Design Optimization for Weight Reduction of Locomotive Wheel using ANSYS

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Abstract – Weight reduction of locomotive wheel is beneficial to reduce manufacturing and material cost without much compromise in strength of wheel. This research is intended to reduce weight in hub region and tread region of locomotive wheel. Finite element analysis is performed using ANSYS software and CAD model of wheel is developed using Creo 2 software. Equivalent stresses and fatigue life of wheel is determined along with safety factor. The design of locomotive wheel is optimized for mass minimization using Response Surface Methodology.

Keywords: Locomotive wheel, weight reduction, FEA, ANSYS

I. INTRODUCTION

A train wheel or rail wheel is a type of wheel specially designed for use on rail tracks. A rolling component is typically pressed onto an axle and mounted directly on a rail car or locomotive or indirectly on a bogie, called a truck. Wheels are cast or forged (wrought) and are heat-treated to have a specific hardness. New wheels are trued, using a lathe, to a specific profile before being pressed onto an axle. All wheel profiles need to be periodically monitored to insure proper wheel-rail interface. Improperly trued wheels increase rolling resistance, reduce energy efficiency and may create unsafe operation. A railroad wheel typically consists of two main parts: the wheel itself, and the tire around the outside. A rail tire is usually made from steel, and is typically heated and pressed onto the wheel, where it remains firmly as it shrinks and cools. Mono block wheels do not have encircling tires, while resilient rail wheels have a resilient material, such as rubber, between the wheel and tire.



Fig 1: Locomotive wheel [1]

Nomenclature of different regions of locomotive wheel can be seen in figure 1 above. Tread and flange are the regions which comes in immediate contact with rail track.

II. PROBLEM DESCRIPTION

Structural and fatigue life analysis of railway wheel is done using Finite Element method. The method involves three stages of analysis i.e. Preprocessing, solution and post-processing.

- Preprocessing stage involves CAD modeling, meshing into elements and nodes (discretization), assigning loads and boundary conditions.
- Solution stage involves matrix formulations, matrix inversions and multiplication, assemblage of element stiffness matrix, global stiffness matrix.
- Postprocessing stage involves viewing results, contour plots, vector plots and optimization of input parameters.

The base design reference is taken from KLW data sheet which provides range of dimensions of hub, tread, flange, rim and web. The dimension ranges of these parameters are provided in figure 2 below.

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Outside diam- eter Ø D, mm	linside diameter Ø d _y , Ø d ₃ mm	of rim H, mm	of hub Ø d, mm	Height of hub L, mm	Diameter of hole in hub Ø d _o mm	Thickness of disk t ₁ , t ₂ , mm	Mass, kg
650-1269	600-1100	95-160	185-500	90-405	60-200	15-80	165-1050
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Fig 2: Wheel dimension range [4]

Table 1 below shows material properties of wheel and axle load. The axle load specified in table 1 below is used for structural and fatigue life analysis.

Table 1: Material properties and Loads

Axle Load	146.2 KN
Young's Modulus	205GPa
Density	7850 Kg/m ³
Ultimate Strength	450MPa
Yield Strength	250MPa

III. FINITE ELEMENT ANALYSIS

The CAD model of locomotive wheel and track is modeled using data reference ranges provided in figure 2. The CAD model developed is 1/4th of actual size to save computational time in meshing and solution.



Fig 3: CAD model of wheel and track

The model is meshed using hexahedral elements and fine sizing as shown in figure 4 below. Number of elements generated is 27461 and number of nodes generated is 4988. Smoothing is set to medium, inflation set to smooth transition, transition ratio .272.



Fig 4: Meshed model of wheel and track

Bottom surface of track is provided with fixed support [c] and right surface of wheel is provided with frictionless support[A] and downward direction force of 146200N is applied on hub as shown in figure 5 below.



Fig 5: Loads and Boundary Conditions

After performing the above steps, the solver is set to run for static structural analysis. Equivalent stress plot and deformation plot are obtained as shown in figure 6 and figure 7 below.



Fig 6: Equivalent stress plot

The fatigue life analysis is performed under fully reversed load as shown in figure 7 and safety factor along with fatigue life is determined. The life is determined in terms of number of cycles.



Fig 7: Fully reversed load

Safety factor is determined and minimum value of safety factor obtained is 3.21 as whown in figure 8 below.



Fig 8: Safety factor

IV. OPTIMIZATION USING RESPONSE SURFACE METHODOLOGY

Response surface methodology (RSM) is a collection of mathematical and statistical techniques for empirical model building[5]. By careful design of experiments, the objective is to optimize a response (output variable) which is influenced by several independent variables (input variables). An experiment is a series of tests, called runs, in which changes are made in the input variables in order to identify the reasons for changes in the output response. When behavior (response, y) that should be taken into consideration for design is determined as a function of multiple design variables (x_i), the behavior in response surface method is expressed by the approximation as a polynomial y =f(x) on the basis of observation data. A quadratic response function with two variables with a regression model is expressed by

 $y=\beta_0+\beta_1x_1+\beta_2x_2+\beta_3x_1^2+\beta_4x_2^2+\beta_5x_1x_2$

where β_0 , β_1 , β_2 , β_3 , β_4 and β_5 are the regression coefficients.

The optimization is performed on 2 design parameters i.e. tread depth (x_1) and tread width (x_2) using response surface methodology. The response surface method (RSM) is a statistical and mathematical method to model approximately and analyze the response surface with the design variables, when the interesting responses are influenced by various design variables. RSM was to use regression methods based on least square methods. In the study, RSM was used to determine the optimum design for the minimization of the weight within the specific life. The significant process variables were identified by using the central composition design (CCD), which is a kind of design of experiments (DOE). Central composite design is the default DOE type. It provides a screening set to determine the overall trends of the metamodel to better guide the choice of options in Optimal Space-Filling Design. The CCD DOE type supports a maximum of 20 input parameters

Table of Schenatic 82: Design of Experiments (Central Composite Design : Auto Defined) 🔹 🕫 🕽							
	A	8	с	D	E	F	G
1	Nane 💌	Update Order 💌	P6 - tread_depth (mm) 💌	P7 - treadwidth (mm) 💌	P4 - Safety Factor Minimum 💌	P5 - Equivalent Stress Maximum (MPa) 💌	P8 - Geometry Mass (kg) 💌
2	1	5	117.42	120	3.2104	26.85	676.28
3	2	4	105.68	120	2.9388	29.331	684.3
4	3	6	129.16	120	3.1069	27.744	668.26
5	4	2	117.42	108	3.2392	26.612	669.15
6	5	8	117.42	132	2.9177	29.544	683.44
7	6	1	105.68	108	3.7218	23.161	678.53
8	7	3	129.15	108	3.3737	25.551	659.65
9	8	7	105.68	132	2.3934	36.016	690.1
10	9	9	129.16	132	1.5598	55.264	676.93

9: Tread depth and tread width optimization

In Central Composite Design (CCD), a Rotatable (spherical) design is preferred since the prediction variance is the same for any two locations that are the same distance from the design center. However, there are other criteria to consider for an optimal design setup. Among these criteria, there are two that are commonly considered in setting up an optimal design using the design matrix. The degree of non-orthogonality of regression terms can inflate the variance of model coefficients. The position of sample points in the design can be influential based on their position with respect to others of the input variables in a subset of the entire set of observations. After DOE, a response surface is generated for all the input and output values using the least squares methodology. The data points are fitted with a standard 2nd order model. The points generated on the response surface are then used to perform the optimization. The goodness of fit plots for all the subsystems are shown below.



Fig 10: Goodness of fit curve

"Goodness of Fit" of a linear regression model describes how well a model fits a given set of data, or how well it will predict a future set of observations. An X-Y Scatter plot illustrating the difference between the data points and the linear fit



Fig 10: Safety factor at different design points

The above graph shows safety factor at different design points (x_1 :tread depth and x_2 :tread width). The safety factor is found to be maximum at design point number 6 for which tread depth is 117.42mm and tread width is 132mm. The safety factor is minimum for point number 9 for which tread depth is 129.16mm and tread width is 132mm.



Fig 11: Equivalent stress at different design points

The equivalent stress is found to be maximum at design point number 9 for which tread depth is 129.16mm and tread width is 132mm and minimum at design point number 6 for which tread depth is 117.42mm and tread width is 132mm.



Fig 12: Geometric mass at different design points

The geometric mass of wheel is found to be maximum at design point 8 for which tread depth is 105.68mm and tread width is 132mm. The geometric mass is minimum at design point 7 for which tread depth is 129.16mm and tread width is 108mm. Contour plots developed through RSM analyze the effect of input variable with respect to one output variable keeping all other variables fixed. Effect of tread depth and tread width on locomotive wheel are analyzed with contour plots.



Fig 13: Response surface chart for safety factor output



Fig 14: Response surface chart for equivalent stress output



Fig 15: Response surface chart for mass optimization

Sensitivities chart are used to graphically view the global sensitivities of each output parameter with respect to input parameter. The global, statistical sensitivities are based on a correlation analysis using generated sample points, which are located throughout the entire space of input parameters.



Fig 16: Local sensitivity graph for safety factor and equivalent stress

As can be seen from figure 16 above for safety factor tread width has more effect in causing variation of safety factor as compared to tread depth. For equivalent stress the tread width has more effect in causing variation of equivalent stress as compared to tread depth. From sensitivity graph. It can be noticed that tread depth has more contribution (near to 52%) in affecting geometric mass of wheel as compared to tread width (near to 48%) in affecting geometric mass of wheel. Mass is optimized using two variables x_1 (tread depth) and x_2 (tread width).

Table 2: Results from response surface

Name	Calculated Minimum 💌	Calculated Maximum 💌
P4 - Safety Factor Minimum	1.5598	3.7218
P5 - Equivalent Stress Maximum (MPa)	22.34	55.264
P8 - Geometry Mass (kg)	659.65	690.1

Maximum and minimum values of output variables (safety factor, equivalent stress, geometric mass) are generated and shown in table 2 below. The minimum geometric mass calculated from RSM 659.65 Kg and maximum geometric mass is 690.1Kg.

IV CONCLUSION

Finite Element Analysis of locomotive wheel is performed using ANSYS 18.1 software package. The design of locomotive wheel is optimized using response surface methodology and input parameters for optimization are tread depth and tread width. The output parameters are equivalent stress, safety factor and geometric mass. The minimized geometric mass is 659.65Kg.

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