



MODELLING AND ANALYSIS OF INDIAN RAILWAY WAGON WHEEL USING ANSYS AND ARTIFICIAL NEURAL NETWORK

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Abstract: In the present study, the wear analysis of an Indian railway wagon wheel (IRWW) was modelled using modelling software CATIA and applied various material combinations and tested for its performance and wear slippage at distinct load applications. In the real-world applications, wear produces wheel-surface slippage, resulting in deformation and movement of the wheel beneath the track surface. To address this issue, a thorough investigation of rolling contact on train wheels was undertaken to lessen the likelihood of failure. In the present investigation, the IRWW was initially designed and modelled in CATIA and uploaded to ANSYS to make the analysis. The stress generated by increasing contact load at rail-wheel assembly in terms of stress, strain, total deformation, and safety factor were determined for various load applications. Later, the acquired results were validated using the Artificial Neural Network (ANN) of Machine Learning (ML) Approach. The results showed that the overall deformation applied under various loads was within the limit.

Keywords: CATIA, ANSYS, stress, strain, total deformation, IRWW, ANN

1. INTRODUCTION

In 1825, the world's first train crossed the English countryside between Stockton and Darlington. R.M. Stephenson proposed the establishment of India's railway system (IRS) in 1844, and the East India Company (EIC) agreed. Various researchers executed distinct types of analysis using different modelling software like CATIA, SOLIDWORKS, ANSYS etc., with various loads. The wear phenomena should be focused on their impact on environmental costs and operational efficiency, with various experimental trials. A smartphone app uses convolutional neural networks to detect and classify railway wheel defects. Users take photographs of the wheels, which are evaluated by a trained convolutional neural networks (CNN) model. The app generates bar graphs for maintenance personnel, and reliability is assessed using metrics like accuracy, precision, recall, and F1 score [1]. The Anchor-Free YOLOv8 (AFYv8) model, a deep learning-based classifier, has been proposed as a replacement for human wheel inspection in the Train Rolling Stock Examination (TRSE). Tests show that the model detects TRSEs with 10% higher accuracy than previous classifiers, potentially increasing railway safety and reducing operational disruptions [2]. Two machine learning methods are proposed to detect wheel defects in railway wagons, reducing noise and vibration emissions. The first uses distinct features to anticipate issues, while the second uses CNN [3]. Robotic systems are increasingly utilized in manufacturing to reduce costs, increase efficiency, and improve product and service. These automated machines, built with artificial intelligence and machine learning algorithms, are beneficial investments in automotive plants and hazardous environments like explosive disarming and radioisotope monitoring [4]. An enhanced YOLOv3 framework has been developed for rail wheel surface defect identification, achieving an average accuracy of 0.92, addressing the challenge of accurately classifying and positioning flaws [5]. A Deep Learning (DL) technique uses smartphone photos to identify tire tread flaws, enhancing automated predictive maintenance by reducing lead time and engineering hours, thereby ensuring railroad vehicle safety and rolling-stock asset lifespan [6]. The Indian Railway is developing a prototype railway coach to reduce maintenance costs and improve reliability, using event-driven maintenance approaches and ultrasonic vibration intensity to identify defects and prevent mishaps [7]. The study uses CAD models and FEA to analyse rail-wheel fatigue life under increasing axle loads and railway infrastructure growth, highlighting the importance of rail-wheel quality and physical contact [8]. The study explores the link between noise propagation, rail safety, and wheel wear on rolling stock, emphasizing the importance of detecting cracks early to prevent potential hazards [9]. The study examines the interface between railroad car wheels and rails, focusing on contact stresses from mechanical loads. It uses analytical and experimental techniques, including ANSYS's finite elements method, to evaluate wheel performance and wear estimation [10].



The project involves creating a 90-ton pay load trolley for cylindrical specimen transportation using propellants, using Ansys for structural analysis, Unigraphics for 3D modelling, and manual calculations [11]. Researchers and railroad businesses are using AutoCAD and Pro-E modelling programs, Universal Mechanism, and ANSYS to create virtual prototypes for predicting dynamic hopper wagon behaviour [12]. The study investigates the interaction between IRS-T12 rail wheels and UIC-60 using hand calculations and ANSYS. It compares manually estimated stresses and a three-dimensional finite element model, comparing results with hand calculations. Further analysis is recommended [13]. The study uses ANSYS and a three-dimensional finite element study to analyse the impact of axle load and train speed on rail junction performance, suggesting modifications to rail design [14]. The study investigated the impact of wheel re-profiling on deformations and stresses resulting from mechanical and thermal loads on a rail loco wheel using ANSYS software [15].

II. MATERIALS

2.1 Chemical compositions and Specifications

In the present work, the list of materials mentioned in Table-1 are considered for analysis in ANSYS after the IRWW was designed and modelled in CATIA. The nominal chemical composition of various materials and their specifications are summarized for the listed materials in the next Tables.

Table-1: List of various materials used for analysis in ANSYS

MATERIAL NUMBER	MATERIAL NAME	FEATURES
M-I	HIGH CARBON STEEL-1095	Hardened and tempered
M-II	HIGH CARBON STEEL-1340	Hardened and tempered
M-III	LOW ALLOY STEEL-4135	Hardened and tempered
M-IV	ALLOY STEEL, TRIP, YS450	-----

2.2 MATERIAL - I: (HIGH CARBON STEEL – 1095)

HCS-1095 steel, a high-carbon steel, is heat-treated by hardening (heating and quenching) and tempering to obtain hardness and toughness, making it ideal for applications that require sharp edges and edge retention. The Chemical composition and specifications of material-II (HCS-1095) are listed in Table-2 and Table-3.

Table 2: Chemical Composition of Material-I (HCS- 1095 hardened & tempered) in wt.%

Elements	Carbon	Manganese	Silicon	Phosphorus	Sulphur	Iron
Acronym	C	Mn	Si	P	S	Fe
HCS- 1095 Hardened and Tempered	0.90-1.03	0.30-0.50	0.15-0.35	Max 0.040	Max 0.050	0.25

HCS-1095 steel is plain carbon steel, meaning it primarily relies on carbon for its strength and hardenability, with manganese and silicon present in small amounts.

Table 3: Specifications of Material-I (HCS-1095 Hardened & tempered)

Material	Youngs Modulus (MPa)	Poisson's ratio	Bulk Modulus (MPa)	Shear Modulus (MPa)	Tensile Yield Strength (MPa)	Tensile Ultimate Strength (MPa)	Density (Kg/m3)	Coefficient of Thermal Expansion (/ °C)
HCS-1095 (Hardened & tempered)	221800	0.29	176030	85969	1042	1480	7850	0.000007457

2.3 MATERIAL -II (HIGH CARBON STEEL-1340)

HCS-1340 steel is a carbon-manganese alloy that can be hardened and tempered. The Chemical composition and specifications of material-II (HCS-1340) are listed in Table-4 and Table-5. It normally includes 0.38-0.43% carbon and 1.60 -1.90% manganese.

Table 4: **Chemical Composition** of Material-II (HCS- 1340 hardened & tempered)

Elements	Carbon	Manganese	Silicon	Iron
Acronym	C	Mn	Si	Fe
HCS- 1340 Hardened and Tempered	0.38-0.43 %	1.60-1.90 %	0.15-0.35 %	remaining %

Table 5: **Specifications** of Material-II (HCS-1340 Hardened & tempered)

Material	Youngs Modulus (MPa)	Poisson's ratio	Bulk Modulus (MPa)	Shear Modulus (MPa)	Tensile Yield Strength (MPa)	Tensile Ultimate Strength (MPa)	Density (Kg/m ³)	Coefficient of Thermal Expansion (/°C)
HCS-1340 (Hardened & tempered)	207400	0.29	164600	80388	1584	1798	7850	0.00001195

2.4 MATERIAL -III (LOW ALLOY STEEL-4135)

LAS-AISI 4135 steel is well-known for its high strength-to-weight ratio and improved qualities brought about by heat treatment, particularly hardening and tempering, which makes it appropriate for a range of applications needing strong material performance. The Chemical composition and specifications of MATERIAL-III (**Low Alloy Steel-4135**) are listed in Table-6 and Table-7.

Table 6: **Chemical** Composition of Material-III (Low Alloy 4135 Steel Hardened and Tempered)

Acronym	C	Mn	Si	P	Cr	Fe	Mo
Low Alloy Steel - 4135 Hardened and Tempered	0.33-0.38	0.70-0.90	0.15-0.35	≤ 0.035	0.80-1.10	97-98	0.15-0.25

Table 7: **Specifications** of Material-III (Low Alloy Steel- 4135, Hardened and Tempered)

Material	Youngs Modulus (MPa)	Poisson's ratio	Bulk Modulus (MPa)	Shear Modulus (MPa)	Tensile Yield Strength (MPa)	Tensile Ultimate Strength (MPa)	Density (Kg/m ³)	Coefficient of Thermal Expansion (/ °C)
Low Alloy Steel-4135 (Hardened and Tempered)	221060	0.3265	203100	79382	915.2	1090	7850	0.00001273

2.5 MATERIAL -IV (ALLOY STEEL, TRIP, YS450)

YS450-steel alloyed with vanadium, molybdenum, and chromium. Aircraft and missile components are among the uses for it that call for great strength, durability, and resistance to heat and wear. The Chemical composition and specifications of MATERIAL-IV (**Alloy steel, TRIP, YS450**) are listed in Table-8 and Table-9.

Table 8: **Chemical** Composition of Material-IV (Alloy steel, TRIP, YS450)

Elements	Carbon	Manganese	Silicon	Phosphorus	Aluminum	Chromium	Sulphur	Nickel	Molybdenum
Acronym	C	Mn	Si	P	Al	Cr	S	Ni	Mo
Alloy steel, TRIP, YS450	0.10-0.25	1.5-2.5	0.5-1.5	≤ 0.03	0.01-0.10	0.1-0.5	≤ 0.01	0-0.5	0 - 0.15

Table 9: **Specifications** of Material-IV (Alloy steel, TRIP, YS450)

Material	Youngs Modulus (MPa)	Poisson's ratio	Bulk Modulus (MPa)	Shear Modulus (MPa)	Tensile Yield Strength (MPa)	Tensile Ultimate Strength (MPa)	Density (Kg/m ³)	Coefficient of Thermal Expansion (C ⁻¹)
Alloy steel, TRIP, YS450	221800	0.3	184800	85308	519.6	837.9	7850	0.00001196



III. DESIGN OF WHEEL IN CATIA

The internal components of the IRWW are shown in Figure 3.1, and its modelling in shown in Figure 3.1(a) to Figure 3.2 (h). In general, the actual railway wagon wheel is made without any slots in it, in the present design a hexagonal slot is introduced to check its performance and reduction of weight and save the material while fabrication.

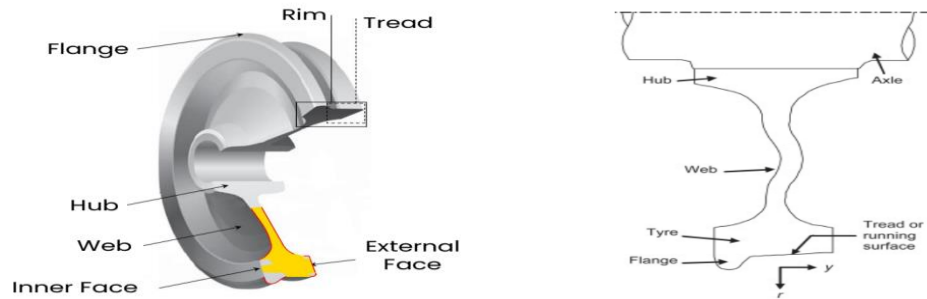
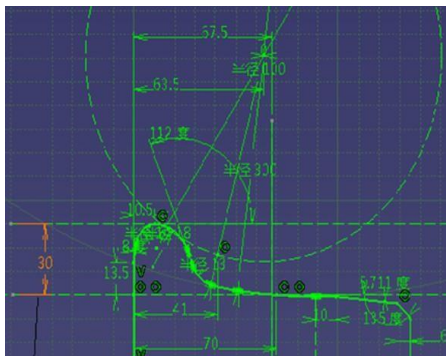
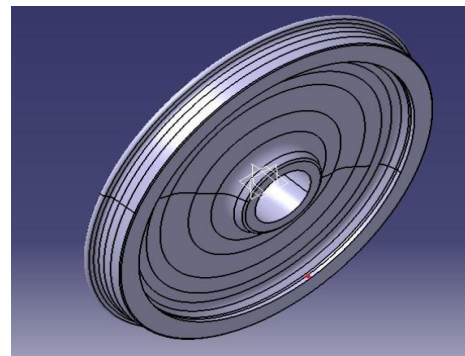


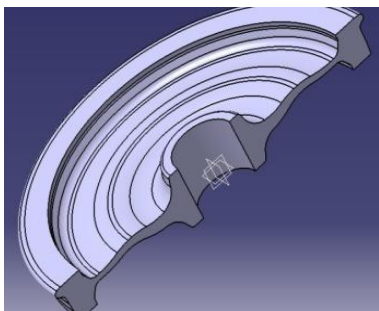
Figure 3.1: Nomenclature of IRWW



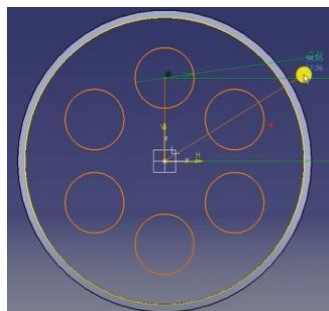
(a) 2D illustration of the IRWW



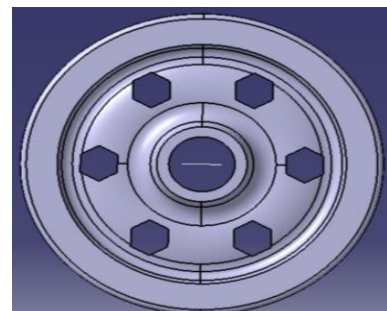
(b) External Part of the IRWW



(c) Sectional Analysis of the IRWW.



(d) Slot creation in 2D sketch.



(e) Reduction of material through design

(f)

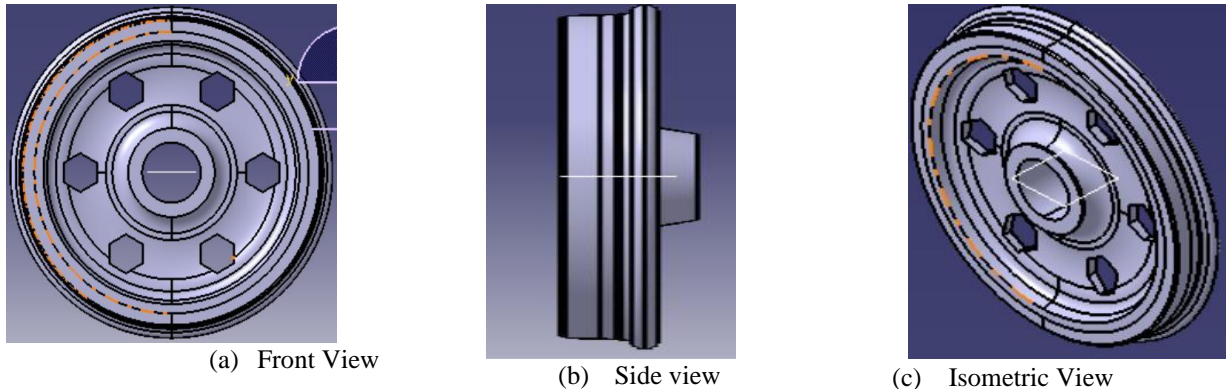


Figure 3.2: Modelling of Railway wagon wheel with Array of slot

IV. FINITE ELEMENT ANALYSIS OF WHEEL USING ANSYS

ANSYS, developed by John Swanson in 1970, is a finite element analysis (FEA) software that saves time and money in product evaluation, ensuring precise and effective product development. ANSYS helps engineers understand how their products work under real-world conditions, using numerical approaches for civil structure and mechanical product design.

4.1 BOUNDARY CONDITIONS

Material properties like Density, Young's Modulus, Tensile Yield Strength and other details are shown in Figure-4.1. In the present analysis the meshing is done by selecting the Tetrahedra element with 5 mm size of the element. The meshing details like mesh quality, element size, number of nodes and other details are shown in Figure-4.2. The contact details between rail and wheel are described in Figure-4.3. The Force and Displacement details are described in Figure -4.4 and Figure-4.5.

Details of "Carbon steel, 1340, hardened & temp..."	
Common Material Properties	
Density	7850 kg/m ³
Young's Modulus	2.074e+11 Pa
Thermal Conductivity	49.75 W/m.°C
Specific Heat	478.3 J/kg.°C
Tensile Yield Strength	1.584e+09 Pa
Tensile Ultimate Strength	1.798e+09 Pa
Nonlinear Behavior	True
Full Details	Click To View Full Details
Statistics	
Assigned Bodies	2

Figure 4.1: Properties of Materials

Details of "Mesh"		Quality	
Display		Check Mesh Quality	Yes, Errors
Display Style	Use Geometry Set	Error Limits	Aggressive Mechanic
Defaults		<input type="checkbox"/> Target Element Quality	Default (5.e-002)
Physics Preference	Mechanical	Smoothing	Medium
Element Order	Program Controlled	Mesh Metric	None
<input type="checkbox"/> Element Size	5.0 mm	Inflation	
Sizing		Advanced	
Use Adaptive Sizing	Yes	Number of CPUs for Parallel Processing	Program Controlled
Resolution	7	Straight Sided Elements	No
Mesh Defeaturing	Yes	Rigid Body Behavior	Dimensionally Reduced
<input type="checkbox"/> Defeature Size	Default	Triangle Surface Mesher	Program Controlled
Transition	Fast	Topology Checking	Yes
Span Angle Center	Fine	Pinch Tolerance	Please Define
Initial Size Seed	Assembly	Generate Pinch on Reference	No
Bounding Box Diagonal	1992.8 mm	Statistics	
Average Surface Area	41661 mm ²	<input type="checkbox"/> Nodes	1696489
Minimum Edge Length	2.3362e-003 mm	<input type="checkbox"/> Elements	1062406

Figure 4.2: Meshing of Wheel

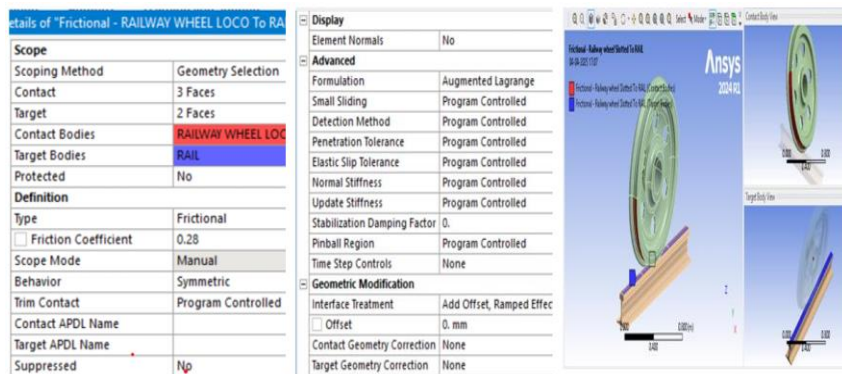


Figure 4.3: Details of contact information between two bodies

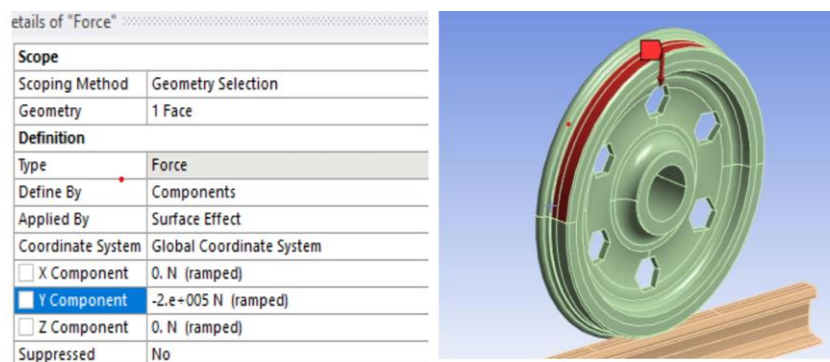


Figure 4.4: Details of Force application

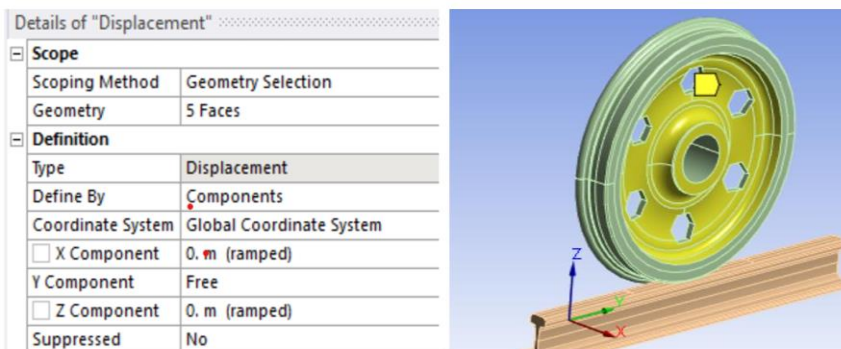


Figure 4.5: Details of Displacement

V. MACHINE LEARNING

Machine Learning (ML) has been defined in a variety of formal ways. Alpaydin (2016) described machine learning as "using example data or prior experience to program computers to optimize a performance criterion." Burkov (2019) stated ML as "a branch of computer science that allows computer programs to conduct planning, diagnosis, prediction, and behaviour pattern recognition by learning from historical data, i.e., without prior knowledge."

5.1 ARTIFICIAL NEURAL NETWORK (ANN)

An artificial neural network (ANN) is a computational model that processes input data through layers of interconnected neurons or nodes to predict output. It can execute classification and regression tasks, with one task common for each network.

ANNs can be classified as supervised or unsupervised based on their learning type. They learn basic principles from symbolic situations rather than human-established laws. ANNs are widely used in various industries due to their ability to learn from examples, making them beneficial for systems with large amounts of complex and ambiguous information. The layers consist of an input, hidden, and output layer.

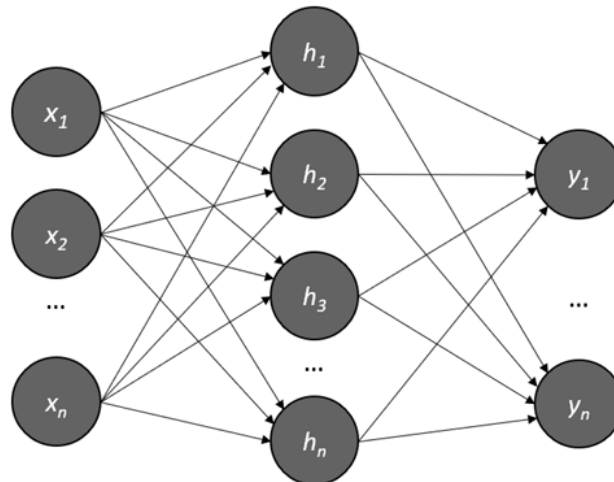


Figure 5.1: Diagram of Artificial Neural Network

VI. METHODOLOGY

The flow chart of the modelling and analysis of the present work is described in Figure 6.1, where the work is carried out in three stages.

In Stage-I, the modelling and design of the railway wagon wheel was done using the modelling CATIA software, Later in Stage-II, the outcomes from the CATIA were uploaded to ANSYS and the analysis part of the wagon wheel has been carried out at various load applications with different materials.

Further, in Stage-III of the work, the obtained results from the ANSYS analysis at different loads for different materials are summarised and taken as input data and are submitted to the ANN module of MATLAB, to analyse the outcomes, by training, testing and validating the ANSYS results with the help of neural network.

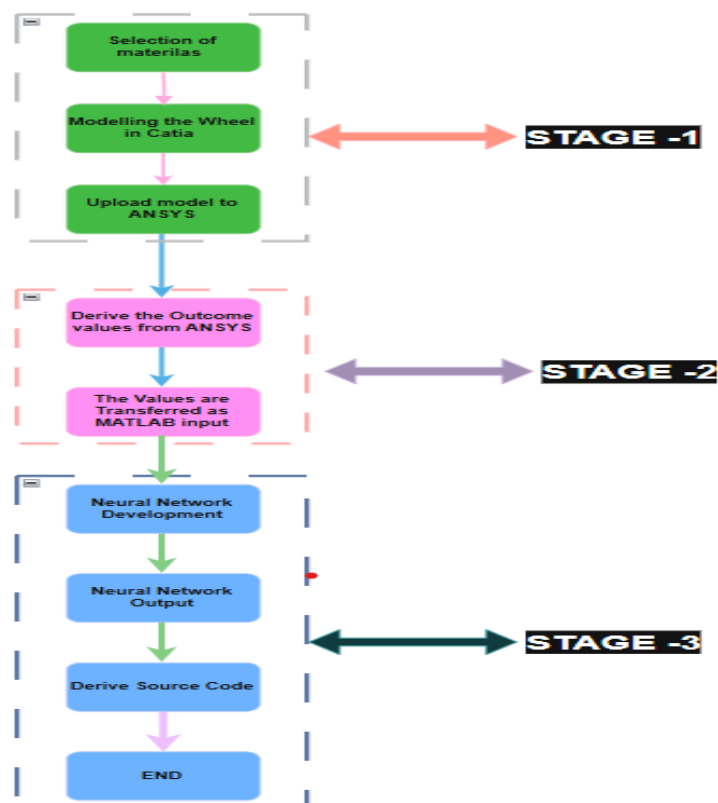


Figure 6.1: Flowchart of methodology of work

VII. RESULTS AND DISCUSSIONS

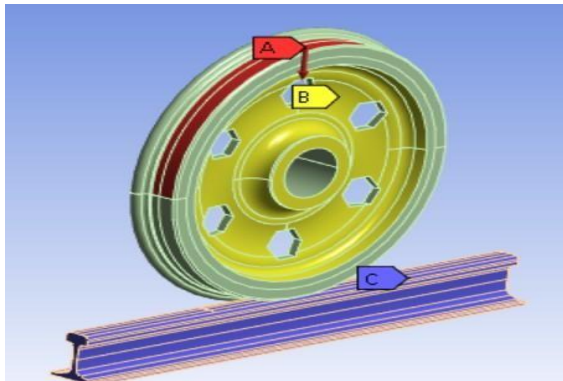


Figure 7.1: Load Application of 90000N

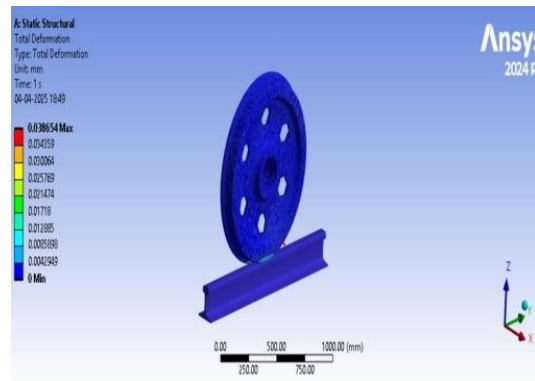


Figure 7.2: Total Deformation (at 90000N)

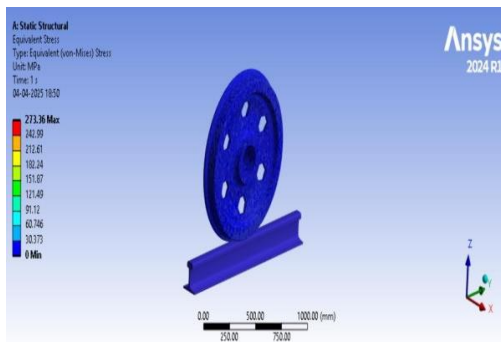


Figure 7.3: Equivalent (von-mises) Stress (at 90000N)

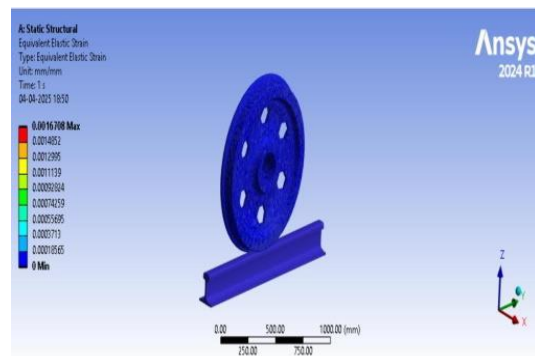


Figure 7.4: Equivalent Elastic Strain (at 90000N)

Table 7.1: Total deformation of Materials at various loads

Load (KN)	HCS- 1095 (Hardened & Tempered)	HCS-1340 (Hardened & Tempered)	Alloy steel, TRIP YS 450	LOW ALLOY STEEL 4135 (Hardened & Tempered)
90	0.08665	0.085252	0.08309	0.0852226
180	0.12176	0.12323	0.1202	0.1232000
270	0.15353	0.15707	0.13729	0.1569700
360	0.18445	0.1885	0.18356	0.1882300
450	0.21232	0.21827	0.21237	0.2177400
540	0.23893	0.24627	0.23953	0.2454600
630	0.26425	0.2728	0.26513	0.2716500



7.1 ANN RESULTS

INPUTS									
FORCE ANALYSIS									
	Youngs	Poisson's	Bulk	Shear	Tensile Yield	Tensile Ultimate	Density (Kg/m3)	Coefficient of Thermal Expansion	Load(KN)
HCS-1095	221800	0.29	176030	85969	1042	1480	7850	0.00007457	90
	221800	0.29	176030	85969	1042	1480	7850	0.00007457	180
	221800	0.29	176030	85969	1042	1480	7850	0.00007457	270
	221800	0.29	176030	85969	1042	1480	7850	0.00007457	360
	221800	0.29	176030	85969	1042	1480	7850	0.00007457	450
	221800	0.29	176030	85969	1042	1480	7850	0.00007457	540
HCS-1340	207400	0.29	164600	80388	1584	1798	7850	0.00001195	90
	207400	0.29	164600	80388	1584	1798	7850	0.00001195	180
	207400	0.29	164600	80388	1584	1798	7850	0.00001195	270
	207400	0.29	164600	80388	1584	1798	7850	0.00001195	360
	207400	0.29	164600	80388	1584	1798	7850	0.00001195	450
	207400	0.29	164600	80388	1584	1798	7850	0.00001195	540
LA-4135	221060	0.3265	203100	79382	915.2	1090	7850	0.00001273	90
	221060	0.3265	203100	79382	915.2	1090	7850	0.00001273	180
	221060	0.3265	203100	79382	915.2	1090	7850	0.00001273	270
	221060	0.3265	203100	79382	915.2	1090	7850	0.00001273	360
	221060	0.3265	203100	79382	915.2	1090	7850	0.00001273	450
	221060	0.3265	203100	79382	915.2	1090	7850	0.00001273	540
Alloy trip	221800	0.3	184800	85308	519.6	837.9	7850	0.00001196	90
	221800	0.3	184800	85308	519.6	837.9	7850	0.00001196	180
	221800	0.3	184800	85308	519.6	837.9	7850	0.00001196	270
	221800	0.3	184800	85308	519.6	837.9	7850	0.00001196	360
	221800	0.3	184800	85308	519.6	837.9	7850	0.00001196	450
	221800	0.3	184800	85308	519.6	837.9	7850	0.00001196	540

Figure 7.5: Input Data-I

INPUTS									
ROTATIONAL VELOCITY ANALYSIS									
	Youngs	Poisson's	Bulk	Shear	Tensile Yield	Tensile Ultimate	Density (Kg/m3)	Coefficient of Thermal Expansion	Load(KN)
HCS-1095	221800	0.29	176030	85969	1042	1480	7850	0.00007457	70
	221800	0.29	176030	85969	1042	1480	7850	0.00007457	120
	221800	0.29	176030	85969	1042	1480	7850	0.00007457	170
	221800	0.29	176030	85969	1042	1480	7850	0.00007457	220
	221800	0.29	176030	85969	1042	1480	7850	0.00007457	270
	221800	0.29	176030	85969	1042	1480	7850	0.00007457	320
HCS-1340	207400	0.29	164600	80388	1584	1798	7850	0.00001195	70
	207400	0.29	164600	80388	1584	1798	7850	0.00001195	120
	207400	0.29	164600	80388	1584	1798	7850	0.00001195	170
	207400	0.29	164600	80388	1584	1798	7850	0.00001195	220
	207400	0.29	164600	80388	1584	1798	7850	0.00001195	270
	207400	0.29	164600	80388	1584	1798	7850	0.00001195	320
LA-4135	221060	0.3265	203100	79382	915.2	1090	7850	0.00001273	70
	221060	0.3265	203100	79382	915.2	1090	7850	0.00001273	120
	221060	0.3265	203100	79382	915.2	1090	7850	0.00001273	170
	221060	0.3265	203100	79382	915.2	1090	7850	0.00001273	220
	221060	0.3265	203100	79382	915.2	1090	7850	0.00001273	270
	221060	0.3265	203100	79382	915.2	1090	7850	0.00001273	320
Alloy trip	221800	0.3	184800	85308	519.6	837.9	7850	0.00001196	70
	221800	0.3	184800	85308	519.6	837.9	7850	0.00001196	120
	221800	0.3	184800	85308	519.6	837.9	7850	0.00001196	170
	221800	0.3	184800	85308	519.6	837.9	7850	0.00001196	220
	221800	0.3	184800	85308	519.6	837.9	7850	0.00001196	270
	221800	0.3	184800	85308	519.6	837.9	7850	0.00001196	320

Figure 7.6: Input Data-II



OUTPUTS			
FORCE ANALYSIS			
	TOTAL DEFORMATION	Equivalent Strain	Equivalent Stress
HCS-1095	0.08665	0.0045261	890.78
	0.12176	0.0049687	976.25
	0.15353	0.0052236	1060.6
	0.18445	0.0054531	1108.2
	0.21232	0.0054388	1111.3
	0.23893	0.0053342	1082.2
HCS-1340	0.26425	0.005387	1112.7
	0.085252	0.0043105	861.57
	0.12323	0.0050047	1004.6
	0.15707	0.0053383	1075.5
	0.1885	0.0053539	1102.8
	0.21827	0.005333	1107.7
LOW ALLOY STEEL 4135	0.24627	0.0054001	1115.3
	0.2728	0.0053767	1116.1
	0.0852226	0.00043095	861.65
	0.1232000	0.0055025	1116.5
	0.1569700	0.0064631	1325.2
	0.1882300	0.0072311	1493.5
Alloy Trip YS 450	0.2177400	0.0075912	1563.8
	0.2454600	0.0076839	1587.7
	0.2716500	0.0078434	1622.6
	0.08309	0.0041369	830.22
	0.1202	0.0052991	1078.6
	0.13729	0.0062369	1282.2
	0.18356	0.0070587	1461.1
	0.21237	0.007705	1603.1
	0.23953	0.0082242	1717.4
	0.26513	0.0083635	1741.1

Figure 7.7: Output Data-I

OUTPUTS			
ROTATIONAL VELOCITY ANALYSIS			
	TOTAL DEFORMATION	Equivalent Strain	Equivalent Stress
HCS-1095	0.027378	0.00012606	24.817
	0.080458	0.00037045	72.931
	0.16147	0.00074347	146.37
	0.27043	0.0012451	245.13
	0.40732	0.0018754	369.21
	0.57214	0.0026343	518.62
HCS-1340	0.76491	0.0035218	693.35
	0.028041	0.00012911	24.817
	0.0820405	0.00037942	72.931
	0.16538	0.00076147	146.37
	0.27697	0.0012753	245.13
	0.41718	0.0019208	369.21
LOW ALLOY STEEL 4135	0.58599	0.0026981	518.62
	0.78342	0.0036071	693.35
	0.02838	0.0001321	25.138
	0.083403	0.00038822	73.875
	0.16739	0.00077914	148.26
	0.28033	0.0013049	2483.3
Alloy Trip YS 450	0.42223	0.0019654	373.99
	0.59309	0.0027607	525.33
	0.69309	0.0027607	625.33
	0.02742	0.0001266	24.92
	0.08058	0.00037208	73.235
	0.16172	0.00074674	146.98
	0.27084	0.0012506	246.15
	0.40794	0.0018836	370.75
	0.57301	0.0026459	506.8
	0.76605	0.0027145	532.03

Figure 7.8: Output Data-II

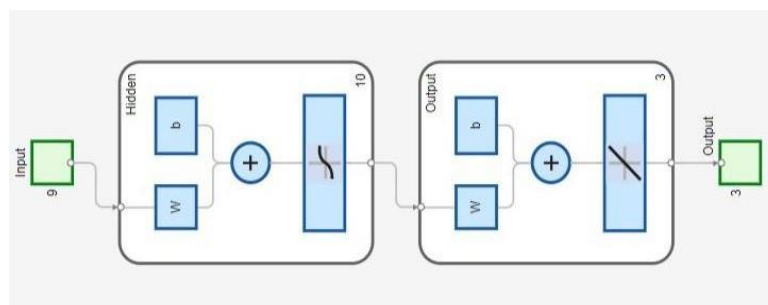


Figure 7.9: Neural Network for the given input and output in ANN

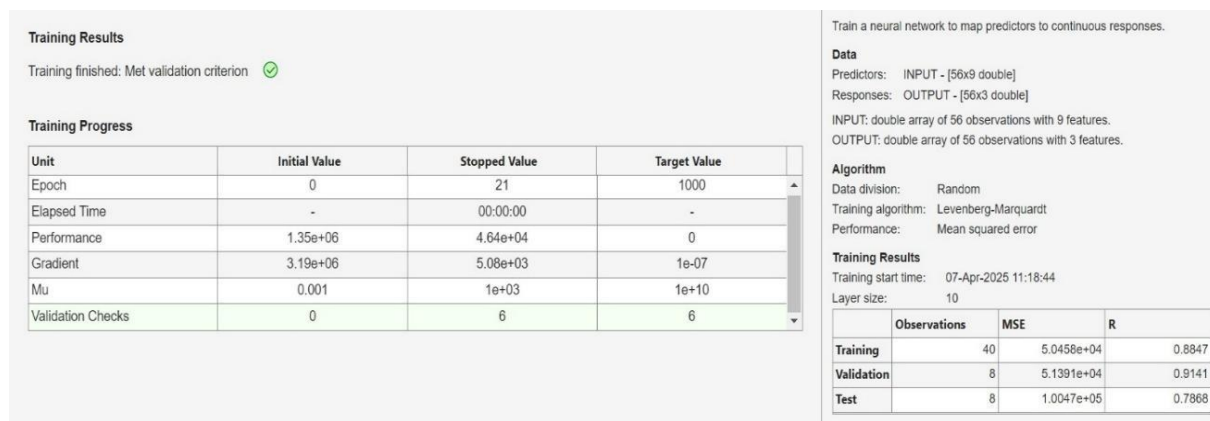


Figure 7.10: Details of Training

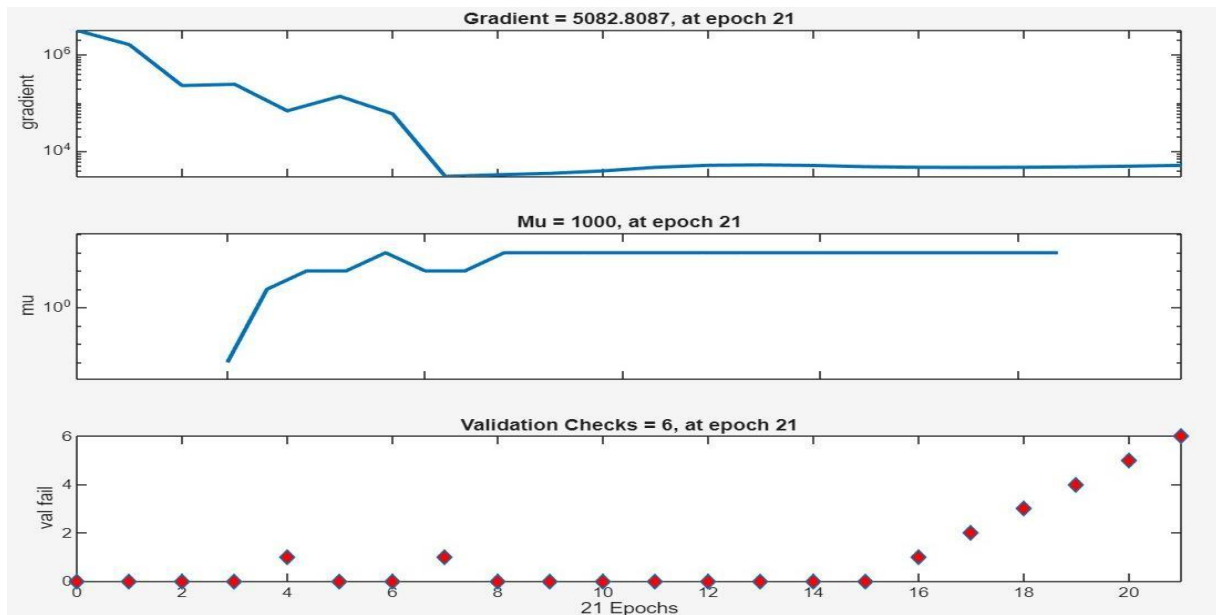


Figure 7.11: Details of Training state plot

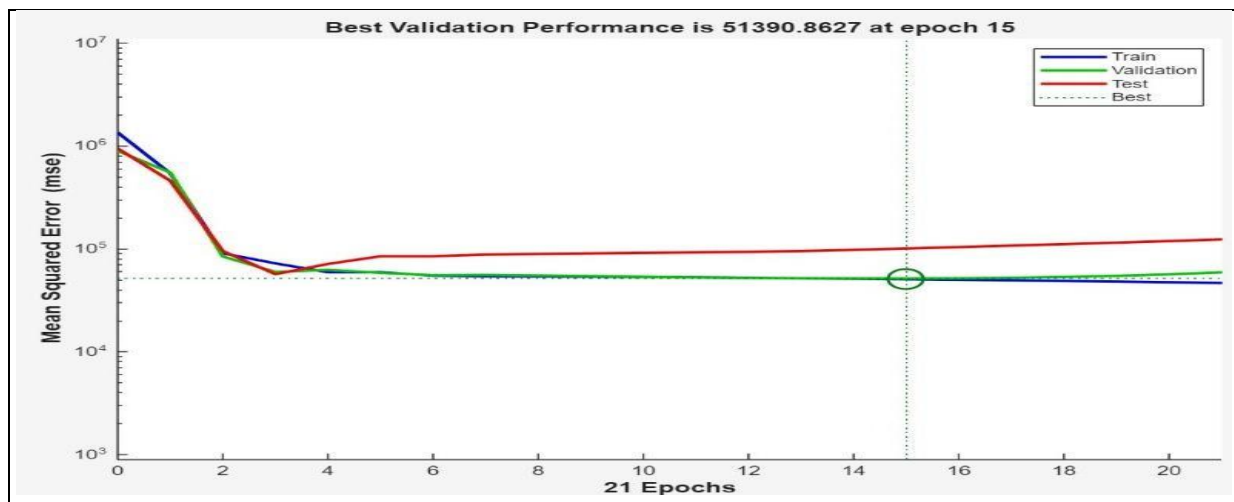


Figure 7.12: Details of Performance plot

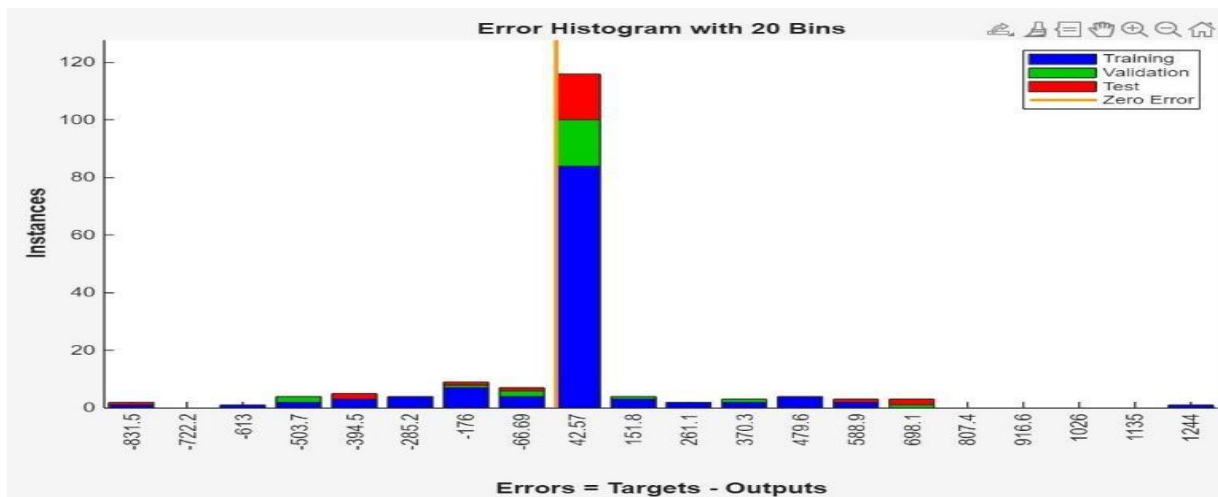


Figure 7.13: Details of Error Histogram plot

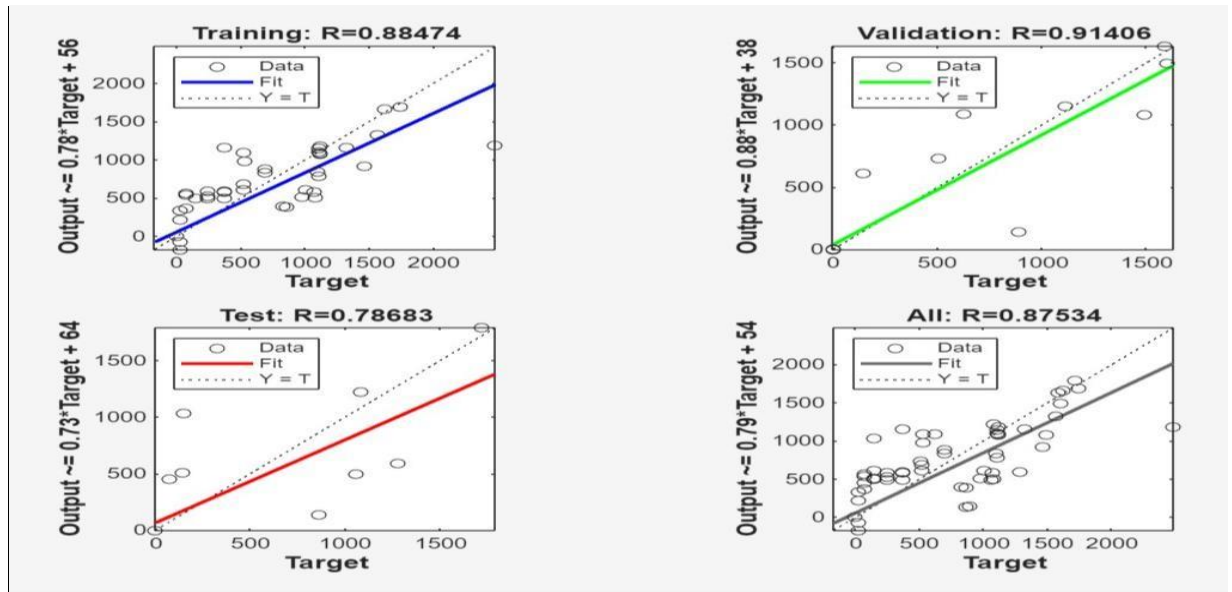


Figure 7.14: Details of Regression plot

I. 7.2 SOURCE CODE (FROM MATLAB V2024A, MODULE: ANN)

```
function [y1] = myNeuralNetworkFunction(x1)
%MYNEURALNETWORKFUNCTION neural network simulation function.
%
% Auto-generated by MATLAB, 07-Apr-2025 11:22:12.
%
% [y1] = myNeuralNetworkFunction(x1) takes these arguments:
% x = Qx9 matrix, input #1
% and returns:
% y = Qx3 matrix, output #1
% where Q is the number of samples.
%#ok<*RPMT0>
% ===== NEURAL NETWORK CONSTANTS =====
% Input 1
x1_step1.keep = [1 2 3 4 5 6 8 9];
x1_step2.xoffset = [207400;0.29;164600;79382;519.6;837.9;7.457e-06;70];
x1_step2.gain = [0.000138888888888889;54.7945205479452;5.1948051948052e-
05;0.00030362835888872;0.00187899285982713;0.0020831163420477;379290.726341741;0
.00357142857142857];
x1_step2.ymin = -1;
% Layer 1
b1 = [2.0412053139549688474; -0.2289250638755573608; -0.97687632213923136781;
0.83520793051493891213; -0.59934839464145728272; 0.17870063912304010034; -
0.0066480182145796798757; -2.2160574531713472801; -1.4544052144899062284; -
1.7590711682512947256];
IW1_1 = [-0.48165228782056979107 -0.46879196744328816004 0.30527175360904384993 -
1.2862960791974353825 0.6664508546287243318 0.22987577491575769684
1.1166718566081743624 -0.017711412789539526802;2.1172213244337432236
1.1433636082665481482 1.2633717693328527787 -0.20154641648400742349
0.783645288556616193 -0.39406305145958026026 -0.36682259151261692454 -
1.0377539732898988234;0.092287347672370151352 -0.80174023555775864036 -
0.63738923891680943079 0.78681023132970073775 -0.88434204378670877578 -
1.0279018589760895441 -0.38500534176722200908 -0.014262224368714509007;-
0.36254693132449133941 -0.092210759908535305795 -0.43293261919675646299 -
1.1535806318214756327 -0.43424707823376318405 0.38872488575582098136 -
0.90185248375956894584 0.90915882631711764095;-0.074257035433323834162 -
0.74025802914313409975 0.53600448420896096291 -0.20601923802526678209 -
```




```

0.77358500305430855093      0.8299619674539366887      0.0048684386148264910399
2.3552667878391999601;0.84393219259521856657      0.86195746082689717049
0.16756140178933243146      0.21592137950951195702      0.089003264199754017483      -
0.86255331847576155457      0.82340564875599053796      -
0.91388328776363081385;1.0655941270881019722      -1.0018612334218812698      -
0.33902986000414764289      0.73304825217700120277      -0.041089417533779100389      -
1.1811898114749452837      -0.44928846976385783396      0.38876999450814264669;-
0.94067819664236274058      0.80299073409340537832      0.73191804095544810149
0.13195416209148039255      -0.46646005771781590132      0.63656813102463438714      -
0.84744641285026001132      -2.8266728747779539255;0.13306836630104171282      -
0.20935571225587878974      1.0032434711329090149      -0.94731162197002205527
0.40178670056413989808      -0.24121056895245387985      0.98998873241162488323
0.13875072701487844995;0.13618751578376500633      -0.79796368604783707301      -
0.73613500433561618319      1.0873232606794263067      0.54207163834050164919
0.83532249023909699304 -0.59044765787523478817 -0.81286891981422926268];
% Layer 2
b2 = [0.4747542805386367748; 0.89383198643441841291; -0.82960827788093349788];
LW2_1 = [-0.45022337021532837786      -0.0046777386626125757804
0.44649062972765529711      0.10057976805617939442      0.61686436431957547555      -
0.57191657208299362392      -0.97229536598786281409      -0.50164063888124532653
0.66152154821583675215      -0.23919305918712108205;      -0.98797807691682537623
0.07568572897235241459      0.33617188672337705579      0.91974998303486954487
0.96906471351055722963      -0.93073970824803597957      -0.052578526121875537869      -
0.22715437958339199098      0.64929365314014286792      0.85173693717976872719;-
0.13025603929287654648      -0.36170060616903171313      -0.23658817126591971669      -
1.0080260763084918363      0.75019322438115310092      0.59500209942920978534      -
0.43672898091726752856      -1.4535478963979320266      0.15972675852792028728
0.87874527330932128422];
% Output 1
y1_step1.ymin = -1;
y1_step1.gain = [2.64535568129813;242.79387770958;0.000813509794454548];
y1_step1.xoffset = [0.027378;0.00012606;24.817];
% ===== SIMULATION =====
% Dimensions
Q = size(x1,1); % samples
% Input 1 x1 = x1';
xp1 = removeconstantrows_apply(x1,x1_step1); xp1 = mapminmax_apply(xp1,x1_step2);
% Layer 1
a1 = tansig_apply(repmat(b1,1,Q) + IW1_1*xp1);
% Layer 2
a2 = repmat(b2,1,Q) + LW2_1*a1;
% Output 1
y1 = mapminmax_reverse(a2,y1_step1); y1 = y1';
end
% ===== MODULE FUNCTIONS =====
% Map Minimum and Maximum Input Processing Function function y = mapminmax_apply(x,settings)
y = bsxfun(@minus,x,settings.xoffset); y = bsxfun(@times,y,settings.gain);
y = bsxfun(@plus,y,settings.ymin); end
% Remove Constants Input Processing Function function y = removeconstantrows_apply(x,settings) y =
x(settings.keep,:);
end
% Sigmoid Symmetric Transfer Function function a = tansig_apply(n,~)
a = 2 ./ (1 + exp(-2*n)) - 1; end
% Map Minimum and Maximum Output Reverse-Processing Function function x =
mapminmax_reverse(y,settings)

```



```
x = bsxfun(@minus,y,settings.ymin); x = bsxfun(@rdivide,x,settings.gain); x = bsxfun(@plus,x,settings.xoffset);
end
```

VIII. DISCUSSION

Research on railway wagon wheels aims to improve wheel-rail contact, minimize the noise and wear, increase safety, and maximize the performance, including investigating novel materials and designs. Both the original profile and the modified wheel-in have undergone examination, where the material in the inner structure optimized. Additionally, these two studies' outcomes are contrasted. Plotting of displacements and stresses against the wheel is done, and observed that,

- When the load changes, there is very tiny variation in strain, stress, and total deformation.
- There is very small variation in total deformation, strain, and stress, as the applied force varies.
- The natural frequency variations in modal analysis result in very slight variations in total deformation, strain, and stress.

IX. CONCLUSION

In this practice, 3D Rail-Wheel (R/W) contact static analysis, fatigue, elastic strain, and equivalent von-mises stresses are analysed using MATLAB. To guarantee accurate findings, boundary conditions and realistic-FE loading are applied. The total deformation, equivalent strain, equivalent stress (von mises), and level all affect how long tiredness lasts.

MATLAB enhances earlier techniques for simulating, modelling, and evaluating rail-wheel contact mechanics. Sometimes, traditional methods and computer approaches yield static results without considering the full rolling motion of the wheel. MATALB is used to calculate stress, employing a sub-modelling technique for increased speed and precision. The fatigue life is calculated using the stress history.

A critical plane method for multi-axial fatigue life prediction is presented in this paper. Unlike earlier models that just considered stress, the current critical plane model takes material properties and stress into account. The fatigue start life of wheel/rail contact issues are predicted using the new multi-axial fatigue model, and after the analysis the following conclusions are derived.

- ❖ The stresses on the roadwheel assembly are investigated in this study. Contact sites were shown to have greater levels of stress. Additionally, the rail will encounter the highest stresses while in operation.
- ❖ We made design and material improvements to the models. This study demonstrated that design and material optimization may be accomplished with little extra requirements.
- ❖ To change the material and reduce weight, we improved the rail wheel design. In railway weight optimization, various alloy steel and carbon steel grades are assessed using the same boundary conditions.
- ❖ For alloys, the railway wheel's weight is reduced by around 3%.

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