Addis Ababa University

Addis Ababa Institute of Technology
School of Mechanical and Industrial Engineering

Contact Fatigue Analysis of Helical Transmission Gear Using Finite Element Method with Material property Prediction by Artificial Neural Network Model

A Thesis Submitted to Addis Ababa Institute of Technology, School of Graduate Studies, Addis Ababa University

In Partial Fulfillment of the Requirement for Degree of Master of Science

In Mechanical Engineering (Mechanical Design Stream)

By

Dejenie Wletaw

Advisor: Dr.Daniel Tilahun (Associate professor)

Co-advisor: Hailemariam Nigus (PhD Candidate)

Addis Ababa, Ethiopia

February, 2020

Addis Ababa University

Addis Ababa Institute of Technology (AAIT)

School of Graduate Students

Contact Fatigue Analysis of Helical Transmission Gear Using Finite Element Method with Material property Prediction by Artificial Neural Network Model

By

Dejenie Wletaw

Approved by Board of Examiners

Dr. Daniel Tilahun (Associate Professor)		
Advisor	Signature	Date
Hailemariam Nigus (PhD Candidate)		
Co-Advisor	Signature	Date
Internal Examiner	Signature	Date
External Examiner	Signature	Date
Chairman of the School	Signature	Date

Declaration

This is to certify that the thesis presented by Dejenie Wletaw, entitled as **“Contact Fatigue Analysis of Helical Transmission Gear Using Finite Element Method with Material property Prediction by Artificial Neural Network Model”** and submitted to the School of Mechanical and Industrial Engineering in the partial fulfillment of the requirements for the award of the degree of masters of science in Mechanical Design Engineering with the regulations of the university, and meet accepted standards with respect to originality and quality.

Dejenie Wletaw		
Name	Signature	Date

This thesis has been submitted for examination with approval as a university advisor.

Dr. Daniel Tilahun (Associate Professor)		
Advisor Name	Signature	Date
Hailemariam Nigus (PhD Candidate)		
Co-Advisor Name	Signature	Date

Contents

Acknowledgment

First of all GOD of our ancestor thank you for the knowledge and ability that you give me when I prepared this thesis. Next I would like to say thanks to my advisor Dr. Daniel T. for his outstanding advice throughout the research. Finally thanks to my Co-Advisor Mr. Hailemariam N. for his support from giving research title to progressively helping in each work.

Abstract

Gear is the most essential element in power transmission system. Helical transmission gear can operate at high speed with large load carrying capacity. Due to this high contact stress is created at the mating surfaces. One of the main gear tooth failure type is contact fatigue failure due repetition of high contact stresses. In addition to design aspects, two important areas need to be addressed in order to enhance helical gear damage due to contact fatigue; improvements of material and enhancement in heat treatment. But it is very difficult to develop a complete theoretical/analytical model to improve the material property and heat treatment. In addition, to perform those enhancements, it needs an experimental work. In this study prediction of mechanical property of helical gear material using artificial neural network (ANN) and analyzing the contact fatigue of the predicted materials has been performed. After training the network, different performance measurements of the neural network accuracy was taken and prediction of the new concept (mechanical property) was performed. From five candidate materials, concept one was selected. By using the developed mechanical properties, contact fatigue was analyzed using AGMA standard and Finite Element Method. The results indicates, the fatigue life is infinite until the contact stress reach 959.7 Mpa. But beyond this contact stress, the fatigue life is limited and decreased. The comparison of contact stress by using AGMA and Ansys for the predicted material using ANN has shown and an error of 4.46 % and below was obtained. The material has best performance until the applied tangential load reaches 2000 N, because for applied tangential load of 2000 N, the factor of safety for AGMA as well as Ansys is greater than one. This indicates that, it is selective technique to predict the mechanical properties of materials using ANN model, when there is limited condition to use experimental investigation, because ANN simulates any correlations that are difficult to describe using physics based models.

Key Words: Artificial Neural Network, Contact stress, contact fatigue, fatigue life, Finite Element Method,

List of Figures

List of Tables

Chapter One

1. Introduction

1.1. Background

Helical gear can be used to transmit torque and rotational motion between parallel and non-parallel shafts. The initial contact in helical gear mesh is a point contact, which develops in to a diagonal line on a tooth face as the tooth come into more engagement. This leads to a more gradual engagement of meshing tooth and such smoother transfer of load from the driving tooth to the driven. Cyclic load produce major stresses in tooth and possible fluctuating load problems that could cause fatigue failure of the tooth [1]. Fatigue is the general phenomenon of material failure that occurs in structures subjected to dynamic and fluctuating stresses to a stress level considerably lower than the tensile or yield strength. Each stress cycle causes some degradation or damage of the material or component. Fatigue failure consists of three stages namely, crack initiation, crack propagation, and final fracture. Each of these stages is an extremely complex process [2].

Damage of gear due to contact fatigue occur in the three areas of gear tooth contact; along the pitch line, in the addendum and dedendum.

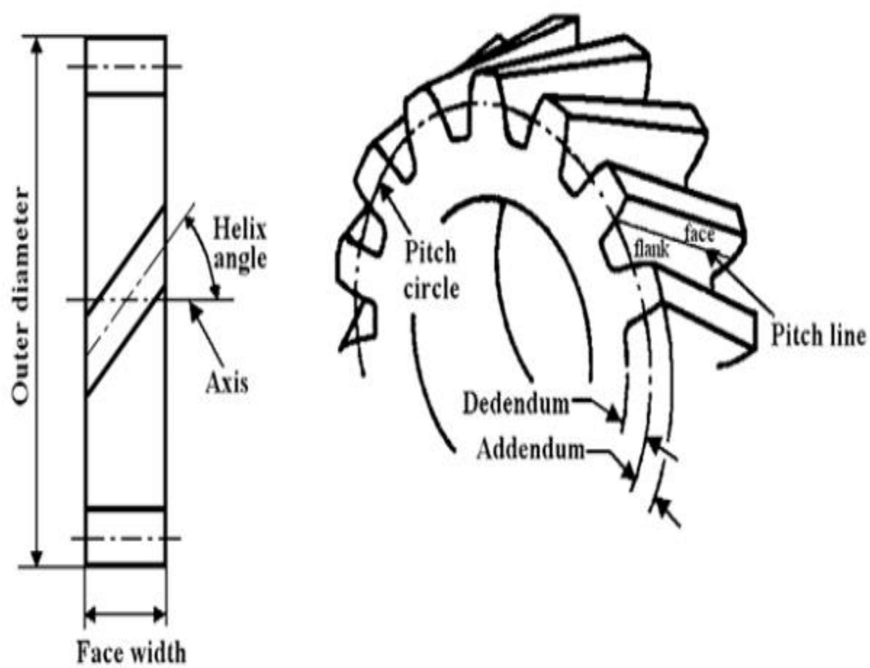


Figure 1. 1 Nomenclature of helical gear [3]

Contact fatigue failure of gear pair is a common form of gear failure. According to fatigue damage cumulative theory, the fatigue failure occurs when the cumulative fatigue damage reaches a certain value. According to the statistics, the ratio of the failure with gear contact fatigue can be accounted for 20.3% of gear failure forms in all. Therefore, contact fatigue analysis of gear pair is of great significance to improve the gear transmission performance and prevent gear failure [4]. Macro pitting of gear teeth is generally due to contact fatigue, which occurs from localized plastic deformation, crack initiation, and finally macro pitting from crack propagation in and near the contact surface. Macro pitting results from the subsurface growth of fatigue cracks, which may have a surface or subsurface origin.

Macro pitting fatigue life is inherently statistical because defect severity and location are randomly distributed among macroscopically identical contact components. Two major classes of macro pitting damage are distinguished according to the location of the initiating defect. Subsurface-origin macro pitting (results from inclusions or material microstructure alterations.) and Surface-origin macro pitting (caused by preexisting defects, such as nicks, dents, grinding furrows, surface discontinuities and micro scale pits). There are numerous factors influence fatigue strength of gear; hardness distribution, microstructure (as a function of retained austenite percentage and grain size), defect control (as a function of residual compressive stress, surface finish, geometry and inter granular toughness) [5]. When trying to improve fatigue properties, two important areas need to be addressed; improvements of material property and improvements in heat treatment technology [6]. Mechanical properties of material are complex function of numerous variables. It is thus very difficult to develop a complete theoretical (analytical) model to predict the material property. It is important to develop a new methodology for properties of materials determination. Artificial neural network (ANN) is a mathematical model capable of simulating complex non-linear relationships through the application of many non-linear processing units called neurons, especially when system involves several variables. This process adopts sets of input–output data to train a defined network structure. It has successfully been applied to solve wide varieties of complex scientific and engineering problems [7]. After the network has trained with input and output data obtained from experimental work, new concept from the similar domain can then be predicted without performing additional experiments.

1.2. Statement of the Problem

In power transmission system, helical gears are mostly used for carrying large loads with higher operating speed. Because of high contact force which is created at the mating surfaces, failure of tooth due to contact fatigue is the most critical thing. Contact fatigue failure will occur at the surface of tooth contact area due to high contact pressure. Resistance of this contact fatigue failure was the concern area of different researcher and so many improvement techniques were developed . Various studies show that heat treatment and appropriate material property determination are the most preferable techniques in resisting the contact fatigue stress of transmission gear system. But materials mechanical property determination as well as heat treatment techniques require experimental work and it is difficult to develop a complete theoretical (analytical) model to determine the material property. It is important to develop a new methodology for properties of materials determination. An artificial neural network is very simple and efficient biologically inspired mathematical model which can be successfully used for prediction statistical parameters. So using artificial neural network, it is necessary to predict mechanical properties of the required new material for helical gear transmission system and to analyze the contact fatigue stress.

1.3. Objective

1.3.1. General Objective

The general objective of this study is in order to perform contact fatigue analysis of helical transmission gear by using Finite Element Method with material property prediction by using Artificial Neural Network model.

1.3.2. Specific Objective

The Specific objective of the thesis is to:

- Select appropriate improved material using artificial neural network.
- Predict contact stress using artificial neural network using input and output data
- Perform contact fatigue life analysis using analytical analysis and Finite Element Method (Ansys).
- Compare results of FEM and analytical analysis of the contact stress.

1.4. Scope and Limitation

This research concern on contact fatigue analysis of single helical transmission gear system for an intermediate weight vehicle. This is performed by prediction of mechanical properties of gear material using artificial neural network (ANN) model and contact fatigue analysis using FEM and theoretical analysis. Any further study from the scope provided is not included in this research work.

1.5. Methodology of the Study

The research methodology started with literature review, especially on areas which concern on the title provided. After the concept of the related research area reviewed, the gap was identified. On the methodology portion of the research, the geometry of the gear was modeled with CATIA and imported to ANSYS software to analyze using finite element method. Using experimental test data from the existing research on chemical composition, heat treatments and mechanical properties of the material, Artificial Neural Network (ANN) training was performed. After perfect prediction network has been obtained, mechanical properties of the new concept with required parameters was developed. Analytical analysis was performed based on materials and conditions. Lastly but not least, result and discussion was perform on the results obtained using FEM, ANN as well as by the analytical analysis. Finally, the conclusion has reached depend on the result of the study and recommend for future work.

1.6. Organization of the Thesis

This study consists of five chapters. In the first chapter, introduction part, the background, statement of the problem, the main and specific objective to be achieved, scope and limitation, methodology and organization of the thesis were included. In the second chapter, a review of literature relevant to this thesis work, which has been investigated by different researchers, was shown. In chapter three, analytical methods has performed by taking assumptions and material properties as initial point. The analysis portion consists of formulas that reflect the property of part like, stress analysis and geometrical dimension determination. In chapter four results of the analysis were summarized and discussed. Finally, conclusion has been reached and feature works areas were set.

Chapter Two

2. Literature Review

2.1. Helical Gear in Automotive Transmission System

Helical gears are used to transmit power or motion between parallel and non-parallel shafts. Helical gears tooth enters the mashing zone progressively and have smother and quieter action. Due to this the load carrying capacity is high and less noise operation will occur. The total length of the line of contact is diagonal across the face of the teeth. In this case the line of contact is more than face width and there is lower unit loading and increase load caring capacity.

In helical gears the helix angle must be the same between the two mating gears but opposite in hand of helix. Helix angle from 5^0 to 45^0 is practical. General scope of transmission helical gear helix angle is 10^0 – 35^0. Helical gears often use 20^0 pressure angle as a standard however higher pressure angle such as 22.5^0 or 25^0 may be used for extra load carrying capacity. In automotive transmission gear system, the range of gear module is depends on the type of vehicle. Table 2.1 shows the module range for different type of vehicles.

Table 2. 1Module range for different vehicle [8]

Vehicle Type	Module Range
light car	Below 2.75
intermediate car	2.75 – 3.0
medium sized truck	3.5 – 4.25
heavy duty truck	4.25 – 7

2.2. Material for Transmission Gear

High speed Gears have to be high quality to keep the contact stress within the limits. Gear wheels should be characterized by high resistance to fatigue, structural stability when working at elevated temperature and resistance of the surface layer to pitting. The gears of modern drive unit operates in extremely unfavorable condition, transmitting very high torque, working with a rotational speed of up to thousands of revolution per minute. It needs to produce parts made from materials of high strength, light weight having the ability to carry extremely large load with low noise. Most of heavy loaded gears are made from ferrous metal. The use of different materials in gear manufacturing needs to specify the range of contact stress because specifying the range helps for appropriate material selection. Now day there are materials used in gear wheels with specified properties. Super high strength aluminum alloys provide the highest mechanical strength of all currently used aluminum alloys matting that of most of steel and titanium alloys. Supper high strength alloys offer a tensile strength of 620-850 Mpa, yield strength of 560-767 Mpa, Brinell hardness from 150-220 HB elongation up to 11% with corrosion resistance and good durability. Aluminum alloy consumption is higher than when using high carbon steel and this leads to the high cost [9]. Aluminum 7068 is the light weight metal. This metal provides the highest mechanical strength of all aluminum alloy. This alloy has yield strength of 641Mpa, tensile strength of 690 Mpa with an elongation of 8 % and good fatigue strength**.** Magnesium alloy are also used for gear material in transmission gear system. It has yield strength up to 200 Mpa, tensile strength up to 290 Mpa with modules of elasticity of 45 GPA. Magnesium AZ31 has good machinability. Disadvantage is that it is flammable, so extreme care should be taken while performing this process. Bronzes have good sliding properties, therefore they are widely used material used for gears, are extremely stable, provide the machine with optimal working properties. The disadvantages is its weight and high price. Brase alloy c3604 is one type of alloy is used for gear wheels in transmission of gear. This alloy has high strength, good ductility, suitable for cold and hot working, good corrosion resistance and no stress corrosion cracking tendency. It has tensile strength about 335 Mpa with young's modulus about 96 Mpa. Magnesium bronze is tough and corrosion resistance. It is used as a material almost exclusively in a double helical gear [3]. Chromium molybdenum alloy steel is also used for gear material. It has tensile strength of 515-750 Mpa and yield strength from 310-450 Mpa. In the study developed by Daniel T.et.al **[**10**],** for two roller contact model test of case carburized Cr-Mo-Si (1% Si) steel and Cr-Mo steel, it is clear that the surface durability of Cr-Mo-Si steel is greater than that of Cr-Mo steel. The surface of the test roller in the study is Vickers hardness of about 770 HV. The dis advantage of Cr-Mo-Si is its cost. AISI 4340 alloy steel [11] is a heat treatable alloy steel containing chromium, nickel, manganese silicon, molybdenum and other elements. It has high toughness and strength in the heat treated condition. The material has Yield strength of 470 Mpa and tensile strength of 745 Mpa with elastic modulus 210 GPA. AISI 4340 is considered to be rich alloy steel and has much better hardenability but, material such as AISl4140 is considered to be a low alloy steel and has rather poor hardenability. Ceramics are also used as material for gear having anti friction properties, but mostly it has low cracking strength. Contact fatigue evaluation of ground and chemically polished gear made of AISI 4118 alloy steel indicates that [12], the material has inferior pitting performance compared to ground 4620M steel gear. For different loading condition analysis using software [13], aluminum-silicon- carbide and gray cast iron are more preferable compared to chromium stainless steel, because at a given load it shows breakage or failure.

2.3. Contact Fatigue Analysis

Macro pitting of gear teeth is generally due to contact fatigue, which occurs from localized plastic deformation, crack initiation, and finally macro pitting from crack propagation in and near the contact surface. Macro pitting results from the subsurface growth of fatigue cracks, which may have a surface or subsurface origin. Macro pitting fatigue life is inherently statistical because defect severity and location are randomly distributed among macroscopically identical contact components. Two major classes of macro pitting damage are distinguished according to the location of the initiating defect. Subsurface-origin macro pitting (results from inclusions and/ or material microstructure alterations) and Surface-origin macro pitting **(**caused by preexisting defects, such as nicks, dents, grinding furrows, surface discontinuities and micro scale pits) [5].

An investigation of effect of load on pitting of gear tooth surface [14] indicates that repeated load cycle, contact stress and load variations are the cause for pitting initiation and propagation. When trying to improve fatigue properties, two important areas need to be addressed: improvements of material and improvements in heat treatment technology [6]. The fatigue life in contact is not only affected by the material or surface treatments and effectiveness of the lubrication but also strongly depends on geometric condition [15]. Two dimensional computational method is proposed for predicting the initiation, position and propagation path of crack for an equivalent contacting cylinders model [16]. Shiferaw et.al [17] analyzing the contact stress and estimating the surface fatigue life of spur gear in rolling- sliding contact by using finite element method show that better surface finish with less roughness result in high fatigue strength. Finite element method [18] is the most appropriate numerical method that can solve nonlinear problems and gives the possibilities for developing appropriate model. A particular real helical gear pair of a high value of transmission ratio with some specified values of maximum stresses and same characteristic to spur gear, there is significant increase of load capacity in helical gear pairs. N. K. Fukumasu. et.al [19] conclude that numerical analysis can improve the material design, similarly evaluation of the residual stress range could improve the gear life.

2.4. Helical Gear Surface Treatments

There are different techniques to improve helical gear contact surface [20] like; carburizing, nitriding, case hardening, shot pinning, thermal coating and so on. Shot pinning is modernized technique but it is affected by different factors. The shot diameter, exposure time, and shot material are the most known factors. There is no fixed process or step in sot pinning, which means that every shot pinning process has its own advantage and limitation**.** Gear with manganese phosphate coating had high pitting proof load capability. Improvement of contact fatigue strength of carburized gear with manganese phosphate conversion coating is visible way. For gear of 8620 steel with four surface finish [21], 1) Baseline shaved 2) chemically polished 3) shot peened and honed 4) chemically polished and chromium nitride coated; shot peening and plastic honing gear did not provide significant increase in fatigue life. But baseline shaved gears increase in pitting life and additional slight increase in life of chemically polished gear. When applying high carburizing temperatures above the range of 980°C to 1000°C, this may lead to an unwanted grain growth. Components with coarse grains have less toughness, especially in the carburized area and lower tooth root bending strength [12]. The hardness is achieved by heating the material to the austenitic range (a temperature that varies, depending on the carbon and alloy content, within the range of about 1500-1600"F) and then quenching and tempering [22]. Then the part is rapidly quenched in oil (or sometimes water) to transform the austenite into martensite. Once the part has been quenched, it needs to be tempered to reduce the brittleness and toughen the steel. The quench and temper process involves heating the gears to form austenite at 800 to 900 °C (1475 to 1650 °F), followed by quenching in a suitable media such as oil. The rapid cooling causes the gears to become harder and stronger by the formation of martensite. Hardened gears then are tempered at a temperature, generally below 690 °C (1275 °F), to achieve the desired mechanical properties. Tempering lowers both the hardness and strength of quenched steels but improves materials properties such as ductility, toughness, and impact resistance. This process is the most commonly used for through-hardened gears. According to AGMA standards, a gear with a hardness of 400 BHN, which has a design life of 10^{7} cycles can handle as much as 20% more load than a gear which is hardened to 300 BHN. For hardness above 400 BHN the capacity increases with respect to pining resistance. But the capacity decreases with respect to bending strength, which deteriorates because the tooth becomes brittle. For situations when the teeth are cut after the material has been hardened, machinability becomes a consideration in determining the hardness. Carburizing gear has an increased amount of carbon in the surface, causing this area to become a hard. The process involves heating the gears to a relatively high temperature and then rapidly quenching to obtain the hardness. This heating and quenching will result in distortion of the gear blank. Contact fatigue evaluation of ground and chemically polished gear made of AISI 4118 alloy steel indicates that [12], the material have inferior pitting performance compared to ground 4620M steel gear. But chemically polished AISI 4118 steel indicates an increase in pitting life.

2.5. Artificial Neural Network (ANN) Prediction

An artificial neural network, first presented in 1943 by the neurophysiologist Warren Culloch and the logician Walter Pits, is a mathematical technique that models complex linear and non-linear relationships and simulates any correlations that are difficult to describe using physics based models. Today, the ANN can be trained to solve problems that are difficult for conventional computer programs or human intelligence. The results computed by the neural network have reasonable accuracy and are much faster than other methods [2].

An artificial neural network is very simple and efficient biological inspired mathematical model which can be successfully used for prediction statistical parameters. It is considered a powerful tool for establishing the nonlinear multivariate projection [23]. In Artificial neural network model it collects the information from data set and learn through experience (training) not from programming. Thus neural network can be excellently used to model and analyze the very complex and nonlinear process that are not well understood [24]. After the network has learned to solve the problems, new data from the similar domain can then be predicted without performing too many, long experiments [22].

Many destructive and nondestructive test need to be carried out in order to define the mechanical properties of gear materials. However many times these tests may not be cost effective and call for some specialized equipment that is not always available. One possible solution to overcome such restriction is to perform computer based simulation [25]. Different learning rules can be used in order to improve the ANN performance. Back propagation is a common algorism for training the ANNs since it has the advantages of being very simple and accurate. After the network is initiated with random weight, the method continuously updates the weight to match the required output until the error is minimized. The result obtained from the experiments, are used as inputs in developing the ANN models [26].

A comparative analysis was performed in order to evaluate the accuracy of the developed ANN models, in terms of statistical measurements. Results revealed that proposed ANN models are able to predict the fatigue life of the gear-like profiles. [27]. Aback propagation learning rule provides a computationally efficient method for changing the weight in feed forward network with differentiable activation function unit to learning a training set of input output example [28]. The study of D. Prajapati et.al presents the evolution of roughness parameters, wear and friction coefficient during pin-on-disc tribo-testing under dry condition using pin on disc apparatus under room temperature condition. This work validates the potential of Artificial Neural Network (ANN) for prediction of roughness parameters, friction coefficient and wear coefficient. Experimental results obtained from wear testing are compared with those obtained using artificial neural network (ANN) analysis. It is suggested that, a well-trained neural network is capable to predict the parameters in wear process.

Feed-forward and recurrent Elman neural network algorithms were used to develop ANN models, which are subjected to training, testing, and validation process. The Leven berg-Marquardt back-propagation algorithm was applied to reduce errors. Log-sigmoid and Purelin were identified as suitable transfer functions for hidden and output nodes. An accurate predictions is obtained from ANN and the feed-forward network performance is superior to the Elman neural network [29].

M. Taskin et.al uses Artificial Neural Network approach for prediction of diffusion bonding behavior of reinforced aluminum alloy metal matrix composites, manufactured by powder metallurgy process, with a back-propagation neural network that uses gradient descent learning algorithm. In neural networks training module, different reinforcement fractions (wt), different temperatures and welding periods were used as input, shear strength of bonded specimens at interface were used as outputs. Then, the neural network was trained using the prepared training set (also known as learning set). At the end of the training process, the test data were used to check the system accuracy. As a result the neural network was found successful in the prediction of diffusion bonding shear strength and behavior [30].

Different learning rules can be used in order to improve the ANNs' performance. Back propagation is a common algorithm for training the ANNs.

Back Propagation

The back propagation neural network (BPNN) methods are the most commonly used ANN methods. The back propagation neural network [31] is a neural network with a layered, feed-forward network structure and the generalized rule which updates its weight for each run of the network. It is a powerful mapping network which has been successfully applied to a wide variety of problems.

Several different Back propagation training algorithms such as Gradient Descent, Gradient Descent with 40 Momentum, Scaled Conjugate Gradient or Resilient back propagation, Levenberg-Marquadt and Bayesian Regularization have been applied either in batch mode or incremental mode of training on different pattern recognition and function approximation problems. Hagan and Mehnaz applied several back propagation training algorithms on function approximation problems and concluded that, Levenberg-Marquadt method was more efficient than that of other techniques and the fastest algorithm. It has also been recommended that for large networks.

Back propagation is one of the finest algorithms that give better performance with relatively more accurate recognition ratio. The back propagation generally has three or more layers: one input layer, one or more hidden layers, and one output layer. Each layer has a number of neurons that are connected with other neurons in neighboring layers by weights. The output is computed by the network for each input in the training subset. The error between the computed output and the actual measurement value (target) is then propagated backward, and weights and biases are updated.

Training is proficient by presenting the patterns to be classified to the network and determining its output. The higher the error value the less efficient the network is. Thus an effort has been made to decrease the error value for the Back propagation network. The network is trained with particular specifications. The obtained output after training the network is compared with the target output and error is calculated based upon these values.

Neural Network Architecture

The most commonly used neural network architecture is consists of one input layer, one output layer, and one hidden layer. The added hidden layer contains intermediary parameters that are automatically generated by the model. This layer is necessary in case of complex non-linear relationships between the inputs and the outputs. One or multiple neurons connect the input to the hidden layer. Similarly, one or multiple neurons connect the hidden layer and the output layer.

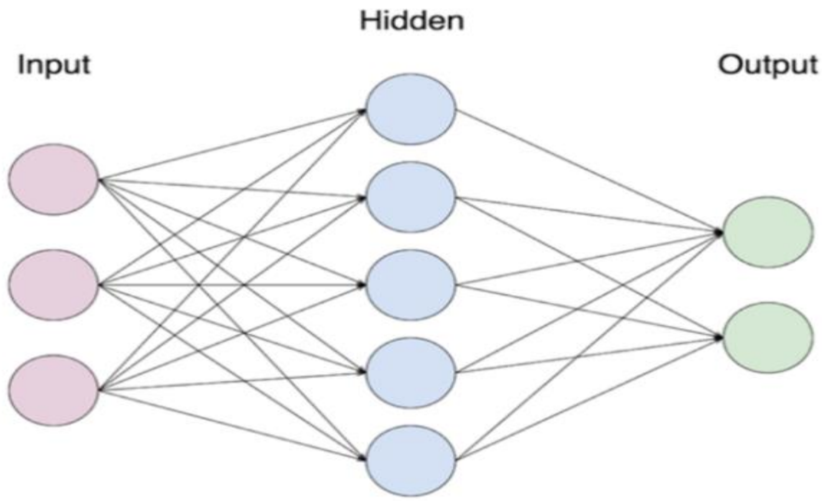


Figure 2. 1 schematic of a neural network [31]

Simple Neuron Model

An ANN has non-linear basic processing units called neurons. The neuron model and architecture of a neural network describe how a network transforms its inputs into outputs. The neural network architecture consists of multiple layers of neurons which have a summing up junction and a transfer function.

The neuron takes input p which is transmitted through a connection that multiplies its strength by the weight w to form the product w_p. A bias b is also applied that is much like a weight except that it has a constant value of 1 and can be omitted if desired. The transfer function then takes the net input n which is the sum of the weighted inputs (w_p + b) and produces the output Y.

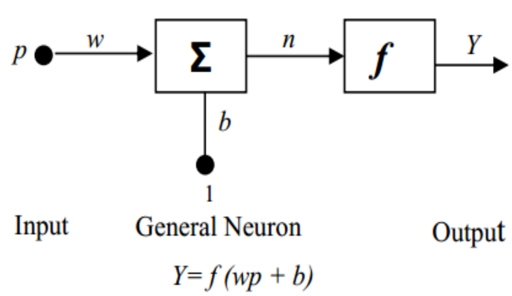


Figure 2. 2 Simple neuron model

Transfer Functions

A transfer function is necessary to translate the input signals to output signals. The choice of the transfer function in ANNs is of great importance to their performance. However there isn't a strict rule for selecting transfer function. The selection depends mostly on experience. The ideal transfer function and the number of neurons and hidden layers should be found through a trial and error method. Sometimes the users can also specify their own transfer functions based on their requirement [32].

The commonly used transfer functions are:

a) Linear transfer function: Neurons of this type are used as linear approximates.

b) Sigmoid transfer function: is commonly used to develop non-linear relationships

Number of neurons

The number of neurons forms one parameter of the Feed-forward neural network. The neural network architecture consists of multiple layers of neurons. The number of neurons in the input layer is determined by the number of input variables. The number of neurons in the hidden layer is determined by trial and error with various weights and biases, whereas the number of target is considered to be the number of neuron in the output layer.

Chapter Three

3. Materials, Methods and Conditions

3.1. Material for Helical transmission Gear

Mechanical property determination is one of the main areas where an artificial neural network (ANN) has been recognized as a potentially effective modeling tool. An artificial neural network structure with the feed-forward back propagation with Levenberg-Marquadt type and sigmoid transfer function (commonly used to develop non-linear relationships) can be used to estimate the mechanical properties of helical gear material and predict contact stress. The results obtained from the experiments were used for the development of the ANN models.

The total experimental data was randomized and divided into three categories named as training subsets, validation subsets and testing subsets. The input and output data for material property prediction was obtained from literature, on experimental investigation of mechanical property of 4340 steel with specified chemical composition and heat treatment, which is shown in table 3.1and table 3.2. By adding other elements like Al and Si (table 3.1and table 3.2) to the base material (4340 steel); the tensile strength, yield strength, hardness and toughness was obtained by the researcher. The heat treatment procedures in his investigation were, austenitizing the specimen blank for 1 hour in vertical tube furnace and quenched in agitated oil. Specimen blanks were tempered for one hour and air cooled.

In this study using input and output data of an experimental investigation shown in table 3.1 and table 3.2, ANN prediction of new concepts will develop. The inputs of the artificial neural network predictions are chemical composition (w %), austenite temperature (^{0}c) and tempering temperature (^{0}c). The outputs are yield strength, ultimate tensile strength, fracture toughness, retained austenite and hardness. Similarly the input (gear dimension and specifications) and output (contact stress) data for contact stress prediction is show in table 3.4 After the network is initialized with random weights, the method continuously updates the weights to match the required output with an experimental target until the error is minimized.

After the network has trained with input and output data obtained from experimental work, new concept from the similar domain can then be predicted without performing additional experiments.

Table 3. 1Input data for material property prediction [11]

Name	COMPOSITION (wt %)											Austnization Temperature	Tempering Temperature
	C	P	S	Si	Mn	Cr	Ni	Mo	Al	Cu	Fe	(oc)	(oc)
4340	0.39	0.007	0.003	0.2	0.74	0.81	1.81	0.25	0	0.18	95.61	870	0
	0.39	0.007	0.003	0.2	0.74	0.81	1.81	0.25	0	0.18	95.61	870	250
	0.39	0.007	0.003	0.2	0.74	0.81	1.81	0.25	0	0.18	95.61	870	300
	0.39	0.007	0.003	0.2	0.74	0.81	1.81	0.25	0	0.18	95.61	870	400
	0.39	0.007	0.003	0.2	0.74	0.81	1.81	0.25	0	0.18	95.61	870	500
4340+ Al	0.38	0.007	0.003	0.2	0.74	0.81	1.81	0.25	0.98	0.18	94.84	900	0
	0.38	0.007	0.003	0.2	0.74	0.81	1.81	0.25	0.98	0.18	94.84	900	250
	0.38	0.007	0.003	0.2	0.74	0.81	1.81	0.25	0.98	0.18	94.84	900	300
	0.38	0.007	0.003	0.2	0.74	0.81	1.81	0.25	0.98	0.18	94.84	900	350
	0.38	0.007	0.003	0.2	0.74	0.81	1.81	0.25	0.98	0.18	94.84	900	400
4340+ 2Al	0.37	0.007	0.003	0.2	0.74	0.81	1.81	0.25	1.95	0.18	93.88	900	0
	0.37	0.007	0.003	0.2	0.74	0.81	1.81	0.25	1.95	0.18	93.88	900	250
	0.37	0.007	0.003	0.2	0.74	0.81	1.81	0.25	1.95	0.18	93.88	900	325
	0.37	0.007	0.003	0.2	0.74	0.81	1.81	0.25	1.95	0.18	93.88	900	375
	0.37	0.007	0.003	0.2	0.74	0.81	1.81	0.25	1.95	0.18	93.88	900	400
4340+ Al+ Si	0.39	0.007	0.003	1.15	0.74	0.81	1.81	0.25	1	0.18	93.66	900	0
	0.39	0.007	0.003	1.15	0.74	0.81	1.81	0.25	1	0.18	93.66	900	250
	0.39	0.007	0.003	1.15	0.74	0.81	1.81	0.25	1	0.18	93.66	900	300
	0.39	0.007	0.003	1.15	0.74	0.81	1.81	0.25	1	0.18	93.66	900	350
	0.39	0.007	0.003	1.15	0.74	0.81	1.81	0.25	1	0.18	93.66	900	400
4340+ 2Al+ 2Si	0.39	0.007	0.003	2.1	0.74	0.81	1.81	0.25	1.97	0.18	91.74	1100	300
	0.39	0.007	0.003	2.1	0.74	0.81	1.81	0.25	1.97	0.18	91.74	1100	350
	0.39	0.007	0.003	2.1	0.74	0.81	1.81	0.25	1.97	0.18	91.74	1100	400
	0.39	0.007	0.003	2.1	0.74	0.81	1.81	0.25	1.97	0.18	91.74	1100	450
	0.39	0.007	0.003	2.1	0.74	0.81	1.81	0.25	1.97	0.18	91.74	1100	500
4340+ Si	0.37	0.007	0.003	1.13	0.74	0.81	1.81	0.25	0	0.18	94.7	900	0
	0.37	0.007	0.003	1.13	0.74	0.81	1.81	0.25	0	0.18	94.7	900	250
	0.37	0.007	0.003	1.13	0.74	0.81	1.81	0.25	0	0.18	94.7	900	300
	0.37	0.007	0.003	1.13	0.74	0.81	1.81	0.25	0	0.18	94.7	900	350
	0.37	0.007	0.003	1.13	0.74	0.81	1.81	0.25	0	0.18	94.7	900	400
4340+ 2Si	0.37	0.007	0.003	2.11	0.74	0.81	1.81	0.25	0	0.18	93.72	900	0
	0.37	0.007	0.003	2.11	0.74	0.81	1.81	0.25	0	0.18	93.72	900	250
	0.37	0.007	0.003	2.11	0.74	0.81	1.81	0.25	0	0.18	93.72	900	300
	0.37	0.007	0.003	2.11	0.74	0.81	1.81	0.25	0	0.18	93.72	900	350
	0.37	0.007	0.003	2.11	0.74	0.81	1.81	0.25	0	0.18	93.72	900	400

Table 3. 2 Output for mechanical properties prediction [11]

Yield strength (Mpa)	ultimate strength (Mpa)	Fracture toughness (KIC)	Retained austenite %(0.2%)	surface Hardness (HRC)
1420	2214	30	4.6	56
1550	1825	65	1.2	51.5
1510	1650	64	0.8	49.7
1420	1580	61	0.8	48
1237	1425	72	0.8	45.3
1405.56	1970.54	73.404	2.5	52.6
1515.8	1777.62	85.1613	3.8	51
1446.9	1688.05	79.557	1.2	49.7
1364.22	1591.59	81	0.2	48
1267.76	1467.57	87	0	46.1
1481.35	1998.1	60.44	1.2	54
1529.58	1805.18	88.678	2.4	51.5
1557.14	1798.29	82.414	0	51.25
1564.03	1750.06	80.216	0	50.7
1502.02	1674.27	81.5	0	50
1502.02	2094.56	47.251	0.5	55.5
1605.37	1901.64	91.205	2.6	53
1577.81	1853.41	89.007	2.9	52.5
1591.59	1818.96	89.007	1.9	52
1550.25	1722.5	90.1	1.1	51
1584.7	2135.9	37.141	0	56.5
1722.5	1998.1	89.337	1.4	54
1736.28	1991.21	86.37	1.6	53.7
1791.4	1984.32	81.535	1.8	54.4
1715.61	1880.97	65.931	1.8	52.5
1543.36	1708.72	75	0	50
1584.7	2073.89	78.568	0.8	45.4
1619.15	1929.2	86.9194	2.1	45.8
1605.37	1867.19	77.2495	2.4	45.3
1557.14	1791.4	79.227	1.8	47
1433.12	1612.26	66.151	0	46
1763.84	2342.6	62.195	0.5	46.5
1770.73	2115.23	82.194	1.6	47.3
1694.94	2004.99	88.348	1.65	46.7
1756.95	1991.21	88.238	1.57	47.2
1694.94	1874.08	63.514	1.15	46.2

Table 3. 3 New input samples for prediction

Name	COMPOSITION (wt %)											Austenite Temperature	Tempering Temperature
	C	P	S	Si	Mn	Cr	Ni	Mo	Al	Cu	Fe	(^{o}c)	(^{o}c)
concept 1	0.26	0	0	0.12	1.46	1.23	0.91	0.54	0	0	95.48	900	0
	0.26	0	0	0.12	1.46	1.23	0.91	0.54	0	0	95.48	900	200
	0.26	0	0	0.12	1.46	1.23	0.91	0.54	0	0	95.48	900	300
	0.26	0	0	0.12	1.46	1.23	0.91	0.54	0	0	95.48	900	400
	0.26	0	0	0.12	1.46	1.23	0.91	0.54	0	0	95.48	900	500
concept 2	0.21	0	0	0.25	1.17	1.15	0.22	0.21	0	0	96.79	900	0
	0.21	0	0	0.25	1.17	1.15	0.22	0.21	0	0	96.79	900	200
	0.21	0	0	0.25	1.17	1.15	0.22	0.21	0	0	96.79	900	300
	0.21	0	0	0.25	1.17	1.15	0.22	0.21	0	0	96.79	900	400
	0.21	0	0	0.25	1.17	1.15	0.22	0.21	0	0	96.79	900	500
concept 3	0.21	0.0025	0.0035	0.4	0.9	1.8	1.7	0.35	0	0	94.634	900	0
	0.21	0.0025	0.0035	0.4	0.9	1.8	1.7	0.35	0	0	94.634	900	200
	0.21	0.0025	0.0035	0.4	0.9	1.8	1.7	0.35	0	0	94.634	900	300
	0.21	0.0025	0.0035	0.4	0.9	1.8	1.7	0.35	0	0	94.634	900	400
	0.21	0.0025	0.0035	0.4	0.9	1.8	1.7	0.35	0	0	94.634	900	500
concept 4	0.18	0.025	0.025	0.2	0.7	1.65	1.55	0.3	0.75	0	94.62	900	0
	0.18	0.025	0.025	0.2	0.7	1.65	1.55	0.3	0.75	0	94.62	900	200
	0.18	0.025	0.025	0.2	0.7	1.65	1.55	0.3	0.75	0	94.62	900	300
	0.18	0.025	0.025	0.2	0.7	1.65	1.55	0.3	0.75	0	94.62	900	400
	0.18	0.025	0.025	0.2	0.7	1.65	1.55	0.3	0.75	0	94.62	900	500
concept 5	0.2	0.025	0.025	0.2	0.7	1.8	1.75	0.3	1	0	94.0	900	0
	0.2	0.025	0.025	0.2	0.7	1.8	1.75	0.3	1	0	94.0	900	200
	0.2	0.025	0.025	0.2	0.7	1.8	1.75	0.3	1	0	94.0	900	300
	0.2	0.025	0.025	0.2	0.7	1.8	1.75	0.3	1	0	94.0	900	400
	0.2	0.025	0.025	0.2	0.7	1.8	1.75	0.3	1	0	94.0	900	500

Table 3. 4 input and output for training contact stress

Number	Material	Torque (N-m)	Pinion tooth	Gear tooth	Face width (mm)	Young's modules (Gpa)	Helix angle	Tangential force (N)	Module (mm)	Pinion Pitch diameter (mm)	Contact stress (Mpa)	Reference
1	Structural steel	15.92	17	51	38.1	200	30	63.84	2.54	49.86	296.51	1
2	Structural steel	14.325	15	24	24.13	200	41.41	56.39	2.54	50.8	363.07	1
3	20MnCr5	835.4	13	50	70	200	23	33636.0	4	52	702.49	32
4	Structural steel	55	22	22	7	200	0	3333.33	3	66	1214.8	17
5	Carbon steel	112.7	19	95	50	230	20	3185.8	3.5	70.77	628.17	20
6	Stainless steel	3.575	20	20	26.39	200	18.7	135.4	2.5	52.787	166	33
7	JIS-SCM415 steel	2.844	16	69	128	207	13	155.78	8	36.52	1336.17	34
8	Carbon steel (0.55%)	6.0	32	128	12.4	205	45	716.4	1	16.75	122.6	35
9	Nylon 66	3.575	20	20	26.39	3.54	18.7	135.4	2.5	52.78	96.1	35
10	14NiCr18	14.6	18	43	14	210	20	81.1	2	36	45.256	36
11	40 Ni2 Cr1 Mo28 Steel	24557.14	15	105	26.7	215	25	137572.6	1.335	20	583.28	37
12	40 Ni2 Cr1 Mo28 Steel	24557.14	15	105	26.7	215	15	137572.6	1.335	20	592.73	37
13	AISIQT400	29.38	11	34	21	207	23	2136.9	2.5	27.5	493.27	38
14	AISI4340	55	22	22	7	200	0	1666.6	3	66	1214.80	33
15	AISI2020	14.25	15	24	24	200	41	560.5	3.5	52.5	313.70	39
16	18CrNiMo	50	20	36	18	206	15	1666.6	3	60	645.64	20

3.1.1. Network Training

The objective of training is to find the set of weights between the neurons that determine the global minimum of the error function. The Back Propagation network uses a gradient descent training algorithm which adjusts the weights to move down the steepest slope of the error surface. One method to determine a reasonable value for the maximum number of runs is to plot the regression fit, or other appropriate error measure for each iteration or at predetermined intervals up to the point where improvement is negligible. Each iteration can be easily plotted. After plotting the mean correlation for a number of randomly selected starting weights, the researcher can choose the maximum number of runs based on the point where the mean correlation stops increasing quickly and flattens [30]. The training set is the largest set and is used by the neural network to learn the patterns present in the data. The testing set, ranging in size from 10% to 30% of the training set, is used to evaluate the generalization ability of a supposedly trained network. A final check on the performance of the trained network is made using the validation set.

In network architecture during training, each input unit of the input layer receives signal X_i and broadcast it into all units of the hidden layer. Each hidden unit Y_j sum up its weighted input signal and apply activation function to complete output signal according to the equation,

$$Y_j = f_{act}\left(\sum_{i=1} W_{ij} X_i\right) \quad \ldots\ldots (3.1.1)$$

Where W_{ij} is the weight of the input unit X_i to the hidden unit Y_j

The following procedures were used in prediction of the mechanical properties of the new input concepts (table 3.3).

1) Start Matlab and Import inputs and targets from experimental data (table 3.1 and table 3.2)
2) Open the the artificial neural network toolbox
3) Create the matlab code.

During creation of the network code (appendix 1), the following parameters was considered for this work.

a) Feed-forward back propagation type of network was selected among the available network types. This is due to the effectiveness and relative ease of this type of network compared to the other.
b) Choose training function.

A network training function that adaptively updates weight values according to gradient descent was selected. This selection was made keeping the network type in mind. Because other alternatives showed less learning capacity. There are different types of training functions. Trainlm, trainbr and trainscq are the most common types of training functions. In this work trainlm training function is used, because it is usually fastest.

c) Choose training algorism

There are three training algorisms; Levenberg-Marquadt, Bayesian regularization and scaled conjugate gradient. Levenberg-Marquadt algorithm typically requires more memory but less time. Training automatically stops when generalization stops improving. Bayesian regularization typically requires more time, but can result in good generalization for difficult, small or noisy datasets. Training stops according to adaptive weight minimization (regularization). Scaled conjugate gradient type algorithm requires less memory. Training automatically stops when generalization stops improving, but it needs more time. For this study Levenberg-Marquadt type can be used.

d) Choose number of hidden layers and number of neurons.

One hidden layer was chosen as it has proven to be sufficient in many cases. The number of hidden neuron depends on the quantity of input and target data. A small quantity of hidden neuron is the decrease in performance and the large quantity of the hidden neuron is the decrease in training time leads to decrease in performance. This indicates an appropriate selection hidden neurons for the given data. But it needs to increase the number of neurons until there is a significant improvement in the accuracy is observed.

The number of hidden neuron for a given input neuron and sample is,

$$N_H = \frac{(N_{in}+\sqrt{N_P})}{L} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (3.1.2)$$

Where, N_{in} is the number of input neurons

N_P is the number of input sample

L is the number of hidden layer

From the input data table, for 13 column with 36 rows the total sample is 468. Here for 468 number of input sample and single hidden layer the hidden neuron using the relation is 35.

e) Arrange Learning Rate, goal and Momentum

The performance of the algorithm is very sensitive to the best value of the learning rate. If the learning rate is a high value, the algorithm may oscillate and don't reach to the best convergence. If the learning rate is too small, the algorithm will take too long to converge. The optimal learning rate changes during the training process, as the algorithm moves across the performance surface. The learning rate is made responsive to the complexity of the local error surface. If the new error exceeds the old error by more than a predefined ratio during training, the learning rate is decreased. Otherwise, the learning rate is increased, if the new error is less than the old error[40].

Goal was set as the stopping criteria during training. If the error on the training or selection test drops below the given target values, the network is considered to have trained sufficiently well, and training is terminated [41]. The error never drops to zero or below (figure 3.2), so the default value of zero is equivalent to not having a target error. The learning rate parameter determines the size of the weights adjustment and the weights was updated during training. The momentum parameter was a factor used to speed network training for escaping the local minima to avoid error fluctuation.

Both learning rate and momentum parameter were usually in the range between 0.1 and 0.9 and choosing the learning rate can be done by trial and error.

The researchers [42] found out that the values of 0.2 and 0.9 for the learning rate and momentum yielded the fastest learning convergence to the minimal number of errors during training attempts.

4) Create the network: the network was created with 13 input, 35 hidden and 5 output neurons

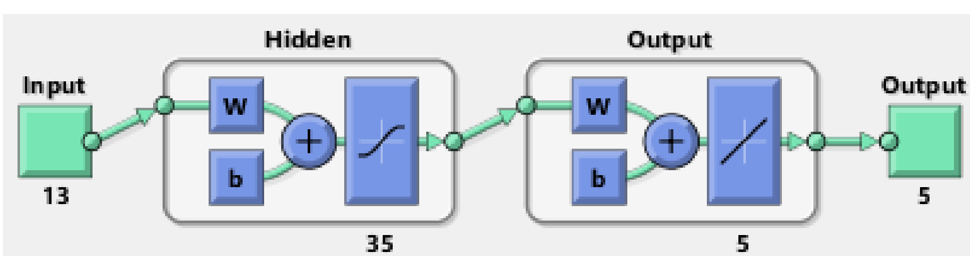


Figure 3. 1 Network input, output and hidden neuron

5) Training the Neural Network: - This is the basic part of prediction work because our result (prediction) perfectness was measured from different perspective. By using the input and

output data from table 3.1 and table 3.2 training of the network was performed. At the completion of first trained network, the result was crosschecked by using performance measurements (Error histogram, Regression fit and output_target deviations).

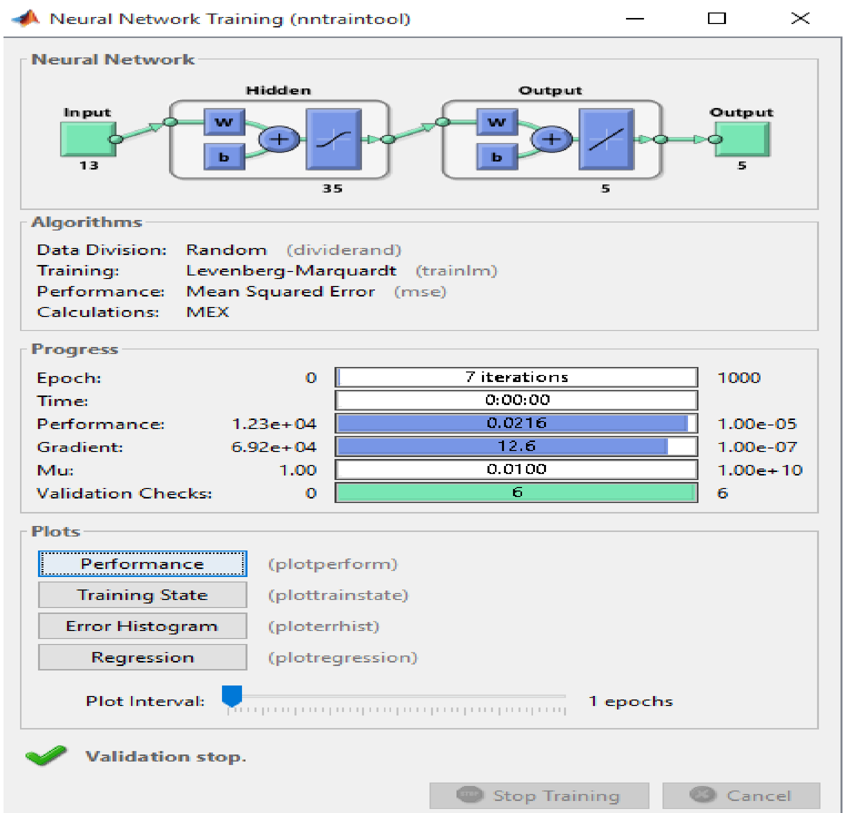


Figure 3. 2 Network training using input and output data (table 3.1 and table 3.2)

6) Simulate the Trained Network

After obtaining best performance from performance measurements, the trained network was simulated to obtain required predicted parametric value with respect concepts in table 3.3

3.1.2. Network performance and predicted value

During the training process the weight in the network are adjusted to minimize the error and to obtain high performance in the solution. The performance of each designed neural network using varies training algorisms were tested by the following basic ways.

1) Error histogram which is statistical and scientific error computation to analyze the error.
2) Using regression fit

3) The neural network prediction were directly compared with the experimentally obtained data (target) to evaluate the learning performance

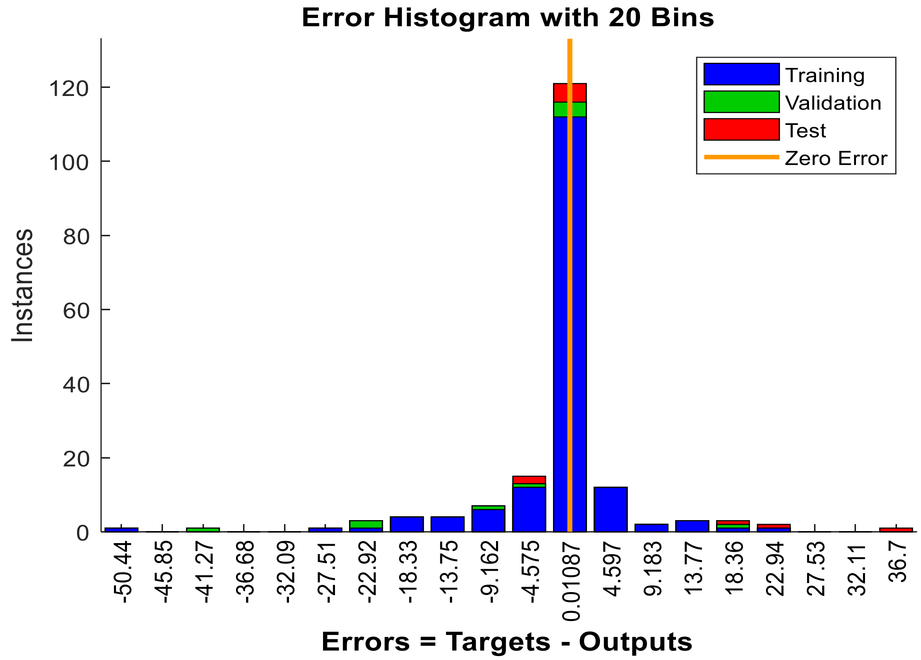


Figure 3. 3 Error Histogram for material property prediction training

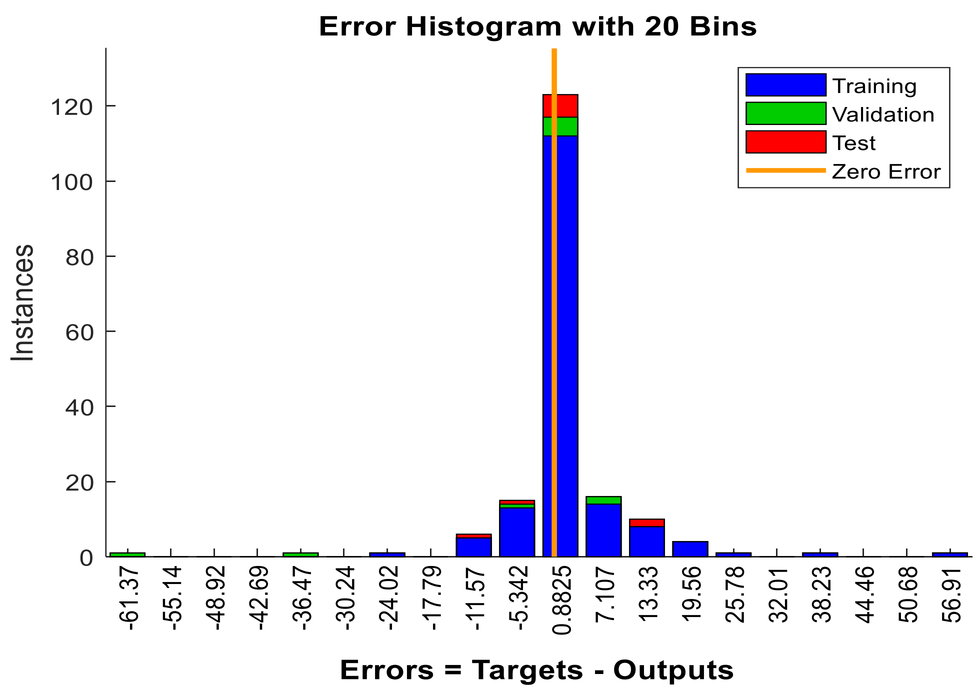


Figure 3. 4 Error histogram for contact stress prediction training

From the graph of Error histogram versus instance, most of the data (training, validation and test) are near to zero. This indicates the developed network has better performance for predicting the new concepts. The data with small deviation from zero error are due to strength variation of weights given for each samples in back propagation algorism. With respect to the number of samples in the input and target, this performance is the best performance in predicting the required mechanical properties of each concepts

Another performance measurement in prediction is the regression fit. In the regression we can see the deviation of each sample output data from the target. The total experimental data was randomized and divided into three categories in training the network (training subsets, validation subsets and testing subsets). When the hidden line Y near or overlaps with the bold (fit) line, then the network output is almost similar to the target (experimental output). As we can see in figure 3.4 almost all sample outputs; training, validation and test are near the fit line. This indicates that, the training network for the specified network parameter is at best performance or minimum error between the experimental target and prediction output.

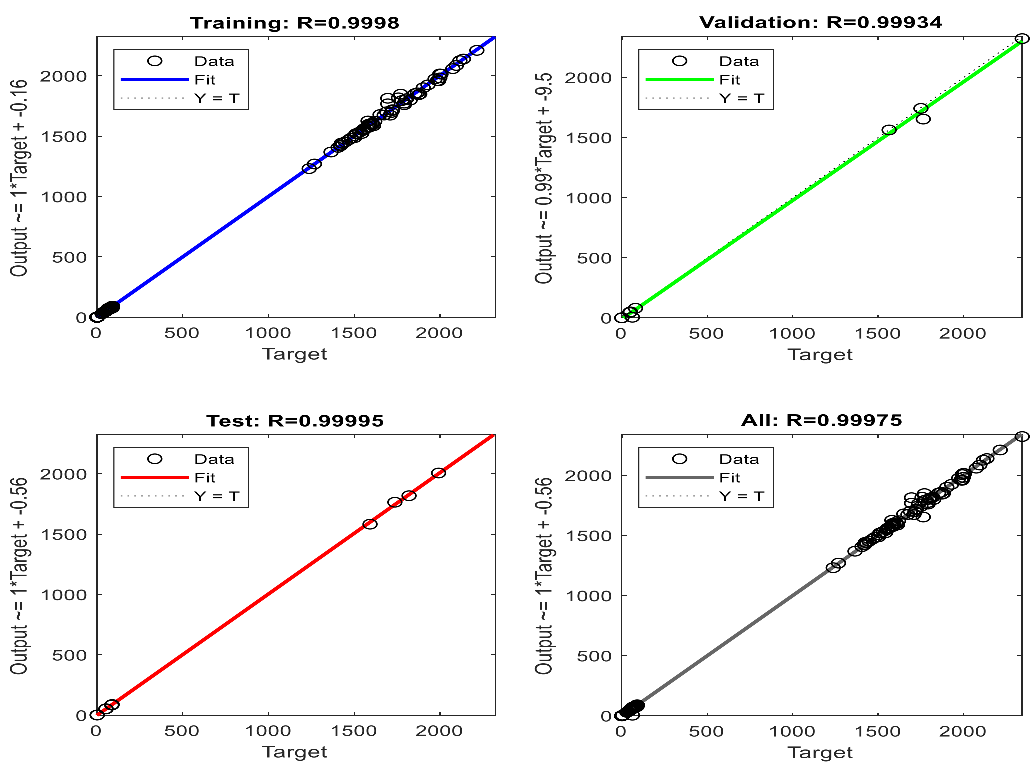


Figure 3. 5 Regression fit for material property prediction training

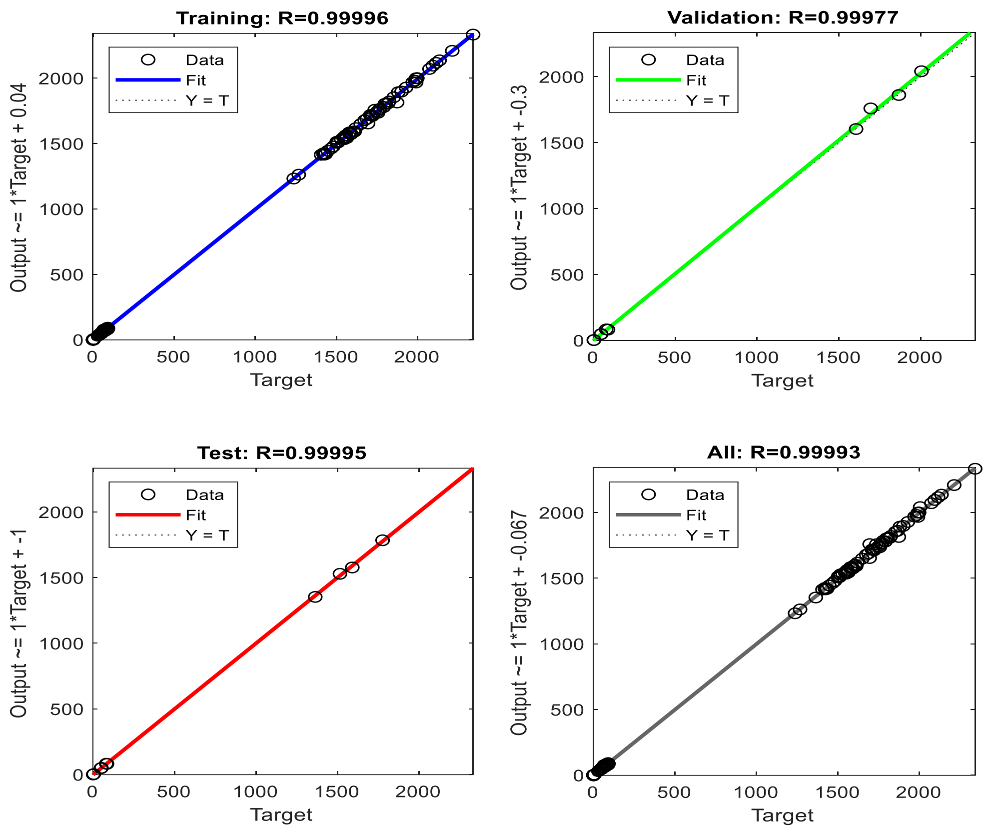


Figure 3. 6 Regression fit for contact stress prediction training

Figure 3.5 reflects the fitting between the target (experimental output) and output (neural network prediction output). The amounts of correlation coefficient (R) with values of, 0.9998, 0.99934 and 0.99995; in training, validation and testing phases respectively has obtained. Similarly figure 3.6 has best fitting in terms of the three sets, revealed a good agreement between predicted and actual values, and show that training of ANN was proper.

We can plot the regression fit for the the mechanical properties separately. For the first graph (fracture toughness) there is some deviation from the fit line. This small deviation indicates the error between the target and output. The hardness, yield strength and ultimate strength graphs are almost near the fit line, indicates the best performance of the developed training setup.

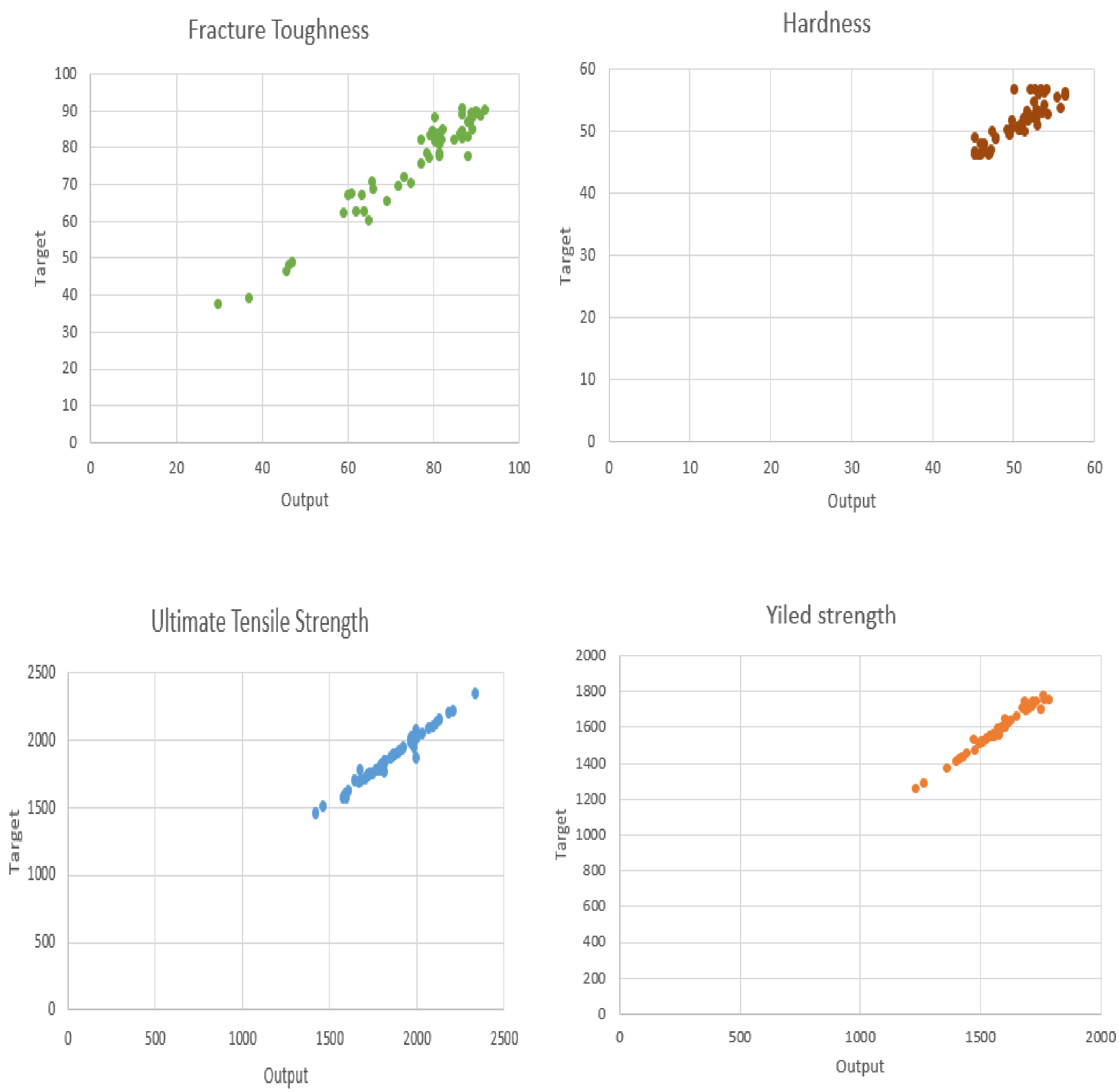


Figure 3. 7 Output-target deviation

After better performance has obtained in training the network, we can conclude that the developed network is ready for predicting and simulate the new concept. The simulated output using new input (concept 1-5) were the predicted mechanical properties that we want to develop. In the neural network prediction it has obtained five mechanical properties (Yield strength, Ultimate tensile strength, fracture toughness, retained Austenite and hardness) for five concepts (concept 1, concept 2, concept 3, concept 4, and concept 5). All the concepts are expressed graphically for ease of understand as shown from figure 3.6 to figure 3.9 and it is at Austenite temperature of 900 ^{o}c.

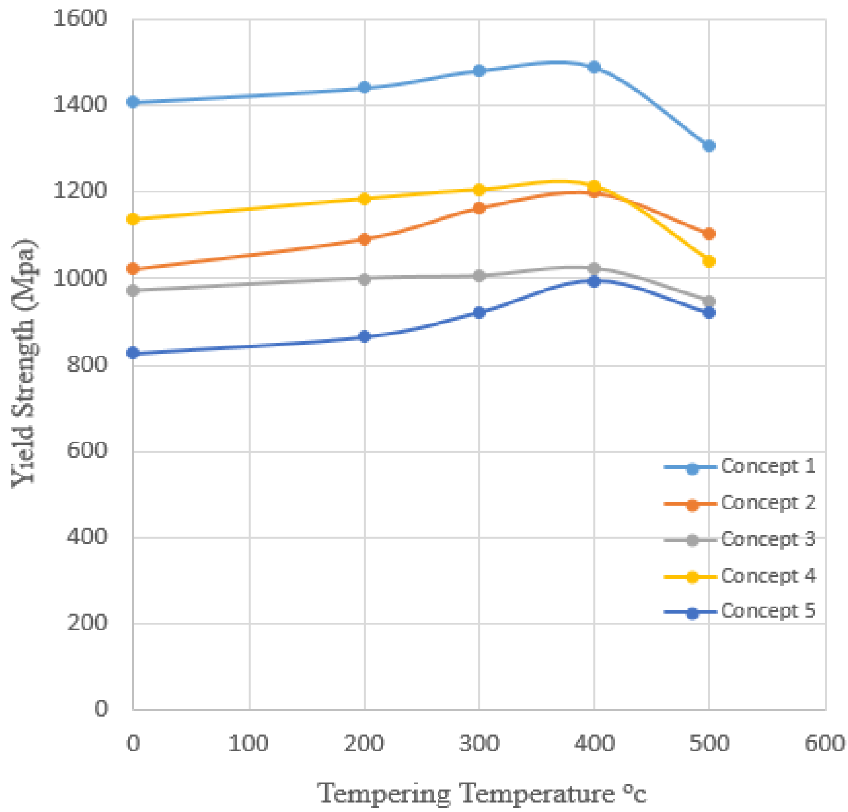


Figure 3. 8 The Yield strength of concepts

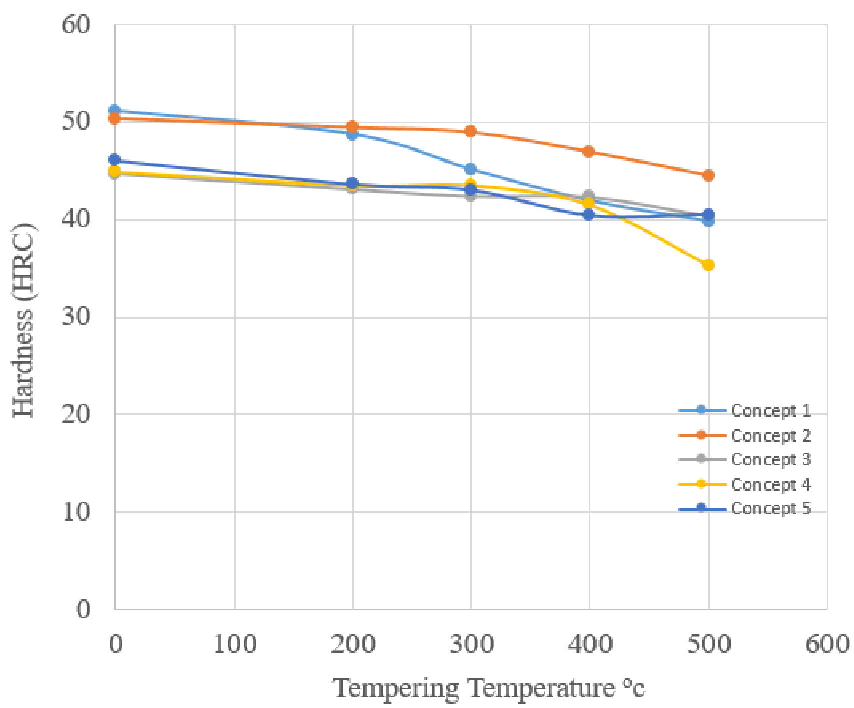


Figure 3. 9 Hardness of concepts

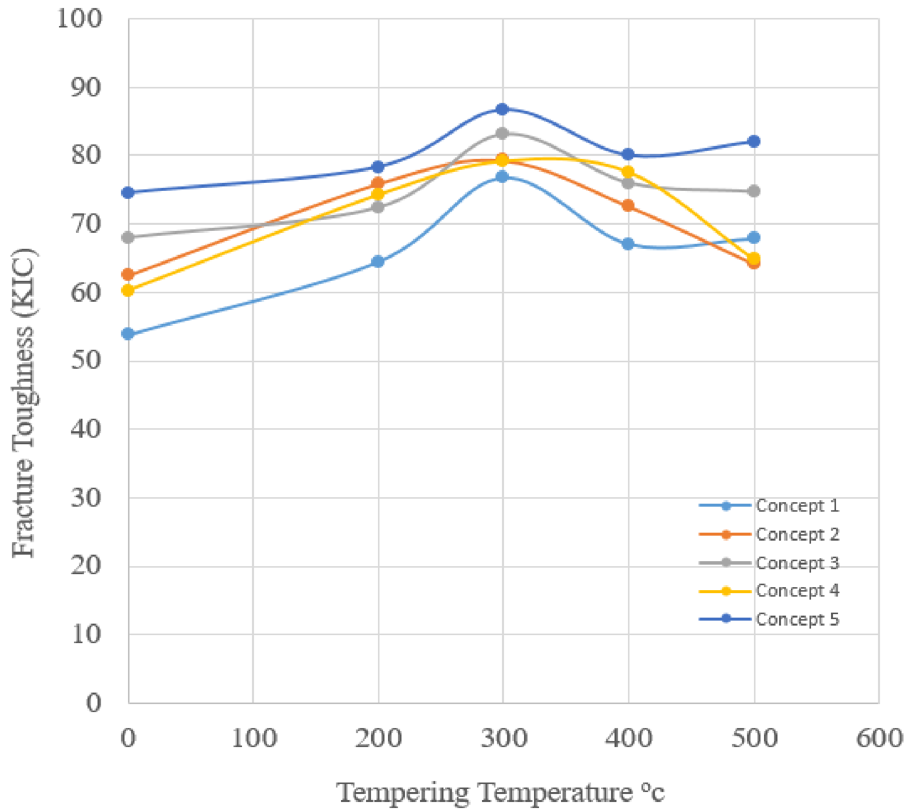


Figure 3. 10 Fracture toughness of concepts

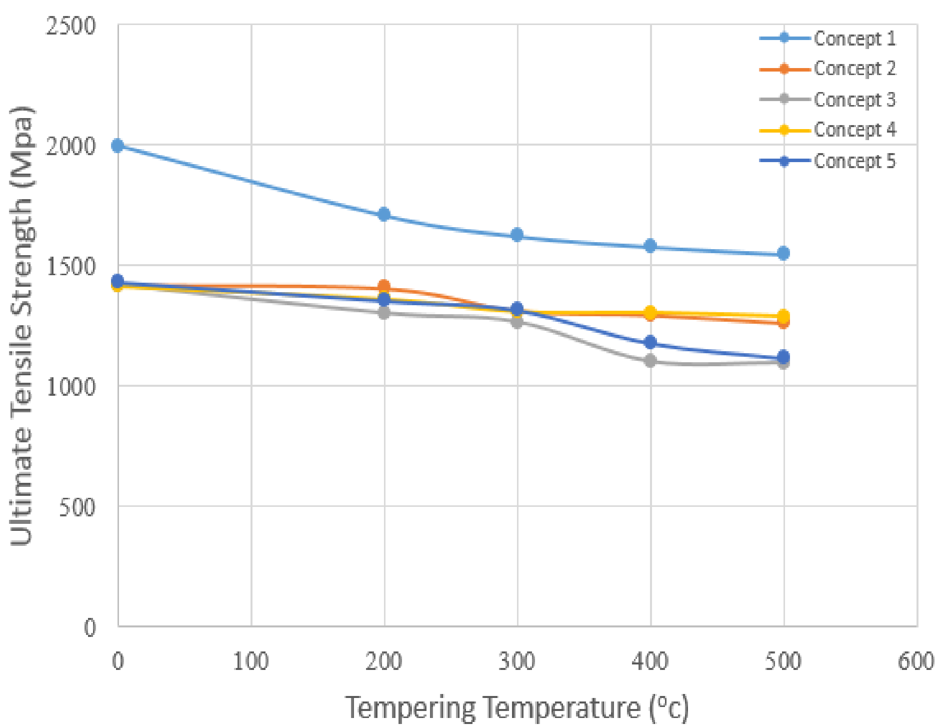


Figure 3. 11 Ultimate Tensile strength of concepts

3.2. Methods

3.2.1. Geometrical Modeling and Involute Tooth Profile Generation

Helical gears that transform rotation between parallel axes in opposite directions are in external meshing and are provided with screw tooth surfaces of opposite directions. The tooth profile of a helical gear is a helicoid or involute. It was assumed in the derivation of this equation that the helicoid is generated by the screw motion of a cross profile about the gear axis. The cross profile is represented in a plane that is perpendicular to the gear axis. However, a helicoid may also be generated by the screw motion of the axial profile, which is a curve represented in the plane drawn through the axis of the helical gear.

In order to conduct analysis of helical gears in mesh, first it should be noted that helical gears in mesh have some inherent complexity in terms of tooth profile. Helical gears can be analyzed conveniently as equivalent spur gears by projecting all geometric data into the transverse plane of the tooth. In involute profile helical gear, pressure angle remains same throughout the operation and the velocity is not affected due to variation in center distance. In addition to that it is easier to manufacture. But in helicoid profile the pressure angle keeps on changing during the operation. It is difficult to manufacture even though it is stronger than involute tooth profile [43]. The twisted angle (helix angle) between the tooth face and the rotating axes produces an oblique tooth surface for helical gears. The involute curve can be generated by driving the position of each pints from the center of tooth circle.

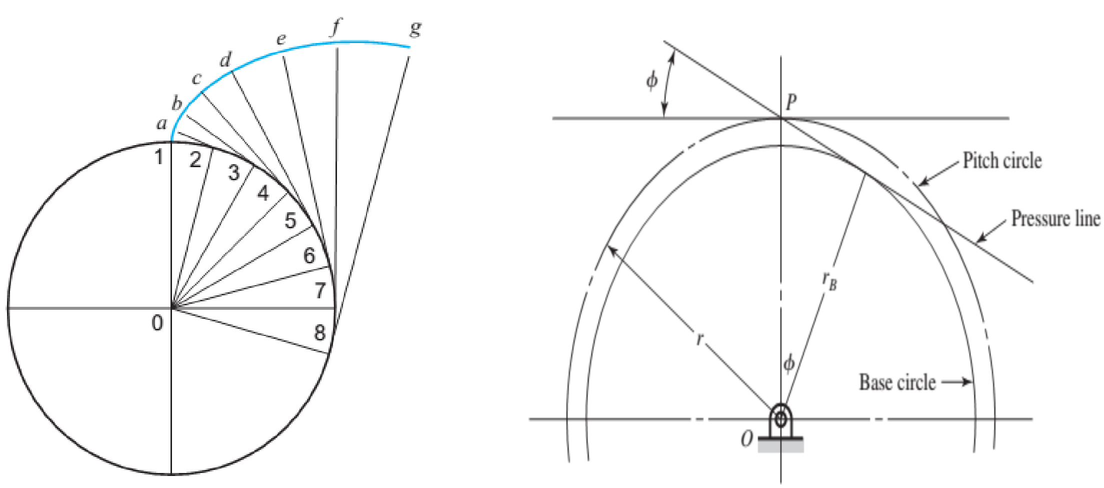


Figure 3. 12 Involute curve [44]

Base circle radius can be related to the pressure angle $\emptyset$ and the pitch circle radius by,

$$r\,b = r \cos \alpha \;.\;\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots. \;(3.4.1)$$

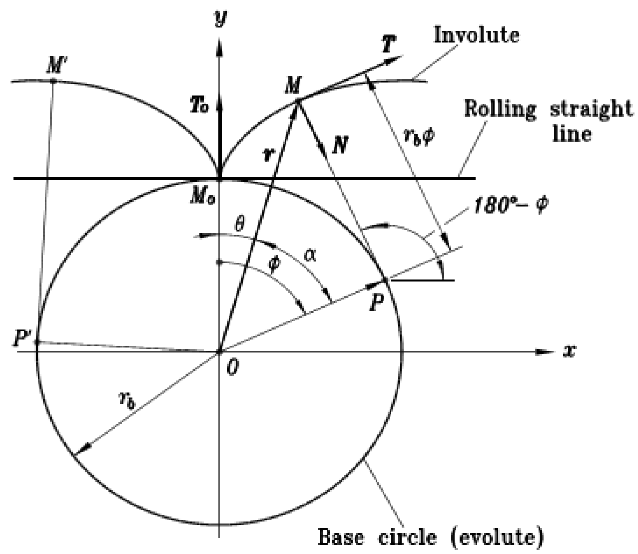


Figure 3. 13 Involute development [44]

We have that r is the pitch circle diameter and r_b is the base diameter of the gear. The profile of the gear will created with pointes (x, y) from the origin.

$$X = r \sin\theta \;,\; y = r \cos\theta \;\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots. \;(3.4.2)$$

Let's take one point M from the curve and form triangle (OPM). The point is at 90 degree from line OP.

$$r_{b} = r \cos\alpha \;\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots. \;(3.4.3)$$

Take radius PM for involute curve circle centered at P.

$$PM = PM_o \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots. \;(3.4.4)$$

From sector OPMo we have that,

$$OP\times \emptyset = \widehat{PMo} \text{ and } \emptyset = \theta + \alpha \;\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots. \;(3.4.5)$$

Let's take an approximate value for $\widehat{PMo} \cong PM$

$$r_b\,(\theta + \alpha) = PM \;\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots. \;(3.4.6)$$

From triangle OPM,

$$PM = r_b \tan\alpha$$

$$PM = r_b\,(\theta + \alpha) = r_b \tan\alpha \;\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots. \;(3.4.7)$$

From this relation we can get that $\theta = \tan\alpha - \alpha$

Now evaluating the x and y value of each individual points from the origin using those parameter expressed above, we can get that;

$$X = \frac{r_b}{\cos\alpha}\sin\theta \text{ , } y = \frac{r_b}{\cos\alpha}\cos\theta \text{ ………………...…. (3.4.8)}$$

By taking the value of alpha from zero to 15 or more degree we can construct the involute curve.

Table 3. 5 X and Y value of points of the involute obtained from equation (3.4.8)

Alpha (deg.)	Alpha (rad)	X	Y
0	0	0	28.2
1	0.017453293	5E-05	28.2043
2	0.034906585	0.0004	28.21719
3	0.052359878	0.001353	28.2387
4	0.06981317	0.003213	28.26886
5	0.087266463	0.00629	28.30772
6	0.104719755	0.010902	28.35533
7	0.122173048	0.017374	28.41177
8	0.13962634	0.026042	28.47713
9	0.157079633	0.037254	28.55149
10	0.174532925	0.051373	28.63498
11	0.191986218	0.068777	28.72773
12	0.20943951	0.089864	28.82986
13	0.226892803	0.115054	28.94155
14	0.244346095	0.14479	29.06294
15	0.261799388	0.179541	29.19424

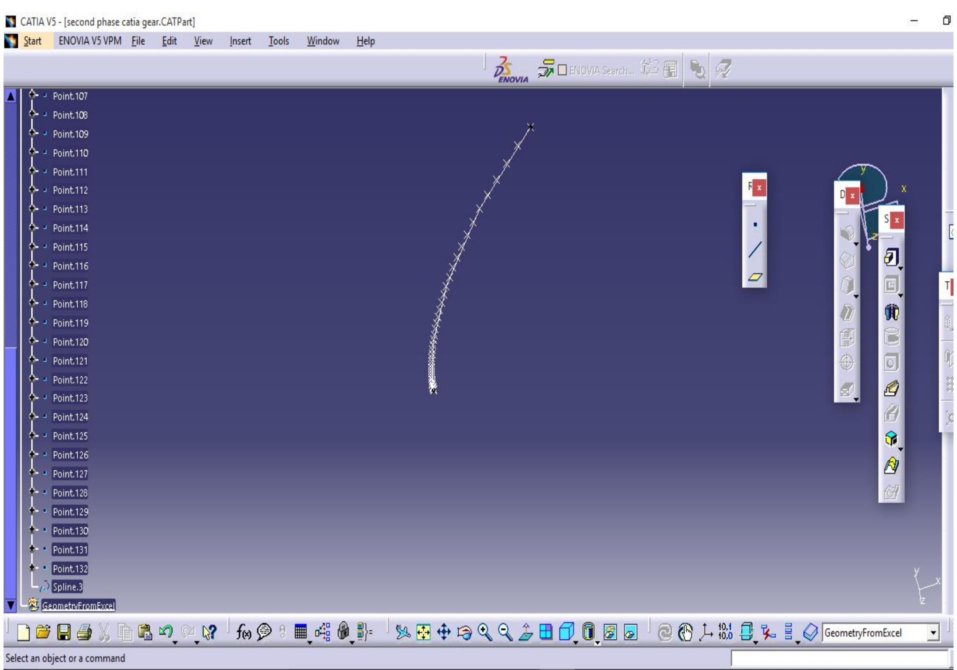
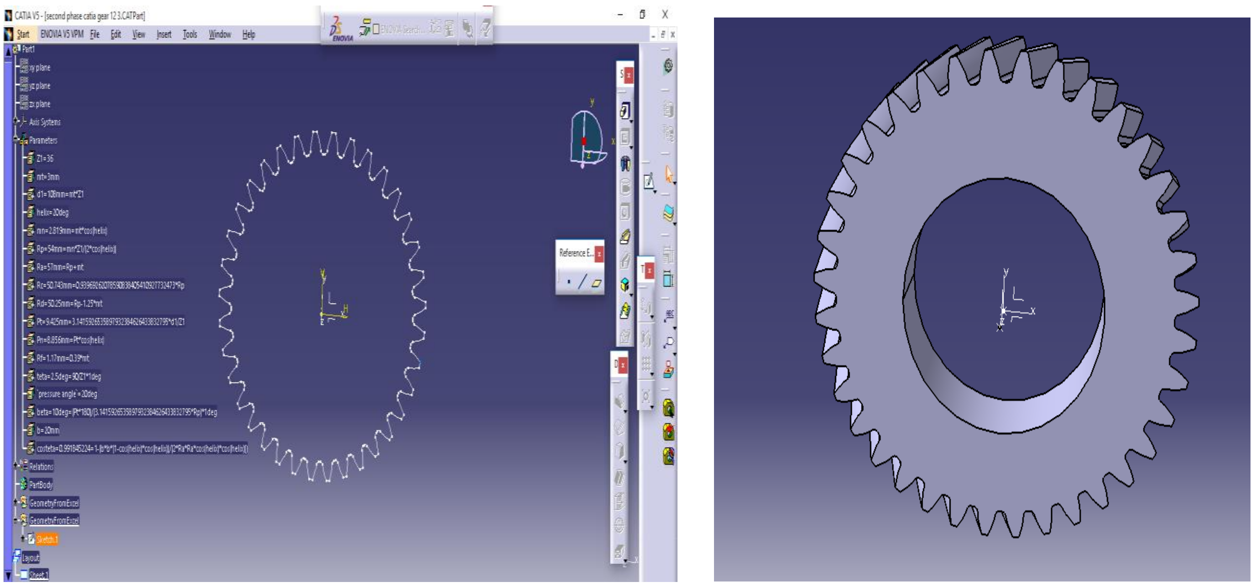


Figure 3. 14 Involute generation using CATIA V5 R 19

All the geometrical dimension of the gear can be related in formula with in CATIA V5 R19, and if we want to change one parameter, all the related parameters in the relation will be changed. Figure 3.13 indicates the 3D model which is developed using the relation of each geometrical dimension of the gear.



a) b)

Figure 3. 15 Helical gear dimensioning using formula in CATIA V5 R19 a) 2-D b) 3-D

3.2.2. Analytical Methods in Contact Stress Analysis

Contact stresses represents a compressive stresses, which is developed from surface pressures between two curved bodies, as a result of the force pressing the bodies against each other. When two bodies having curved surfaces are pressed together, point or line contact changes to area contact, and the stresses developed in the two bodies are three dimensional. The transfer of power between gears takes place at the contact between the teeth. To obtain the expression for surface contact stress of gear we simply use hertz theory of two contacting cylinders. The theory provides mathematical expressions of stresses and deformations of curved bodies in contact. In cylindrical Contact the contacting elements are two cylinders of length L and diameters $d_1$and d_2. As shown in Fig.3.14, the area of contact is a narrow rectangle of width 2b and length L, and the pressure distribution is elliptical. The contact pressure is build up near the pitch circle, where the contact is pure rolling and zero sliding velocity. Fig. 3.14 shows a model for two parallel cylinders in contact and can be applied to the gears.

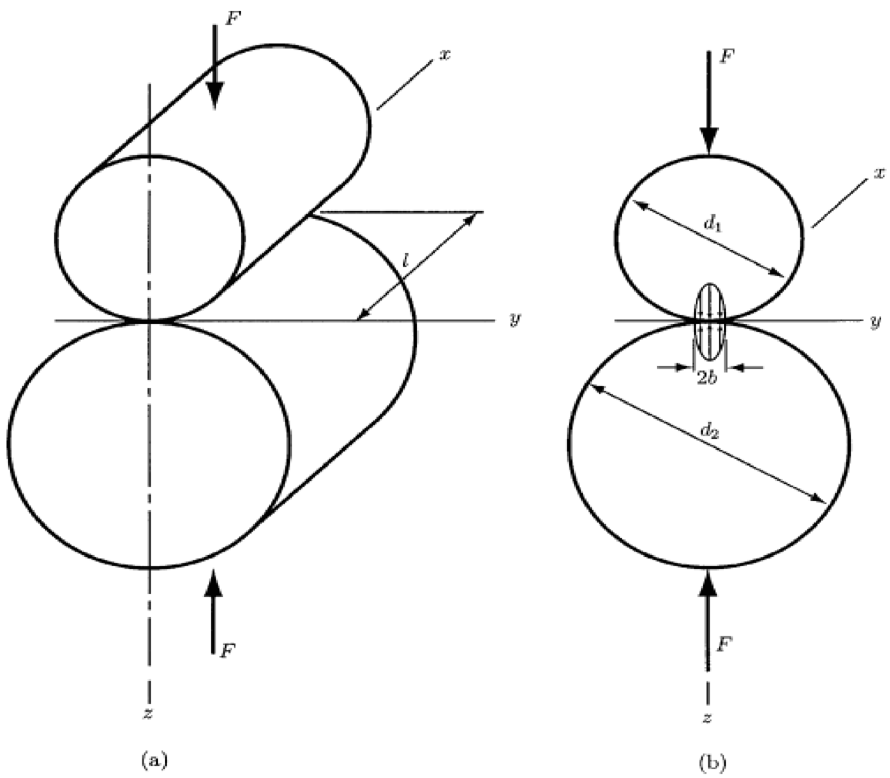


Figure 3. 16 Two contacting cylinders [45]

The half width (b) of the rectangular contact area of two parallel cylinders is

$$b = \sqrt{4F\left[\frac{\left(\frac{1-v_1^2}{E_1}\right)-\left(\frac{1-v_2^2}{E_2}\right)}{\pi L\left(\frac{1}{R_1}+\frac{1}{R_2}\right)}\right]} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(3.4.9)}$$

where E_1 and E_2 are modules of elasticity of cylinder 1 and 2

v_1 and v_2 are poison ratio

R_1 and R_2 are the raius of the two contacting cylinder

The maximum surface pressure at the contact is

$P\ max = \frac{2F}{\pi b L}$ L is length of cylinder in contact and F is appled force

To adapt this relation to the notation used in gearing we replace F by Wt/cosβ and L by face width.

$$P_{max} = \sigma_c = \left[\frac{W_t}{\pi b cos\beta}\ \frac{\left(\frac{1}{R_1}+\frac{1}{R_2}\right)}{\left(\frac{1-v_1^2}{E_1}\right)-\left(\frac{1-v_2^2}{E_2}\right)}\right]^{\frac{1}{2}} \quad \ldots\ldots\ldots\ldots\ldots \text{(3.4.10)}$$

Equation 3.4.10 can be apply for teeth, assuming for R_1 and R_2 the respective radii of the involute curve at the contact point. Let us assume that the contact takes place at pitch point (figure 3.10), and then the respective radii are,

$$R1= r_{p1}\sin \phi ;\ R2 = r_{p2}\sin \phi$$

The actual cylindrical gear-tooth rating formulas for pitting resistance are based on Hertz's approach for calculation of contact pressure between two curved surfaces. There are factors that have influence on the analysis of gear contact and it is neccesary to take considerations. AGMA use some modifications to consider load sharing between adjacent teeth, the load increment due to external and internal dynamic loads, uneven distribution of load, mesh misalignment caused by inaccuracies in manufacture, and elastic deformations, overload (extreamly appliedload),and other factors . American Gear Manufacturers Association (AGMA) standard for pitting resistance and bending strength of spur and helical involute gear teeth, was published with the methods for determining considerable factors.

AGMA contact stress is,

$$\sigma_c = C_p\sqrt{\frac{W_t K_o K v K_s K_m C_f}{bdI}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(3.4.11)}$$

Where, C_p is elastic coefficient

$$C_p = \sqrt{\frac{1}{\left(\frac{1-v_1^2}{E_1}\right)-\left(\frac{1-v_2^2}{E_2}\right)}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(3.4.12)}$$

For torque T the transmitted tangential load is,

$$W_t = \frac{2T}{d} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(3.4.13)}$$

Dynamic factors (Kv): are used to account inaccuracies in manufacturing and meshing of gear tooth in action. Even if the input torque and speed are constant, significant vibration of the gear masses, and therefore dynamic tooth forces, can exist. These forces result from the relative accelerations between the gears as they vibrate. Ideally, a gear set would have a uniform velocity ratio between the input and output rotation. The dynamic factor relates the total tooth load including internal dynamic effects to the transmitted tangential tooth load.

In attempt to account for this effect AGMA 2001-D04 has defined a set of quality number from 3 to 12. It is determined from graph of pitch line velocity and quality number.

$V = \frac{\pi dn}{60} = 31.4$m/s

Using this value of pitch line velocity and by considering precise quality of gear with quality number of 9, the dynamic factor is 1.45

Overload factor (Ko): intended to make allowance for an externally applied load. By considering moderate shock of driven system and light shock source of power, the overload factor is 1.5.

Size factor (Ks) reflects non uniformity of material property due to size and AGMA recommended value of unity for most gear provided appropriate choose of steel.

$$I = \frac{\cos\emptyset_t \sin\emptyset_t}{2M_N} \times \frac{M_G}{M_G+1} \quad \ldots\ldots (3.4.14)$$

M_G is gear ratio

$$M_N = \frac{p_n \cos\emptyset_n}{0.9Z} \quad \ldots\ldots (3.4.15)$$

$$Z = \left(\sqrt{(r_p + a)^2 - r_{bp}^2} + \sqrt{(r_g + a)^2 - r_{gp}^2}\right) - (r_p + r_g)\sin\emptyset_t \quad \ldots\ldots (3.4.16)$$

Where r_{bp} base circle radius for pinion and r_{bp} Base circle radius for pinion and gear

Table 3. 6 Based on AGMA standard calculated factors and corresponding values

Parameter	Value
Dynamic factor (K_v)	1.45
Over load factor (K_o)	1.5
Surface condition factor (Cf)	1
Load distribution factor (Km)	1.168
Geometry factor (I)	0.06309
Size factor (K_s)	1

Helical Gear Surface Fatigue Strength

Surface fatigue strength of the material is given by:

$$\sigma_{sf} = \sigma_{sf}' K_L K_H K_R K_T \quad \ldots\ldots (3.4.17)$$

Where, σ_{sf}', K_L and K_R are surface fatigue strength, Life factor and Reliability factor respectively.

For 10^7 cycle with99% reliability, $K_L = K_R = 1$,

K_H is Hardness ratio factor

- $K_H = 1.0$ for ratio of Brinell hardness of the pinion by Brinell hardness of the Gear < 1.2)

For $T \leq 120^oC$, based on Lubricant temperature, the temperature factor (KT) is 1.

Allowable surface fatigue stress for factor of safety n is given by;

$$\sigma_c = \frac{\sigma_{sf}}{n} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(3.4.18)}$$

3.2.3. Contact Fatigue Life

Fatigue life can be considered as the total number of cycles of stress or strain of a specified character that a given component sustains before a crack initiates and then grows sufficiently to lead to catastrophic failure [46]. Scientifically, *S-N* curves represent fatigue data which are usually obtained from test for a smooth specimen. *S-N* curves are plotted with applied stress as a y-coordinate against the total cycles to failure (N_f) as the x-coordinate. It can be divided into two parts, low cyclic fatigue life time (LCF), which is characterized by high cyclic stress levels, and high-cycle fatigue HCF which is characterized by low cyclic stress levels. The low cycle fatigue life time is based on a small numbers of cycles to cause damage or failure and the material is subjected to high stress levels that can produce significant macroscopic plastic strains.

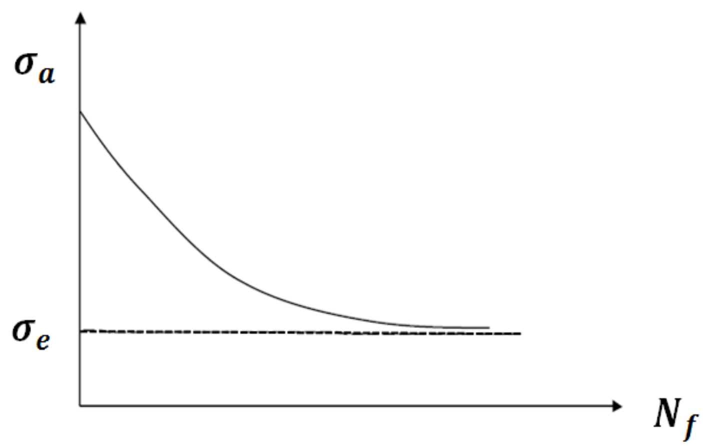


Figure 3. 17 Stress life relationship for HCF [47]

In a fatigue test and in most practical applications the stress is cycled between the minimum and maximum values. This is called constant amplitude stressing.

The stress amplitude (σ_{ar}) can be stated as,

$$\sigma_{ar} = \sigma_a = \sigma'_f (2N_f)^b \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(3.4.19)}$$

Where, σ_{ar} is stress amplitude

σ'_f is the fatigue strength coefficient,

b is known as the Basquin exponent or the fatigue strength exponent.

In Mechanical Engineering Hand book for fatigue [37], we have that,

$$\sigma'_f = S_{UT} + 50\text{ksi} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3.4.20)$$

$$b = -\frac{1}{3}\frac{\log(\sigma'f\ /\ \sigma_{fs})}{\log(2\times10^6)} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3.4.21)$$

Where, σ_{fs} is the fatigue strength or endurance limit

Fatigue life determination for all mechanical components and structures is an essential subject in the operating and design stages. Certain materials have a fatigue limit or endurance limit which represents a stress level below which the material does not fail and can be cycled infinitely. If the applied stress level is below the endurance limit of the material, the structure is said to have an infinite life. Through many years of experience, empirical relations between fatigue and tensile properties have been developed [48]. So the fatigue limit or endurance limit, σ_{fs}, is a property of materials where the component may be cycled indefinitely below this stress amplitude level without failure.

The fatigue cycle life and stress amplitude is,

$$\sigma_{ar} = \sigma_a = \sigma' f(2N f)^{b}$$

$$\sigma_a = (S_{UT} + 50\text{ksi})\ (2N_f)^{b} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3.4.22)$$

$$\sigma_a = (S_{UT} + 345)\ (2N_f)^{b} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3.4.23)$$

Table 3. 7 Calculated values of Stress amplitude for each cycle equation (3.4.23)

Number	Number of Cycle	stress amplitude
1	10	2036.7053
2	10,000	1480.1243
3	100,000	1330.7246
4	1,000,000	1196.4600
5	5,000,000	1110.654
6	10,000,000	1075.824
7	50,000,000	998.7316
8	100,000,000	967.2554

3.2.4. Contact Stress Analysis by FEM

The finite element method is numerical analysis technical of optioning approximate solution to a wide verity of engineering problems. Because of its diversity and flexibility as an analysis tool, it is receiving much attention in engineering school and industries. We find that it is necessary to obtain approximate solution to problems rather than exact close form solution. A static analysis calculates the effects of steady loading condition on a structure, while ignoring inertia and damping effects such as those caused by time varying loads. A static analysis can, however include steady inertia loads (such as gravity and rotational velocity), and time varying loads that can be approximated as static equivalent loads. Static analysis is used to determine the displacements, stresses, strains and forces in structures or components due to loads that do not induce significant inertia and damping effects. The kinds of loading that can be applied in a static analysis include externally applied forces and pressures, steady state inertial forces Assumption [49].

Procedure of finite element analysis

The structural analysis of the helical gear train was performed in six stages namely input of engineering data, definition of geometry, development of model, setup, generation of solution and results. The following procedures are used in FEM analysis

a) Developing IGES form of gear Geometry

The model is generated using the equations of involute profile for helical gear tooth. CATIA V5 has parametric features, you can change one feature and all related features are automatically updated to reflect the change and its effects throughout the part.

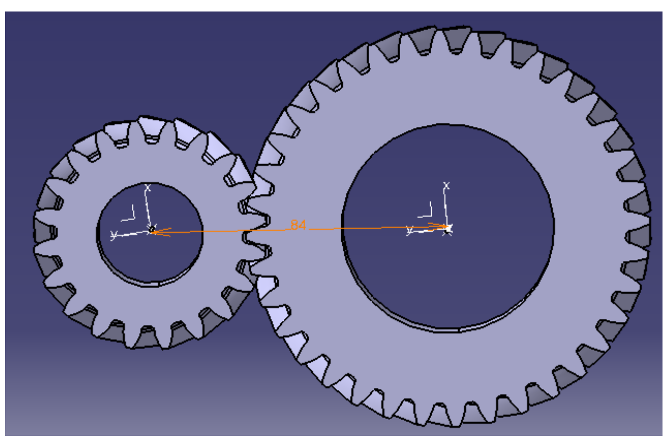


Figure 3. 18 Pinion and gear assembled geometry

b) After developing the 3D model of helical gear tooth and saved in IGES form, it is imported to Ansys 17.2 by selecting the static structural analysis.

c) Apply material for pinion and gear. Define material properties which are necessary to solve the problem. The material for the gear and pinion is concept 1 having similar chemical composition to 20MnCr5Mo and the required material properties for this analysis were developed using artificial neural network prediction.

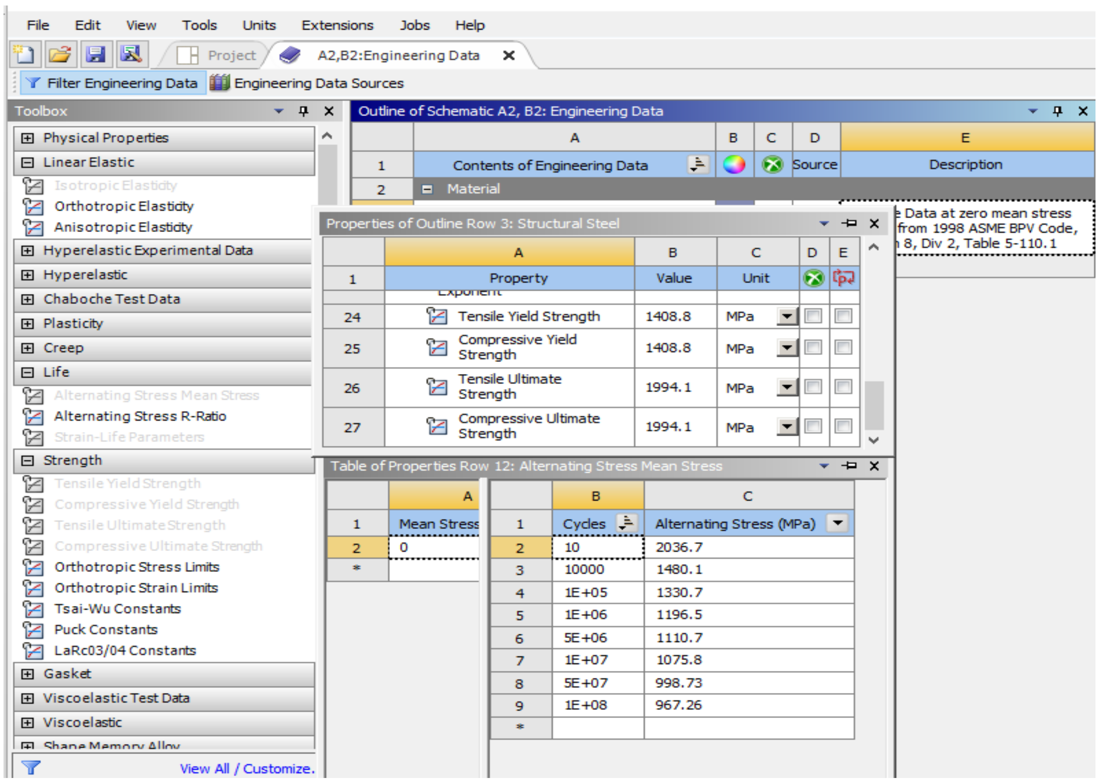


Figure 3. 19 Material define in engineering data

d) Select the contact type

There are two general contact analysis types.

1. Rigid - to - flexible bodies in contact,
2. Flexible - to - flexible bodies in contact

In rigid - to - flexible contact problems, the contacting surfaces are treated as being rigid material, which has a much higher stiffness relative to the deformable body it contacts. Many metal forming problems fall into this category. Flexible-to-flexible is where both contacting bodies are deformable. Flexible-to-flexible analysis include gears in mesh, bolted joints, and interference fits.

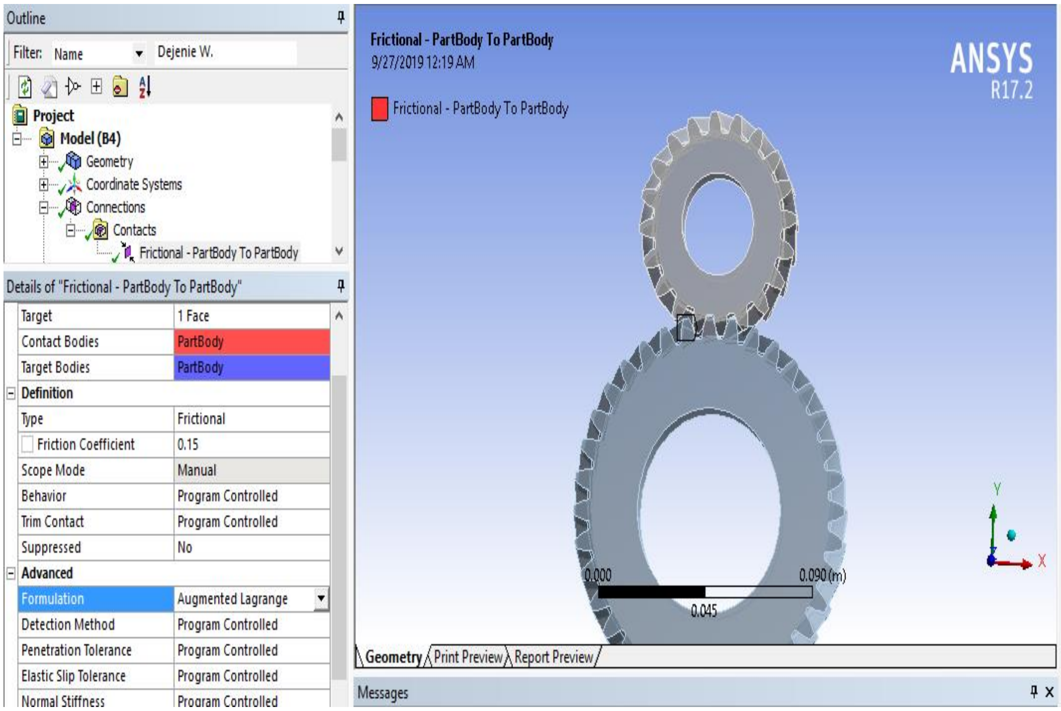


Figure 3. 20 Contact type of gear and pinion

The contact type is frictional contact with augmented Lagrange. Augmented Lagrange formulation is less sensitive to the magnitude of the contact stiffness coefficient and leads to better conditioning.

e) Generate Mesh:

A meshing process serves two primary purposes.

(1) To discretize a continuous domain into a set of elements and nodes, so that the problem has a finite number of unknowns

(2) It approximates the system solution by assembling a set of simple sub-models for elements. Even though the meshing process is performed by the computer automatically, Manual intervention is needed to generate a good mesh.

All of the calculation for a mesh is performed by the computer automatically; users only need to specify the settings for meshing. However, it is a very common case that a meshing process runs into some problems to achieve the required quality of mesh. To solve a problem occurring in the meshing process, one often needs to adjust meshing parameters [50]. The comparative analysis of study on FEM models with a fine mesh, FEA of meshed with course mesh gear teeth and theoretical analysis of gears teeth contact stresses with the Hertz theory indicates that, FEM models with course meshes as the optimal mesh type [18].

Here body sizing with 2 mm mesh size for the pinion and gear, contact sizing of 1 mm and refinement at the edge of contact was applied.

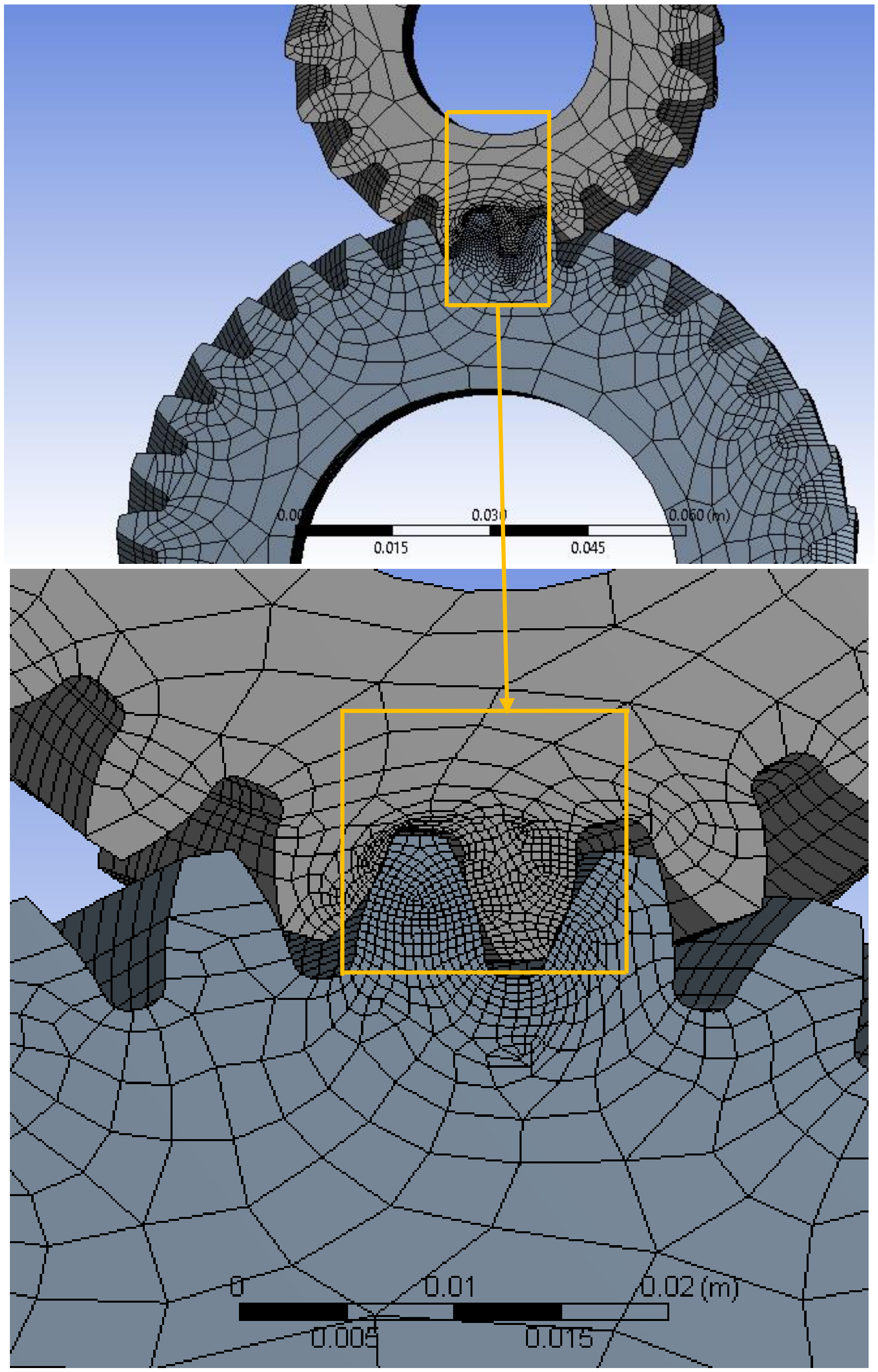


Figure 3. 21 Gear and pinion mesh in contact

f) Define Boundary Condition For Analysis:

Boundary condition play the important role in finite element analysis.

- Take the inner surface of pinion and gear frictionless and fixed support respectively
- Apply displacement along the four faces of the gear and pinion by making the displacement along the z axis zero and free along the x and y.
- Apply moment at the inner surface of the pinion. The torque applied at the inner rim of the pinion can be used as a moment.

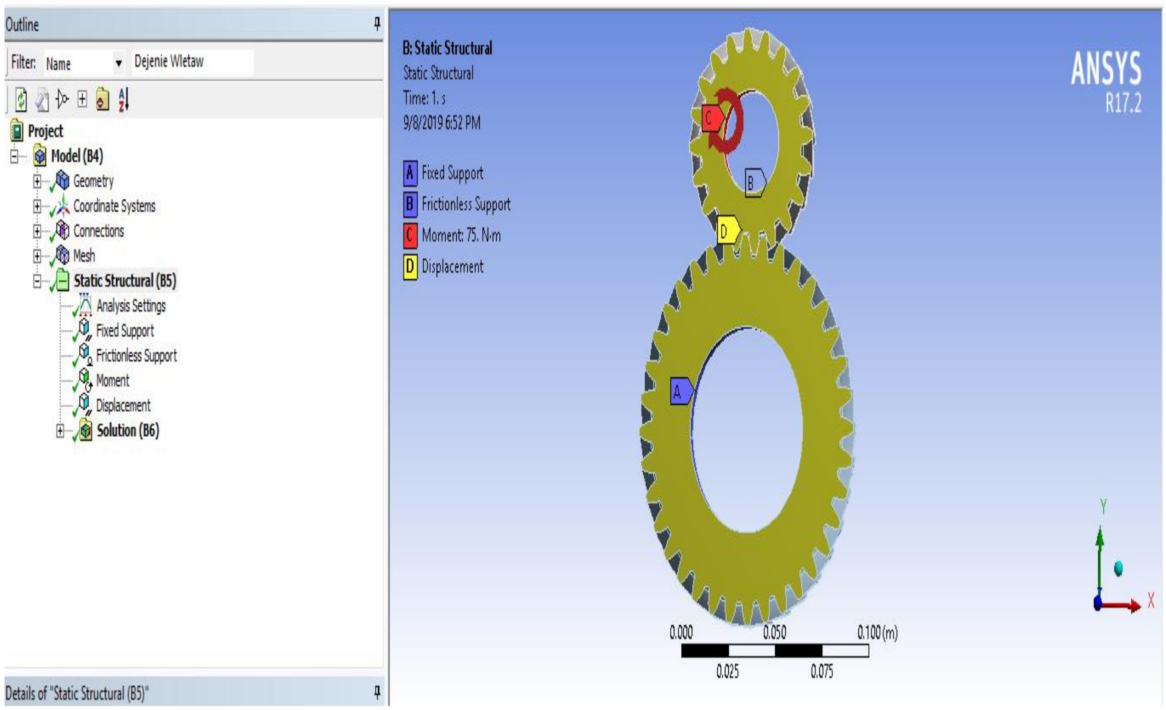


Figure 3. 22 Boundary conditions

g) Generate Solution

The parameters that we want to analyze were inserted before generation of solution. The contact stress, total deformation and contact fatigue tool were considered here. The numerical solutions are compared with that of the analytical analysis. Similarly fatigue stress analysis of remaining helical gears has been accomplished in ANSYS. Surface fatigue strength of the tooth profile is calculated by using allowable surface fatigue stress.

Chapter Four

4. Result and Discussion

4.1. Results

4.1.1. Contact Stress Analysis

To analyze the contact fatigue of helical gear, analytical analysis using AGMA and finite element method (Ansys) was used. Finite element analysis with static structure can be used for determining the contact stress (von-misses stress), fatigue life and safety factors. Using Artificial Neural Network prediction the required mechanical property of gear material was determined for the specified concepts. The material property used for gear and pinion was inserted in engineering data toolbox. Appling material, meshing, properly applying boundary conditions and solving are the procedures used to obtain Ansys results. The contacts stress has determined using the formula which is recommended by AGMA for specified parameters. Using input and output data (table 3.4) ANN training for contact stress has done. In addition to that, using the fatigue strength of the material, the factor of safety has determined with AGMA strength formula. The fatigue life for contact stress was analyzed by using alternating stress and number of cycle relations.

Table 4. 1 Contact stress value of AGMA and Finite element approach

Applied Torque (Nm)	Tangential force (N)	AGMA Contact stress (Mpa)	Ansys Contact Stress (Mpa)	Contact stress difference (%)	Fatigue life (10^6 cycle)
45	1500	1004.52	959.7	4.46	-
50	1666.67	1058.86	1020.7	3.60	31.59
55	1833.33	1110.54	1081.7	2.59	8.889
60	2000.00	1159.92	1142.7	1.48	2.739
65	2166.67	1207.28	1203.7	0.297	0.883
70	2333.33	1252.86	1253.5	0.051	0.376
75	2500.00	1296.83	1289.3	0.58	0.203

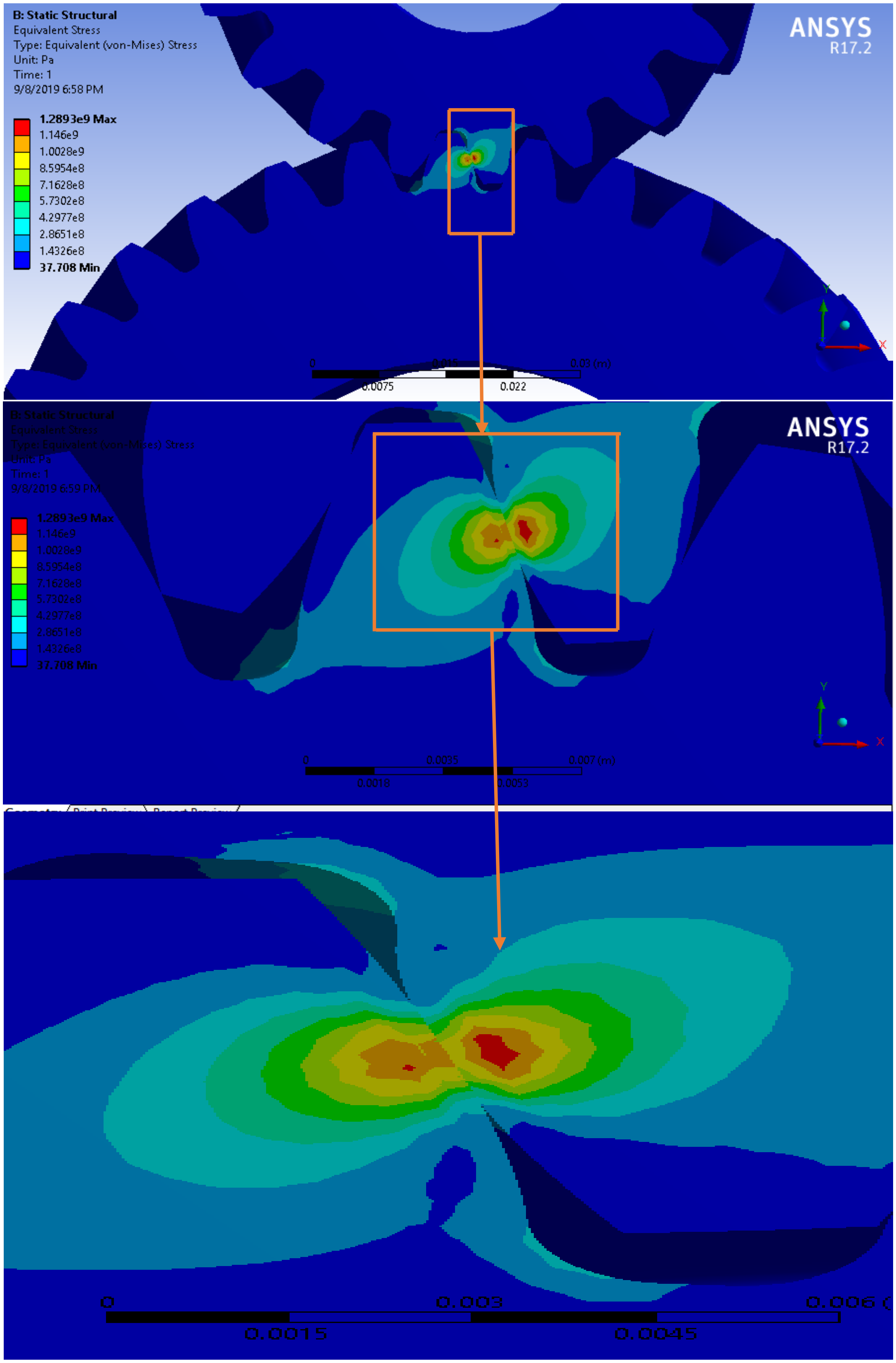


Figure 4. 1 The Von-Misses stress at the constant area

For perfectly generated and refined mesh, the contact stress distribution area varies with friction coefficient. For friction coefficient of 0.15 the contact stress distribution is at a little millimeter depth from the surface of pinion and gear, which is as shown in figure 4.1.

The graph in figure (4.2) below, represents the relation between contact stress, which is determined by using analytical approach and Ansys workbench, and applied tangential load. All the input parameters used in the two approaches are similar but there is small deviation between the results which is called error.

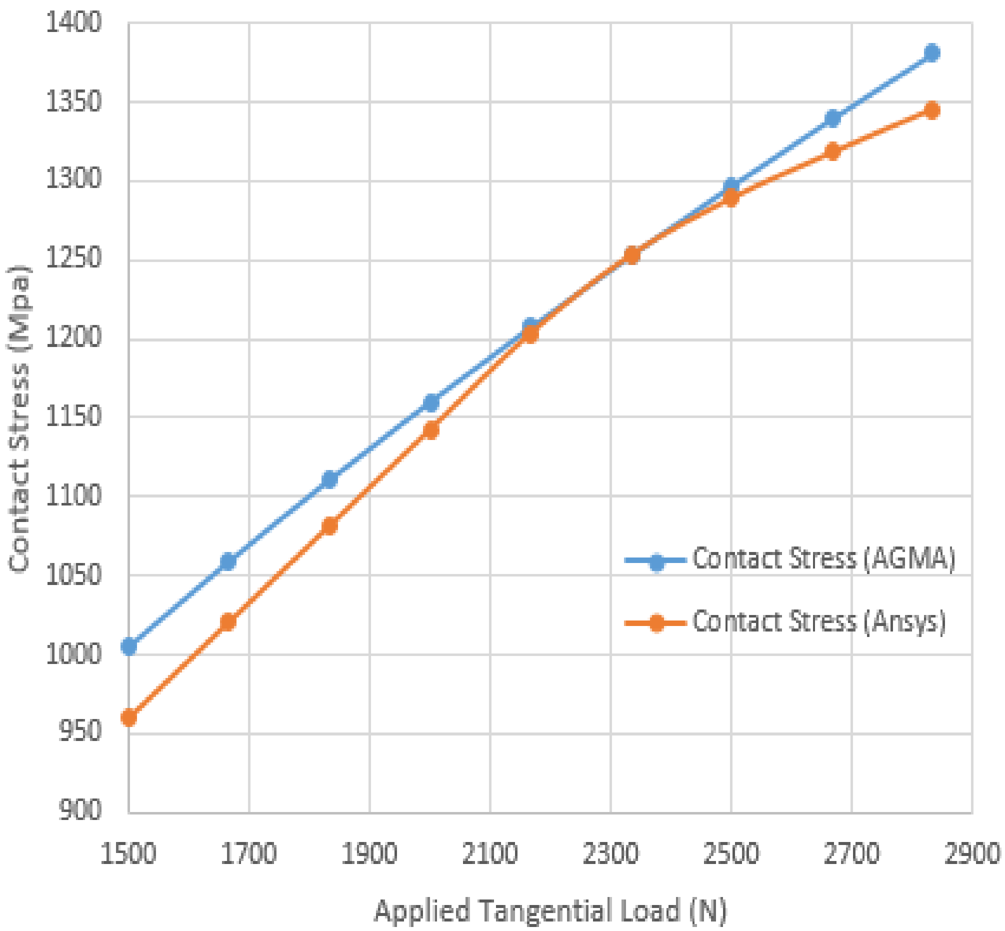


Figure 4. 2 Contact stress for AGMA and Ansys

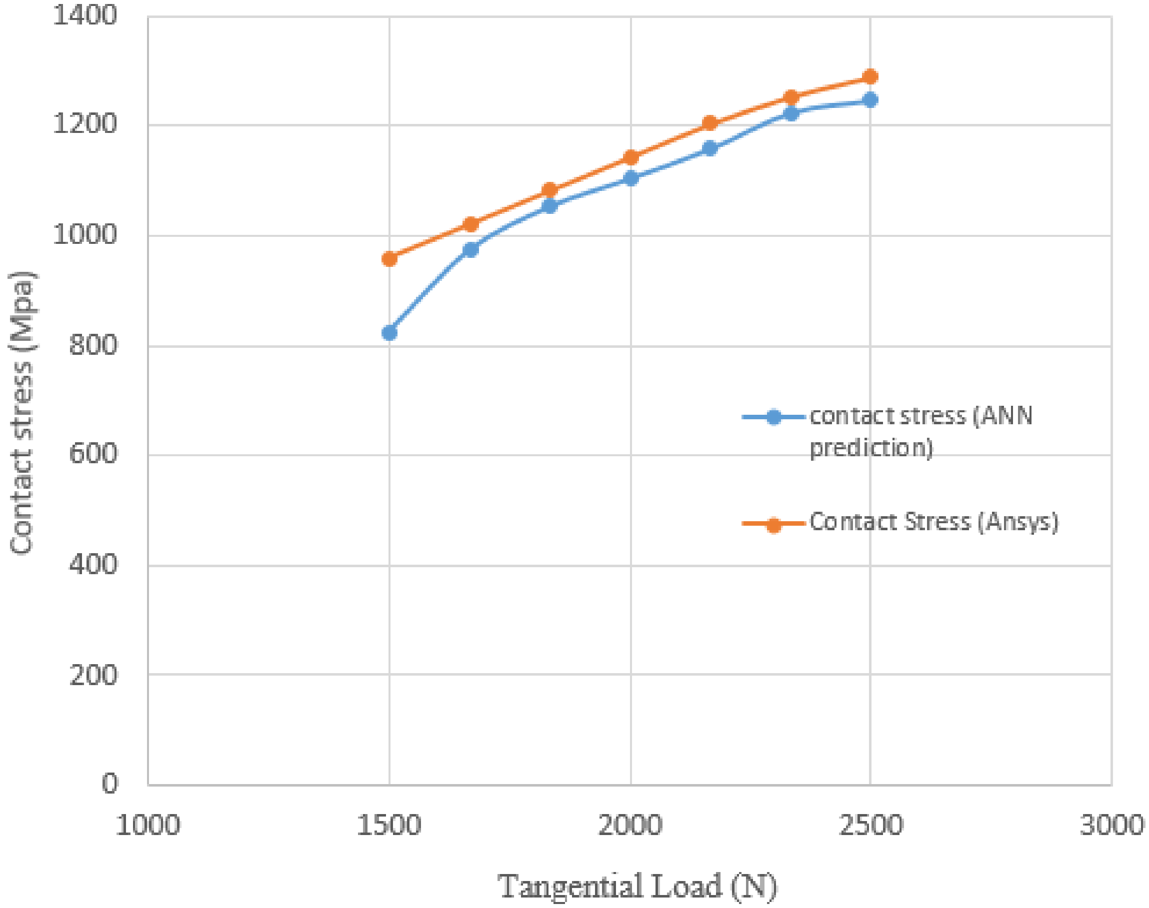


Figure 4. 3 Contact stress for ANN prediction and Ansys

4.1.2. Fatigue Life

For constant amplitude the fatigue life is, the number of cycle in operation until the part fail due to fatigue. As the stress level is below the fatigue limit, the material for gear and pinion does not fail and can said to have an infinite life. As show in table (4.1), the life cycle of the material for each contact stress level below the endurance limit is greater than 10^6, but it is limited when the contact stress level reaches the endurance limit or fatigue strength. If we see figure 4.3, when the applied moment increased from 50 N-m to 75N-m the contact stress area due to fatigue becomes increased. At applied moment of 45 N-m the contact fatigue life is 10^8 and the fatigue life can be considered as infinite.

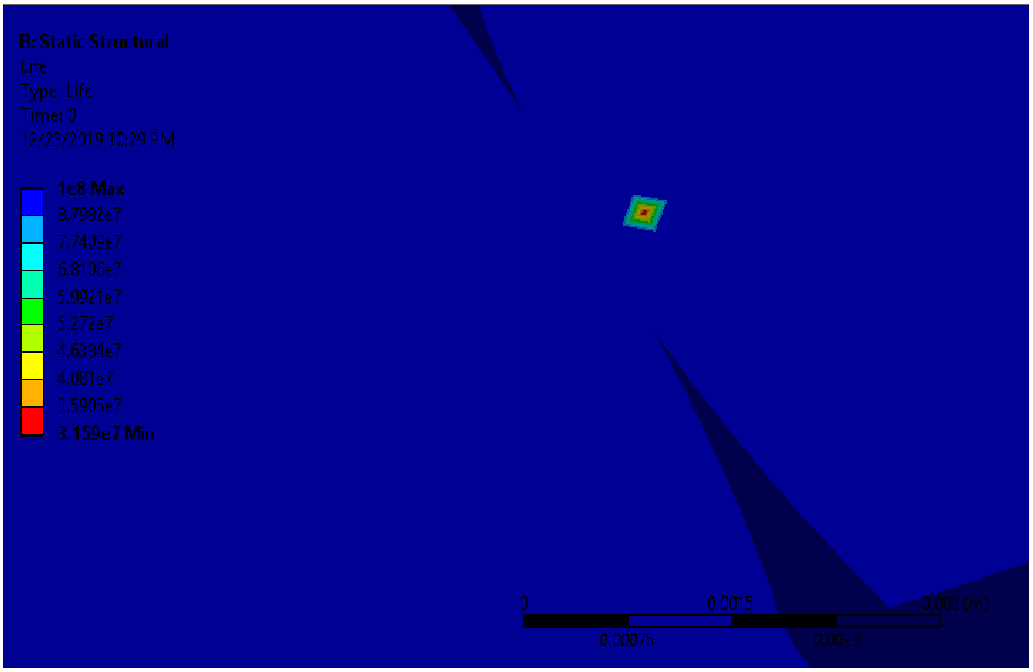


Figure 4. 4 Fatigue life at 50 N-m

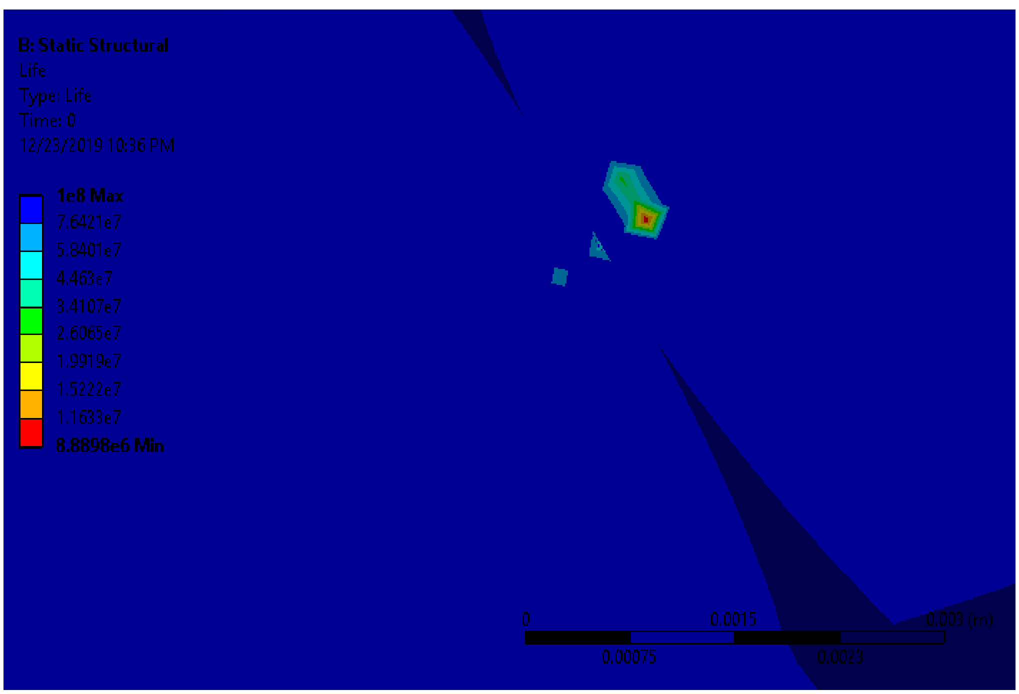


Figure 4. 5 Fatigue life at 55 N-m

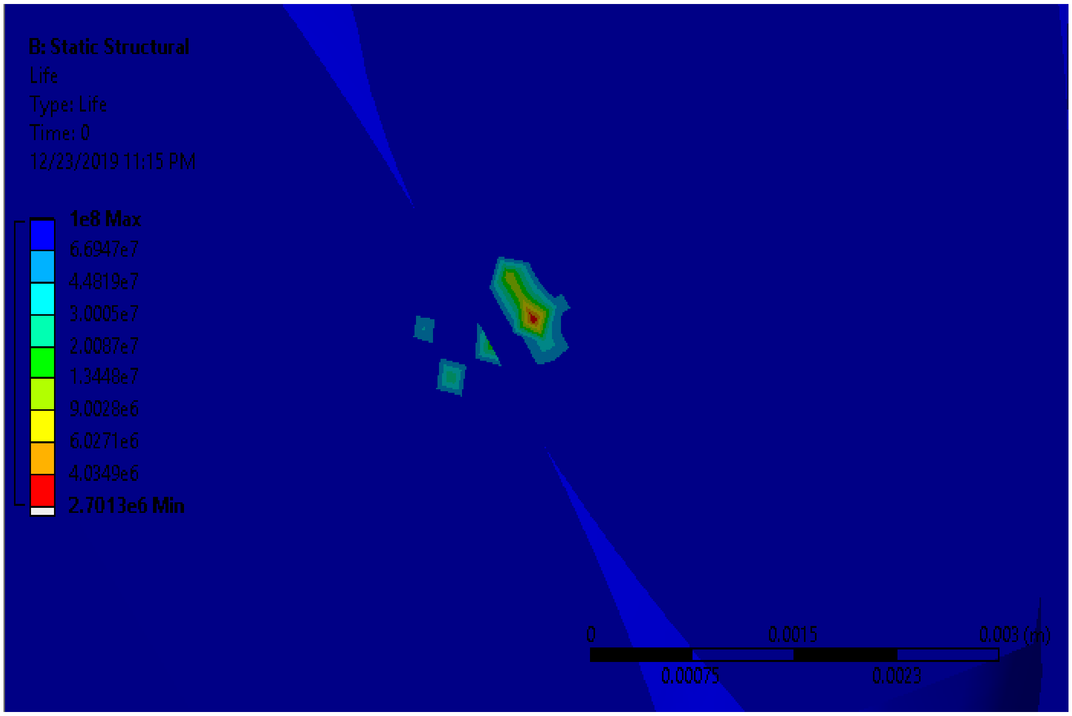


Figure 4. 6 Fatigue life at 60 N-m

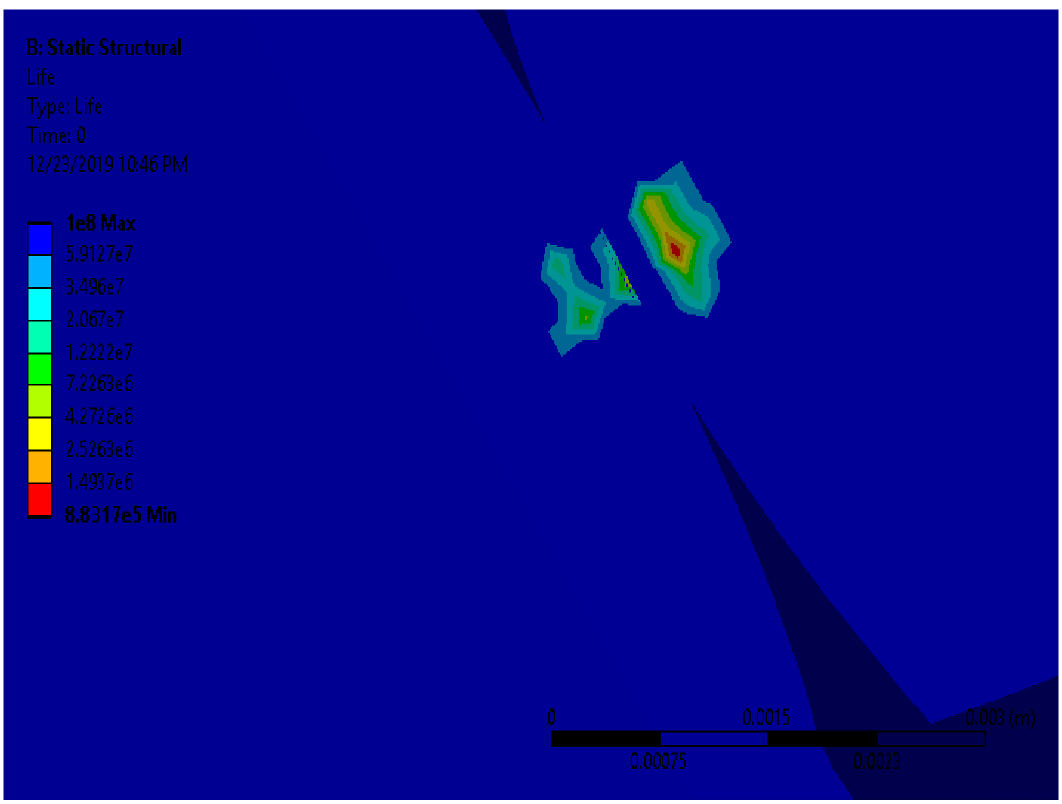


Figure 4. 7 Fatigue life at 65 N-m

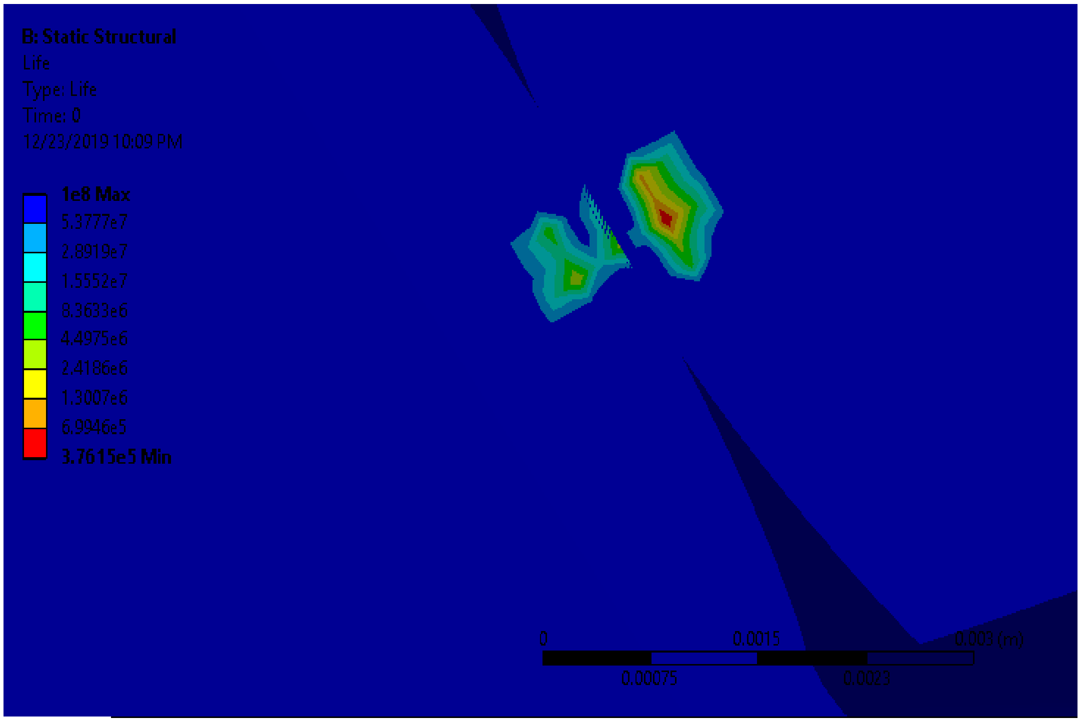


Figure 4. 8 Fatigue life at 70 N-m

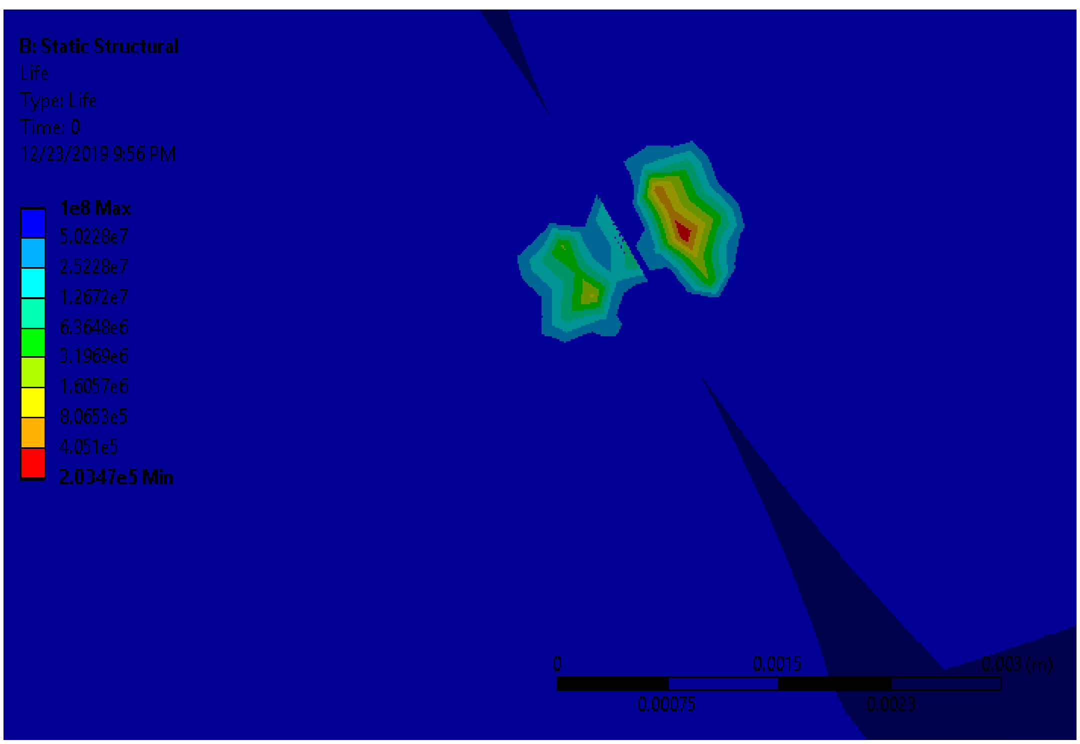


Figure 4. 9 Fatigue life at 75 N-m

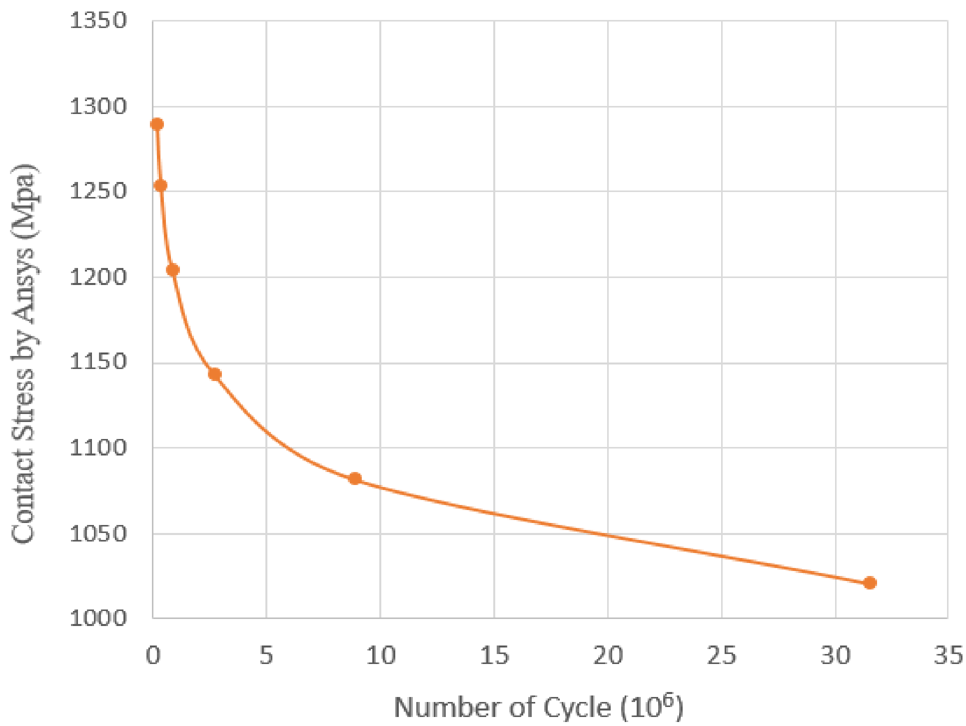


Figure 4. 10 contact stress versus number of cycle

As shown in figure 4.9, the fatigue life decreased rapidly for contact stress above the fatigue strength of the material. But it is decreased slowly when it is below the fatigue strength.

By using the fatigue strength of the material, the factor of safety was easily determined for theoretical analysis (AGMA) and Finite Element Analysis.

Table 4. 2 factor of safety for corresponding contact stress

AGMA Contact stress (Mpa)	Ansys Contact Stress (Mpa)	Factor of safety for AGMA	Factor of safety for Ansys	Factor of Safety Difference (%)
1004.52	959.7	1.19	1.25	4.80
1058.86	1020.7	1.13	1.17	3.41
1110.54	1081.7	1.08	1.11	2.70
1159.92	1142.7	1.03	1.05	1.9
1207.28	1203.7	0.99	0.995	0.5
1252.86	1253.5	0.955	0.954	0.1

By using the fatigue strength of gear material, the factor of safety has determined for Analytical analysis (AGMA) and Finite Element Method (Ansys) for the applied tangential load. There is small difference (error) between the AGMA and Ansys, which is 4.8 % and below.

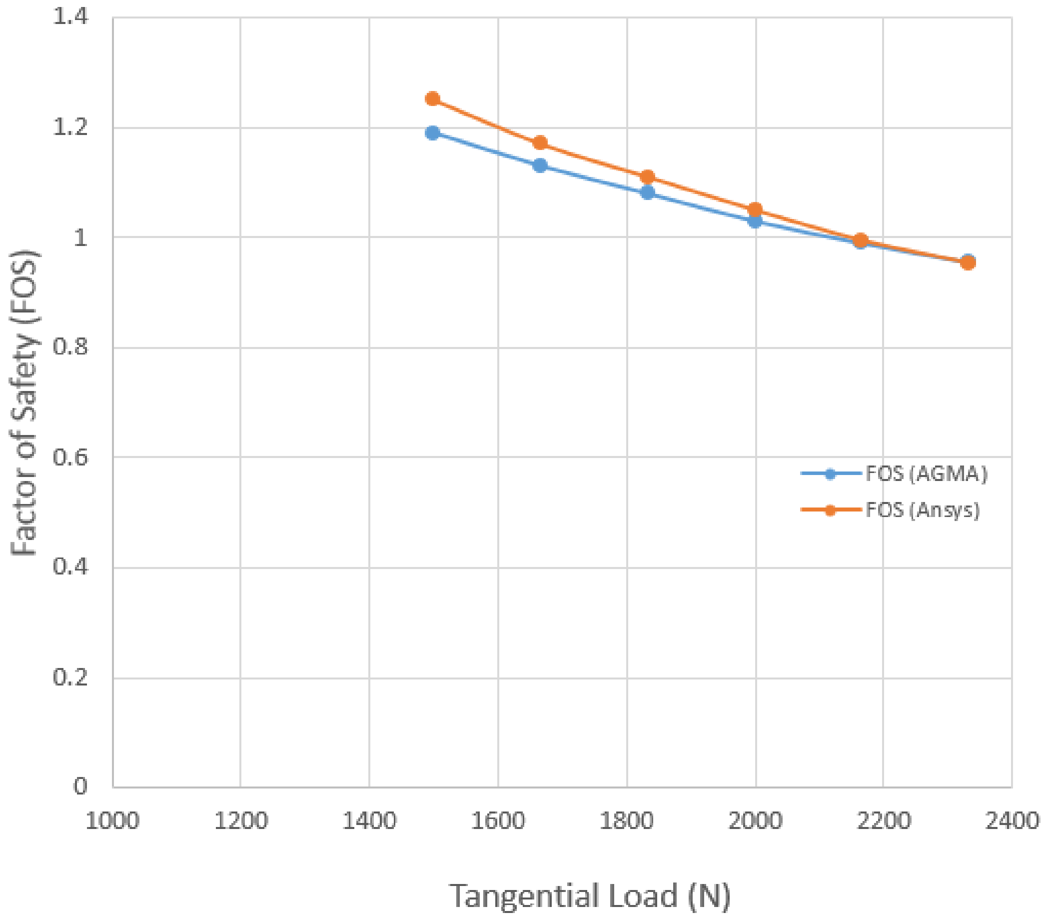


Figure 4. 11 Factor of safety with respect to contact stress in Ansys and AGMA.

4.2. Discussion

From Artificial Neural Network approach, the property of material used for gear model (ultimate tensile strength, yield strength, toughness, retained austenite and hardness) was developed using input and output data from literature on experimental investigation. Before those mechanical properties were developed, the performance of the prediction network was measured using regression fit, target-output and error histogram. As shown in figure (3.5) the developed training network for material property prediction has best agreements to experimental targets based on those performance measurements. This indicates that the network is able to predict the new concepts.

The contact stress analysis was performed by using theoretical analysis, ANN prediction and finite element methods. The theoretical analysis was done by using AGMA formulas. The result obtained using FEM (Ansys) were, the contact stress due to applied torque (moment) and the fatigue life. The maximum von-miss stress with red color in figure (4.1) is the maximum contact stress. The result obtained in the three analysis is listed in graph and table form as shown in the result portion. Finite element approach comparison with theoretical approach has done for the material developed and the difference (error), in terms of contact stress and factor of safety, were plotted in graph. As the shown in figure (4.2), when the moment is increased from 45 Mpa to 75 Mpa the contact stress is also increased from 957.9 Mpa to 1289.3 Mpa and there is an increase in contact stress area due to fatigue load. The factor of safety of AGMA for the corresponding applied moment was compared to Ansys value and the error is 4.8 % and below. The result shown in the figure 4.5 indicates that, the material which is predicted by using ANN has best performance until the applied tangential load reaches 2000 N. Because for applied tangential load of 2000 N, the factor of safety for AGMA as well as Ansys is greater than one. In similar way the error for the contact stress between AGMA value and Ansys is 4.46 % and below. This indicates, the analysis using the two approach is best agreed

Chapter Five

5. Conclusion, Recommendation and Future work

5.1. Conclusion

In this study contact stress and fatigue life analysis has been done using FEM and analytical analysis. The material property which is used for analysis was predicted by artificial neural network. Based on the analysis, using the predicted material with ANN, comparison of FEM and A GMA standard results has done. The result indicates that, it is selective technique to predict the mechanical properties of materials using ANN model, when there is limited condition to use experimental investigation and to analyze the contact stress and fatigue life using FEM by comparing to AGMA

From this study the researcher draws the following conclusion

- It is selective to predict materials mechanical property using Artificial Neural network hen there is limited condition to use experiment. The Predict mechanical properties using ANN model was used as input for AGMA and FEM.
- Contact stress analyzed using AGMA and FEM has compared and best agreed value (error of 4.46% and below) had obtained.
- Comparison of factor of safety for AGMA contact stress and Ansys was also done and maximum error of 4.8 % had obtained.

5.2. Recommendation

It is known that, most of gear analysis is performed by using FEM, experimental and theoretical approaches. To determine the mechanical properties of materials, experimental investigation is necessary. It is possible to predict mechanical property of material by using ANN prediction instead of experimental work. After the network has trained with input and output data obtained from experimental work, new concept from the similar domain can then be predicted without performing additional experiments. In addition to that ANN can be applicable in contact fatigue life prediction, if enough input and output sample data is be obtained to get appropriate and good prediction.

5.3. Future Work

In this research ANN prediction, contact stress and contact fatigue life of helical transmission gear has been investigated. This thesis work needs to extend to the following areas,

- Dynamic loads influence on the fatigue life of helical gear
- Effect of surface finish on contact surface fatigue using ANN prediction.
- Fatigue Life prediction using Neural Network Approaches.
- Fatigue crack of helical gear using Neural Network prediction.
- Bending fatigue analysis (using ANN for material selection).

Reference

[1] E. Osakue and L. Anetor, “HELICAL GEAR DESIGN FOR BENDING,” no. April, 2017.

[2] N. Bano, “Neural Network Approach for Predicting the Failure of Turbine Components,” 2013.

[3] H. Shah, “Design , Modeling And Stress Analysis Of High Speed Helical Gear On Basis Of Bending Strength And Contact Strength By Changing ,” No. May, 2016.

[4] X. Li, C. Li, B. Huang, and S. Li, “Contact Fatigue Analysis of Mine Helical Cylindrical Gear Based on ANSYS Workbench,” pp. 12–16, 2013.

[5] J. R. Davis, Gear Materials , Properties , And Edited By. 2005.

[6] I. Material, “Improved Materials and Enhanced Fatigue Resistance for Gear Components,” no. October, pp. 26–32, 2015.

[7] S. Parvizi, H. R. Hafizpour, S. K. Sadrnezhaad, A. Akhondzadeh, and M. Abbasi, “Neural network prediction of mechanical properties of porous NiTi shape memory alloy,” no. April 2014, 2011.

[8] F. Bao, L. Zeng, and B. Huang, “The Design of Transmission Gear Based on the Dynamic Property,” no. Ifeesm, pp. 30–33, 2015.

[9] Joanna Matczak, Kamil Matczak “Modern Approach to Materials Currently Used In Transmission Gears” 2018

[10] D. Tilahun, R. Tsutomu, And G. Deng, “Surface Durability Of Developed Cr-Mo-Si Steel Under Rolling-Sliding Contact *,” Vol. 2, No. 2, Pp. 214–221, 2008.

[11] H. P. Quality and L. Berkeley, “Lawrence Berkeley National Laboratory Lawrence Berkeley National Laboratory,” Lawrence Berkeley Natl. Lab., p. 12, 2008.

[12] J. M. Franzen, “Contact Fatigue Evaluation of Ground and Chemically,” 2013.

[13] K. Naresh and C. Chandrudhu, “Abstract : Where R M Is Mean Radius of the Screw Thread,” Vol.Vi, No. 4, Pp. 194–203, 2016.

[14] H. Long and M. T. M. Martinze, “Analytical and Experimental Study of Gear Surface Micro-pitting Due To Variable Loading.”

[15] T. E. Faculty, “A New Method For Preventing Premature Pitting Formation On Spur Gears,” Vol. 75, Pp. 4431–4438, 2008

[16] H. Heirani and K. Farhangdoost, “Predicting Depth and Path of Subsurface Crack

Propagation at Gear Tooth Flank under Cyclic Contact Loading," J. Solid Mech., Vol. 9, No. 3, Pp. 587–598, 2017.

[17] Shiferaw. D., "Contact Stress Analysis And Surface Fatigue Life Estimation Of Involute Spur Gear By Finite Element Method (Fem)," 2014.

[18] I. Atanasovska, "Finite Element Model for Stress Analysis and Nonlinear Contact Analysis of Helical Gears," No. 1, Pp. 61–69, 2009.

[19] N. K. Fukumasu, G. A. A. Machado, R. M. Souza, And I. F. Machado, "Stress Analysis To Improve Pitting Resistance In Gear Teeth," Procedia Cirp, Vol. 45, Pp. 255–258, 2016.

[20] Y. Chen, A. Yamamoto, and K. Omori, "Improvement of Contact Fatigue Strength Of Gears by Tooth Surface Modification Processing," Pp. 18–21, 2007.

[21] Bluestein J., 2007, "An Experimental Study of the Impact of Various Tooth Surface Treatments on Spur Gear Pitting Life," M.S. Thesis, the Ohio State University, Columbus, Oh

[22] M. J. Brogne, D. I. F. Smithl, D. T. Group, S. D. Ca, and H. R. C. Rockwell, "Gear Hardness Technology

[23] W. Zhang, Z. Bao, S. Jiang, and J. He, "An Artificial Neural Network-Based Algorithm for Evaluation of Fatigue Crack Propagation Considering Nonlinear Damage Accumulation," 2016.

[24] W. P. Tribotesting, D. K. Prajapati, and M. Tiwari, "Use of Artificial Neural Network (ANN) to Determining Surface Parameters , Use of Artificial Neural Network (ANN) to Determining Surface Parameters , Friction and Wear during Pin-on-Disc Tribotesting," no. June, 2017.

[25] A. Ghiami and R. Khamedi, "Prediction of Ferrite- Martensite Dual- Phase Steels Mechanical Properties by Use of Artificial Neural Networks," no. January, 2014.

[26] J. Jones and D. J. C. MacKay, "Neural Network Modeling of the Mechanical Properties of Ni based Super alloys", 8th International Symposium on Super alloys, Seven Springs, Pennsylvania, USA, pp. 417-424, 1996.

[27] O. Ayer and T. Altinbalik, "Fatigue life modeling of gear like products using ANN," no. January 2017, 2016.

[28] B. Environment and W. I. T. Press, "Fatigue Damage Prediction Via Neural Networks Tiago A Piedras Lopes & Nelson F. F. Ebecken COPPE/UFRJ Caixa Postal 68508 CEP21945-

970 Rio de Janeiro RJ Brasil," vol. 29, 1997.

[29] Y. H. Ali, R. A. Rahman, R. Ishak, And R. Hamzah, "Artificial Neural Network Model For Monitoring Oil Film Regime In Spur Gear Based On Acoustic Emission Data," Vol. 2015, 201

[30] M. Taskin and U. Caligulu, "Artificial Neural Network (ANN) approach to prediction of diffusion bonding behaviour (shear strength) of SiCp reinforced aluminium metal matrix composites," no. January 2016, 2008

[31] Suresh Chandra Satapathy · Siba K. Udgata, Bhabendra Narayan Biswal, "Proceedings of the International Conference on Frontiers of Intelligent Computing Theory and Applicationsm" (FICTA) 2013

[32] S. A. Mote, "FEM analysis of helical gear," vol. 4, no. 2, pp. 1839–1845, 2018.

[33] S. Sai Anusha, P. S. Reddy, P. Bhaskar, and M. Manoj, "Contact Stress Analysis of Helical Gear by Using AGMA and ANSYS," Int. J. Sci. Eng. Adv. Technol. IJSEAT, vol. 2, no. 12, pp. 1012–1016, 2014.

[34] Prafulla P. Jadhav and Santosh V. Bhaskar, "Design Analysis of Helical Gear made of Stainless Steel Nylon under Different Loading Conditions," Int. J. Eng. Res., vol. V5, no. 10, pp. 546–552, 2016.

[35] B. O. Akinnuli, T. I. Ogedengbe, and K. O. Oladosu, "Computer Aided Design and Drafting of Helical Gears.pdf," vol. 3, no. 6, pp. 959–968, 2012.

[36] H. Shah, "DESIGN , MODELING AND STRESS ANALYSIS OF HIGH SPEED HELICAL GEAR ON BASIS OF BENDING STRENGTH AND CONTACT STRENGTH BY CHANGING ," no. May, 2016.

[37] M. D. Babu and M. Kumar, "Design And FEM Analysis of Helical Gear," Int. J. Eng. Res. Adv. Technol., no. 1, pp. 49–58, 2018

[38] H. Htet, H. San, H. H. Win, and M. Thein, "DESIGN AND CONTACT STRESS ANALYSIS OF HELICAL GEAR FOR LIGHT-WEIGHT CAR," no. 8, pp. 7–12, 2017

[39] S. E. E. Profile, "Failure Analysis of a Helical Gear," no. January 2010, 2015.

[40] Sarle, W.S.: Neural networks and statistical models (1994)

[41] L. C. P. Velasco, A. R. B. Granados, J. M. A. Ortega, and K. V. D. Pagtalunan, "Performance Analysis of Artificial Neural Networks Training Algorithms and Transfer Functions for Medium-Term Water Consumption Forecasting," vol. 9, no. 4, pp. 109–116, 2018.

[42] J. Cheng, Q. S. Li, R, Xiao, "A new artificial neural network-based response surface method for structural reliability analysis,", Probabilistic Engineering Mechanics, Volume 23 Issue 1, Elsevier, pp. 51-63, 2008.

[43] S. S. Rao and K. Y. Yoon, “Minimization of transmission error in helical gears,” pp. 447–459, 2001.

[44] Faydor L.litvin, Alfonso Fuentes “gear geometry and applied theory” second eddition, cambridge universit,2001

[45] David Irwin, “Mechanical Engineering Handbook” Department of Mechanical Engineering, Auburn University, Auburn, Alabama, 2001.

[46] FATEMI A., STEPHENS R.I, STEPHENS R.R. and FUCHS H.O. 2000. Metal Fatigue in Engineering, Wiley Inter science.

[47] Dowling, N. E. 2013. Mechanical behavior of materials: Engineering Methods For Deformation, Fracture, and Fatigue. Fourth edition, Pearson education, Inc.

[48] Zahavi E. and TORBILO V. 1996. Fatigue Design, Life Expectancy of Machine Parts.

[49] M. D. Babu and M. Kumar, “Design And FEM Analysis of Helical Gear,” Int. J. Eng. Res. Adv. Technol., no. 1, pp. 49–58, 2018.

[50] P. Approach, A Systematic and Practical Approach Finite Element Analysis Applications.

Appendix

Matlab code for ANN prediction

```
input = input;
target = output;
x = input';
t = output';
% Choose a Training Function
trainFcn = 'trainlm';
% Choose a Training algorism
Levenberg-Marquardt backpropagation
% Create a Fitting Network
hidden_Neuron_Size=35;
net = fitnet(hiddenLayerSize,trainFcn);
% Setup Division of Data for Training, Validation, Testing
net.divideParam.trainRatio = 70/100;
net.divideParam.valRatio = 15/100;
net.divideParam.testRatio = 15/100;
% Train the Network
[net,tr] = train(net,x,t);
net.trainparam.goal=1e-5;
net.trainparam.lr=0.3;
net.trainparam.mc=0.6;
net.trainparam.mu=1;
[net,tr]=train(net,x,t);
% Test the Network
y = net(x);
e = gsubtract(t,y);
mse = performance(net,t,y)
%Predicted output determination code
new_inputt=new_input';
y_pridicted=net(new_inputt);
y_pridicted_new=y_pridicted';
```

```
% View the Network
% Plots
%figure, plotperform(tr)
Performance = plotmse(net,t,y)
%figure, ploterrhist(e)
error_histogram = ploterrhist(e,20)
%figure, plotregression(t,y)
Regression = plotregression(target,output)
```

Basic Helical Gear Nomenclatures/Dimension

Table I Helical gear dimensional formula

No	Parameter	Formula	
		For pinion	For gear
1	No of tooth	Z_1	Z_2
2	Transverse module(mm)	$m_t = d_1/z_1$	$m_t = d_2/z_2$
3	Helix angle	B	B
4	Normal module(mm)	$m_n = m_t\cos\beta$	$m_n = m_t\cos\beta$
5	Pitch line circular diameter(mm)	$d_1= m_n.z_1/\cos\beta = m_t.z_1$	$d_2= m_n.z_2/\cos\beta = m_t.z_1$
6	Transverse pitch(mm)	$P_t = \Pi d_1/z_1$	$P_t = \Pi d_2/z_2$
7	Normal pitch(mm)	$P_n = p_t.\cos\beta$	$P_n = p_t.\cos\beta$
8	Center distance (mm)	$a_d = \frac{mn(z1+z2)}{2\cos\beta}$	$a_d = \frac{mn(z1+z2)}{2\cos\beta}$
9	normal pressure angle(α_n)	$\emptyset_n= \emptyset\cos\beta$	$\emptyset_n= \emptyset\cos\beta$
10	transverse pressure angle (α)	$\emptyset_t = \tan^{-1}(\frac{tan\emptyset_n}{cos\beta})$	$\emptyset_t = \tan^{-1}(\frac{tan\emptyset_n}{cos\beta})$
11	Face width (mm)	$(4.5 \text{ to } 7.5) \times m_t \cos\beta$	$(4.5 \text{ to } 7.5) \times m_t \cos\beta$
13	Addendum(a)	$a = z_1/d_1$	$a = z_2/d_2$
14	Dedendum(b)	$b =1.25a$	$b=1.25a$
15	Pitch circle radius(mm)	$R_p = m_n.z_1/2\cos\beta$	$R_p = m_n.z_1/2\cos\beta$
16	Clearance circle radius(R_c)	$R_c= R_P \cos\emptyset$	$R_c= R_P \cos\emptyset$
17	Dedendum circle radius(R_d)	$R_d = R_P -1.25\times m$	$R_d = R_P -1.25\times m_t$
18	Addendum circle radius(R_a)	$R_a = R_p+m$	$R_a = R_p+m$

Specification of Helical Gear and Pinion

Table I I. Helical gear specification

No	Parameters	Specification
1	Material	Concept1 (nearly same with 20MnCr5Mo)
2	Input torque (N-m)	75 N-m
3	Ultimate tensile strength (Mpa)	1994.1
4	Yield Strength (Mpa)	1408.8
5	Hardness (HRC)	51.1
6	Module (mm)	3
7	Number of pinion teeth	20
8	Number of gear teeth	36
9	Helix angle (β)	15^0
10	Pressure angle (Ø)	20^0
11	Face width (mm)	40