinguished by the optimization, candidates embedded manually, and candidates for which output values have been verified by a design point update. You can indicate the diagram's properties to control the visibility of every axis, achievable examples, candidates you've embedded manually, and candidates with confirmed output values.

On entering the optimization tool and giving the objective as the factor of safety in range of 1.5-2

We get candidate data points which shows optimized results, with three candidate points which represents change in variable keeping the objective variable within the range.

We get candidate table as

Table 9.4: Candidate Point Table
P1-Stress in upper arm (Pa)
P2-Stress in Lower arm (Pa)
P5-Lower Arm Thickness (mm)
P6-Upper Arm Thickness (mm)
P7-Geometry Mass (kg)
P9-Factor Safety for lower arm
P10- Factor of Safety for Upper arm

Name	P5	P6	P1	P2	P7	P9	P10
Candidate Point 1	4.984	3.554	85315514	1.95E+08	21.923	1.213	3.038
Candidate Point 2	4.990	3.742	83434430	1.9E+08	22.027	1.247	3.110
Candidate Point 3	4.987	3.929	81255691	1.87E+08	22.127	1.265	3.197

From this we can select the optimized model for the component. Here we can see that candidate 1 is best model in terms of factor of safety which is 1.213 for lower arm and 3.038 for upper arm and which generates maximum equivalent stress of 85.31 Mpa in Upper Arm and 195 Mpa in Lower Arm with mass of 21.923kg and thickness of upper arm as 4.984mm and lower arm as 3.554mm.

6. Modal Analysis of Suspension system after Optimization

a. Modal analysis of upper arm

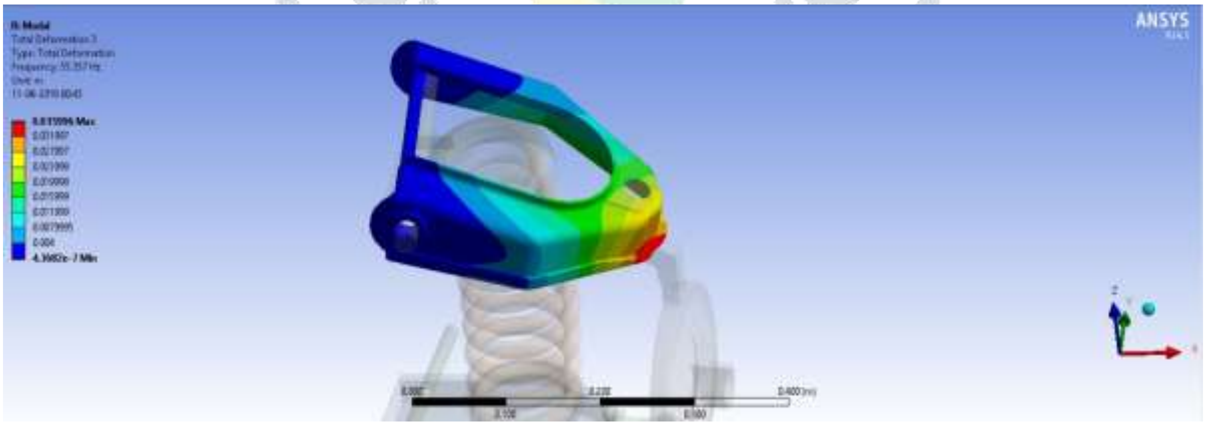


Fig 10.3: Modal analysis of optimized upper arm

The natural frequency of the upper arm is 55.357Hz with deflection of 35.996mm.

b. Modal analysis of lower arm

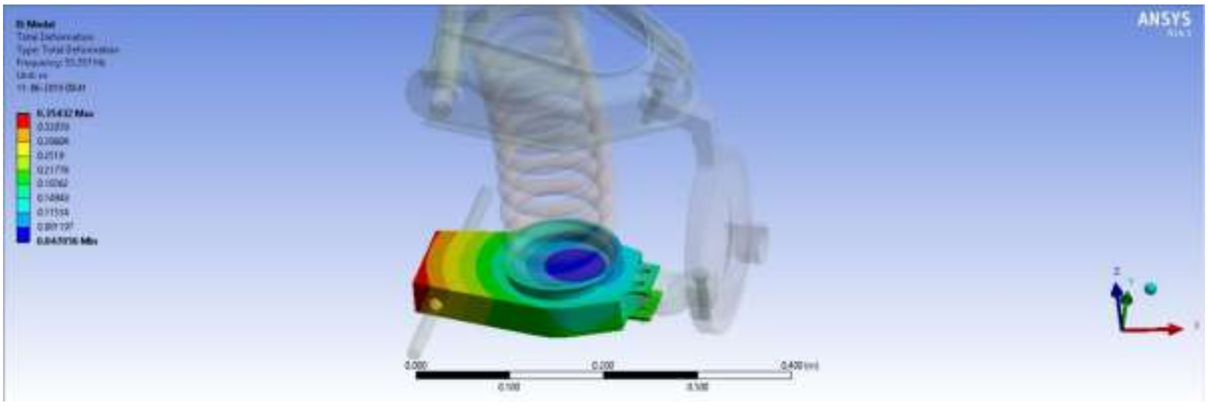


Fig 10.4: Modal analysis of optimized Lower arm

The natural frequency of the lower arm is 55.357 with maximum deflection of 354.32mm.

IV. SUMMARY

Summary of Optimized Suspension

Table 12.2: Optimized Arm Summary

Output Parameters	Von-misses stress	Factor Of Safety	Thickness (mm)	Weight (kg)	Weight Of Suspension system
Upper Arm	85.31Mpa	3.03	3.55	2.60	21.923 kg
Lower Arm	195 Mpa	1.21	4.98	3.00	

V. CONCLUSION

The optimization process was successfully finished by utilizing Solid Edge ST10, ANSYS 14.5, to run the analysis in ANSYS 14.5 software. This optimization method to give an innovative problems and rectified the problem by using this software. This optimized model is utilized in manufacturing industrial development. This optimized model should give more advantages for manufacturing industry. It gives more life time compare to the previous model, cost reduction, material reduction; reduce the man power of the production.

1. The mass of the existing Suspension is 22.955 kg and after design optimization the mass of the optimized suspension has come to 21.923 kg.
2. As the FOS of optimized suspension which is subjected to loading is 1.2 which is desired value, the design is optimum.
3. Also, as the Von-Mises stress obtained in upper control arm is obtained as 85.31 N/mm^2 and lower arm is obtained as 195 N/mm^2 which is within the limits of permissible yield strength of 250 N/mm2, the design is agreeable.
4. And the optimization technique accomplishes 16% weight reduction.

REFERENCES

[1] Design, Analysis and Optimization of front suspension wishbone of BAJA 2016 of Allterrain vehicle: Reena Mishra, Anand Baghel: Vol. 2 Iss.3, pp. 40-52, 28th Feb, 2017 ISSN Print : 2454-1435

[2] Design and optimization of Double wishbone suspension system for ATVs: Shantanu Garud, Pritam Nagare, Rohit Kusalkar, Vijaysingh Gadhave, Ajinkya Sawant: Volume: 04 Issue: 12 | Dec-2017 e-ISSN: 2395-0056

[3] Experimental & Finite Element Analysis of Left Side Lower Wishbone Arm of Independent Suspension System: Prof. A. M. Patil, Prof. A.S. Todkar, Prof. R. S .Mithari, Prof. V. V. Patil: Volume 7, Issue 2, May. - Jun. 2013 e-ISSN: 2278-1684

[4] Response surface optimization of the operating parameters for a complex distillation column based on process simulation: Honghai Wang, Xiaoying Cui, Rongliang Wang and Chunli Li: Volume 16 2018 Elsevier

[5] Static Structural Analysis & Optimization of Concept Automotive A-Arm: Ashish R. Pawar, Madhuri V. Bodke, Aditya R. Wankhade: Volume 03, Issue 12, December – 2017: ISSN: 2455-1457