Artificial Neural Network Analysis of the Multi Cylinder Engine Crankshaft by using MATLAB

V. K. Titariya[1] Vinod Kumar Prajapati[2]
[1]Assistant Professor [2]M.Tech Student
[1]Department of Mechanical Engineering
[1,2]SAMCET, Bhopal, India

Abstract— The crankshaft is a complex component, it subjected to high loads in internal combustion engines, leading to bending and torsion stress cycles. In this work, the study of the parametric performance of the Multi cylinder Engine Crankshaft was carried out. Analyses were done on 3-D model of Crankshaft, making use of symmetry as far as possible. Many governing parameters of the crank throw are included in this study like; journal diameters, journal overlap, crankpin and web thickness. The objective of this work is to study the performance of the Multi cylinder Engine Crankshaft using MATLAB. In this manner artificial neural network analysis was performed. It was found that the simulation of full crankshaft process is too time consuming to be used in everyday engineering work. However, Total Deformation, Equivalent Stress, Equivalent Elastic Strain and Strain Energy can successfully be predicted with simplified models.

Key words: Crankshaft; Simulation; Artificial Neural Network; MATLAB

I. INTRODUCTION

Most typical geometry in the single cylinder engine is a Crankshaft. For a rotating movement of a four link mechanism crankshaft reciprocate motion of the piston. Because of excess load variations during its service life time the crankshaft experiences many parametric changes just like durability and fatigue performance so it will be considered in the designing operation. Developments in designing have always been an important part, in crankshaft production industry. In order to manufacture a component with less weight, expenses, high fatigue resistance and other purposeful requirements. Better result in lighter engines with better fuel efficiency and higher power output is needed.

For a crankshaft engine this study was applicable. In this research we were studied for the parametric performance of the crankshaft from single cylinder engine. For analysis was carried out on the finite element analysis in four static steps. The limits of these analyzes were applied in relation to the dynamic load applied to the crankshaft. To stimulate the prediction of parametric performance of the crankshaft, an additional analysis of Artificial Neural Network was performed. The most typical geometry in a single-cylinder engine is the crankshaft. For rotary motion of the four-joint mechanism, reciprocating motion of the crankshaft piston. Due to the many load changes over the entire lifetime, the crankshaft undergoes many parametric changes, such as durability and fatigue strength, so the total deformation, Equivalent Stress and Equivalent Elastic Strain should be analyse with respect to the various loading condition. Design solution is always a major task for the crankshaft industry. Produce a lower weight component, lower cost, high fatigue resistance and other specific requirements. These improvements mean that lighter, smaller engines offer higher fuel efficiency and higher power output.

II. FUNCTION OF CRANKSHAFT

To convert the movement of the piston (slider mechanism) into a rotary motion, there are four movable crank mechanisms, such as the crankshaft, connecting rod and piston. Centrifugal efficiency is more experimental and is important for entering other devices, because the design of a single-cylinder engine is such that the output will be rotated. Instead of, the linear transport of a single-cylinder engine is not regular because transport is caused by the combustion of gas in the combustion chamber. Therefore, the transport is suddenly shocked, because using this input for another device would be detrimental. To achieve a smooth rotation, from entering many devices such as generators, pumps and compressors, the concept of crankshaft consists in changing the sudden transport. Using the steering wheel helps to reduce collisions.

Jenson (1970) [1] conducted an experimental investigation to determine the load applied to the V8 crankshaft. The determination of the load in this test began with the selection of the crankshaft sections to be tested. To measure the bending and torsion forces applied to each section of the crankshaft, the bending and torsion strain gage bridges were assembled in pairs. After installing the deformation sensors, the crankshaft was carefully mounted on the engine, then mounted and fully installed in the dynamometer holder. Loads were recorded at different speed increments to capture peak and torsional bending forces that do not occur at substantially the same crankshaft angle.

Henry et al. (1992) [2] used a dynamic load in their FEM model that included an internal centrifugal, external bearing, and torsional load. In their study, the internal loads were calculated assuming constant mass forces EMF. Therefore, for any engine speed, the resulting displacements were calculated only once. Given the conventional gas forces and the inertia acting on the journal bearings, they cause external loads on the bearings. A statistically determinable or undefined method was used to calculate cross-bearing reactions taking into account the separation and compliance of the engine block. Finally, a classical spring model was created with a harmonic reaction to calculate the dynamic twisting moments. The result was the internal moment of the crank at each launch and throughout the cycle. A single projection displacement calculation was performed and the displacements at each stage of the cycle were scalar multiples of these results.

An analytical examination of the bending vibrations was carried out for the V6 engine by Mourelatos (1995) [3]. He used the crankshaft system model (CRANKSYM) for the analytical verification of the vibration problem associated with the crankshaft wheel mentioned above. As described in his study, CRANKSYM can perform an analysis taking into account the structural dynamics of the crankshaft, the hydrodynamics of the main bearing and the flexibility of the engine block. The program takes into account the gyroscopic effect of the flywheel, the loads applied to the belt, the crankshaft bent and the block misboring, as well as the anisotropy of the block flexibility as seen from the rotating crankshaft. This program can also calculate the history of dynamic stresses on the crankshaft during the entire engine cycle. CRANKSYM requires a finite grid of elements of the entire crankshaft. The CRANKSYM output includes the natural frequencies of the crankshaft-flywheel system, supporting the loads with respect to the fixed engine coordinate system and the axial displacement of the point located at the outer periphery of the flywheel. In this program, the structural analysis of the crankshaft predicts the dynamic reaction of the crankshaft based on the finite element method.

Prakash et al. (1998) [4] used the advantages of the classical method and the finite element technique in their crankshaft design studies. They used the classical method to calculate the initial and approximate results. Based on this method, a TVAL program has been developed to rapidly transmit natural frequencies, critical modes, displacements and stresses. To obtain more accurate results and evaluate the results of the program, they created a finite element model of the crankshaft. The time of the radial and tangential forces acting on the crankshaft pin came from the cylinder pressure. The movements and the tensions were calculated according to the method of the superposition. They used a motor cycle corresponding to automotive applications to generate a load history for accelerated fatigue tests.

Since the crankshaft has a complex geometry for analysis, it has been found that finite element models offer a precise and reasonable solution when laboratory tests are not available. Uchida and Hara (1984) [5] used the FEM model with one-shot extrapolation of the experimental equation in their studies. In his research, crankshaft thickness of 60° V-6 engine was reduced while maintaining its fatigue strength and pressure resistance of turbocharged gas. When studying the crankshaft dimensions of the V-6 engine at 60°, the stress evaluation of the crankshaft fillet part was extremely critical, because to reduce the overall crankshaft length, it was necessary to maintain the web thickness between main journal and crankpin as much as possible while maintaining its strength. The FEM was used to estimate the thickness concentration coefficient for which no confirmed calculation was available.

The crankshaft durability test program, based on three-dimensional mechanical analysis, was developed by RENAULT and used by Henry et al. (1992) [6] to predict durability and calculate crankshaft fatigue strength. The stress calculation program included a preliminary 3D FEM analysis with a coarse mesh for all crankshaft geometry, and then applied a local BEM zoom technique to round the areas to accurately calculate the stress concentration coefficients. In their durability assessment program, they had chosen a 3D numerical approach. The coarse mesh is used in the whole crankshaft model to avoid cut plane boundary condition approximations. The resulting displacements were then applied to a local small sized BEM fillet model. The resulting BEM fillet stress state was biaxial on the surface, unlike corresponding FEM results. This two-stage FEM/BEM stress calculation method was compared to several other numerical calculations and several crankshaft geometries in their study, which showed increased precision, resulting in improved initial design of a crankshaft.

Theoretical studies followed by the experimental results were carried out by Guagliano et al. (1993) [7] to calculate the stress concentration coefficient for the crankshaft of a diesel engine. They performed experimental tests by installing strain gages at high stress concentration places. A three-dimensional model of crankshaft was developed and numerical calculations were performed according to the linear elastic properties of the material and the various loading conditions. The good conformity of the experimental results with the numerical results indicated the precision of the computation of the coefficient of concentration in tension. In addition, the two-dimensional crankshaft model was constructed numerically and experimentally to quickly evaluate the stress concentration factor. Taking into account similar boundary conditions and load conditions for three-dimensional and two-dimensional models, identical stress concentration coefficients were obtained. They came to the conclusion that the two-dimensional model could simply and efficiently determine the stress concentration factor.

The artificial neural network was developed by Shiomi and Watanabe (1995) [8] to calculate the stress concentration coefficient in the area of the crankpin with the dimensional characteristics of the crankshaft. An artificial neural network was used to calculate the stress concentration factor based on mathematical approximations from a database which contained geometry properties of the crankshaft as well as stress concentration factors. To build a database, a finite element model of crankshafts of different geometries was created. Stress concentration factors were obtained from these models and results were inserted in the database. The finite element model results in accurate values for stress concentration factor and eliminates inevitable measurement errors due to experiments. A large number of mathematical functions had to be solved in order to create the approximation function, but after having the final equation, the stress concentration could be easily calculated for a given crankshaft geometry.

Payer et al. (1995) [9], they presented a non-linear transient stress analysis for the 6-cylinder engine crankshaft. Their study showed a method by which nonlinear transient analysis was very advanced and effective in determining the fatigue behaviour of crankshafts. They used a finite element program that uses two main steps to calculate the transient behaviour of the rotating crankshaft. The software automatically generates a model of the solid body of the crankshaft taking into account both the flywheel and the vibration damper. In order to create a beam mass model, the strain energy method was used. Stiffness calculated with the solid element model of a crank throw was used to generate the beam mass model. This model was used for the calculation of the transient deformations of the crankshaft.

Prakash et al. (1998) [4] modelled a complete crankshaft using the solid elements of ANSYS software. In order to verify the integrity of the FE model natural frequencies of the model was compared with those obtained from practical measurements. They evaluated the stress amplitudes using mode superposition method. As a prerequisite, reduced modal analysis was required for carrying out the mode superposition analysis. They selected the master degrees of freedom to exactly calculate the fist few torsional natural frequencies. This method decouples the equations of motion and reduces computational effort required.

The analysis of the stress distribution in the crankshaft has been studied by Borges et al. (2002) [10]. A stress analysis was performed to evaluate the overall structural effectiveness of the crank, related to the uniformity and magnitude of the stresses, as well as the number and location of stress concentration points. Due to the limitations of memory in the available computers, the crank model had to be simplified, limiting it mainly according to the plane of symmetry. To evaluate the results of finite element analysis, a 3D photo-elasticity study was conducted. An analysis of the stress distribution inside a crankshaft crank was studied by Borges et al. (2002) [22]. The stress analysis was done to evaluate the overall structural efficiency of the crank, concerned with the homogeneity and magnitude of stresses as well as the amount and localization of stress concentration points. Due to memory limitations in the computers available, the crank model had to be simplified by mostly restricting it according to symmetry planes. In order to evaluate results from the finite element analysis a 3D photo-elasticity test was conducted.

Chien et al. (2005) [11] studied the effect of residual stresses induced by the fillet rolling process during the fatigue process of the ductile iron crankshaft. Stress concentrations near the fillet area of the crankshaft were examined by 2D finite element analysis in the ABAQUS software. Then, a 2D FEA elastic-plastic pull was performed to obtain residual stress distributions near the fillet resulting from the rolling process. Part of the crankshaft and roller sections was modelled by four-element quadrilateral elements with eight nodes, with a reduced integration scheme. To accurately capture the characteristics of the stress field in this stress concentration area, a relatively fine mesh was obtained near the fillet.

III. Artificial Neural Network

ANN is a machine type designed to generate the way as brain performs a specific task. To get a good performance, they use a massive combination of simple computer cells called "neurons" or "processing units". Therefore, a neural network can be taken as an adaptive machine which defines as a neural network, which have a parallel distributed processor made of simple processing units that has a tendency to store and share the parametric information. It looks like a brain in two ways:

1) The network acquires knowledge from the environment during the whole learning process.
2) Strengths of connection between neurons, called synaptic weights, are the storage of acquired knowledge.

As in nature, the network function is largely determined by connections between elements. We can create a neural network for perform a specific function by adjusting the connection values (weights) between the elements. In principle, neural networks are tuned or formed in such a way that the input data leads to a specific objective. This situation is illustrated below.

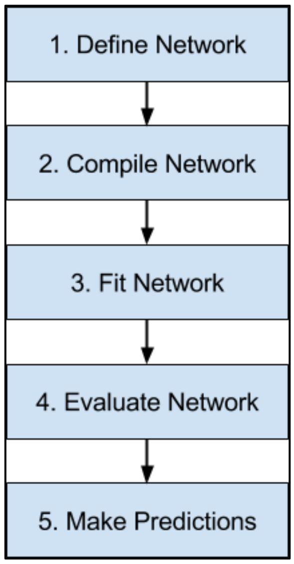


Fig. 1: Neural Network Model

The true power of ANN is their ability to create linear and nonlinear connections and to learn these connections directly from the modelled data. Neural networks are designed to classify as model classifiers.

IV. Why Use Neural Networks

It is obvious that the network of neurons derives its computing power, on the one hand, from its extremely parallel scattered structure, and from its learning ability. The neural network offers the following useful properties and capabilities when uses:

- Massive parallelism
- Distribution and computer representation
- Learning ability
- Ability to generalize
- Input-output mapping
- Adaptability
- Uniform analysis and design
- Damage resistance
- Inherent processing of context information
- VLSI implements the skill

A. *Neuron Model*

Artificial neuron is a tool with large number of inputs and outputs. Each input is multiplied by a corresponding mass, analogous to the synaptic force, and all weighed inputs are summed up to determine the level of neuron activation. These weighted inputs are then summed to obtain a "net" result, and if they exceed the predefined threshold value, a neuron is triggered.

B. *Network Layers*

Evan a single neuron can perform a pattern detection functions; the power of neural calculations comes from combining neurons with network layers. It has been shown that multilayer networks have capabilities that go beyond the capabilities of one layer. These networks are created by a cascading group of individual layers; output from one layer provides input data to the next layer.

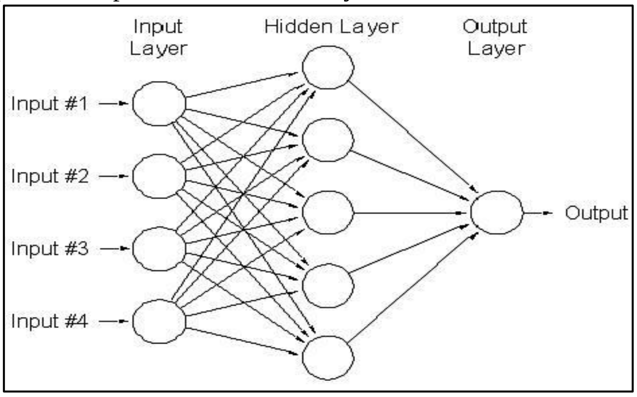


Fig. 2: A Multi-Layer Neuron Model

ANN is a connection of three groups of units: In which the group of "input" is connected to the group of "hidden" units, which is followed by the layer of the "output":

- The activity of the input shows the initial information given to the network.
- The activity of hidden unit depends on the activity of the input and weights in the connections.
- The behaviour of output units depends on the hidden units and weights between hidden and output.
- Hidden units can freely build their own entrance representations.

C. Feed-Forward Neural Networks

Feed-forward ANN (artificial neural network) is allow signals to travel in one direction only; from the input to the output. There is no return (loop), i.e. the result of the any layer does not affect the same layer. These networks are called non-returnable networks and do not require memory because outputs are directly related to inputs and weights. They are widely used in pattern recognition. This type of organization is also called ascending or descending. The figure (9) below shows a simple feed forward network:

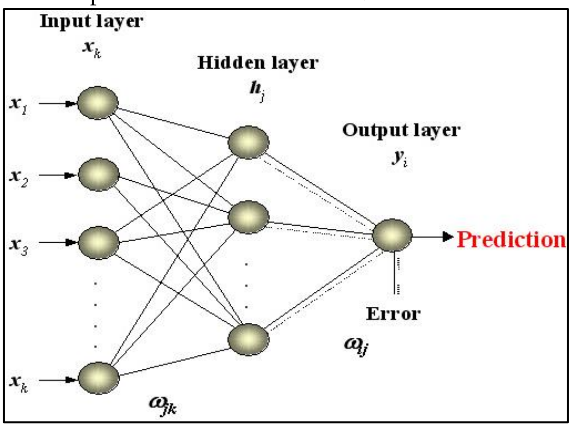


Fig. 3: An example of Feed Forward Network

D. Learning

Learning is important for most of these neural network architectures, so the choice of learning algorithm is a main part of network development. Learning means that the processing unit can modify its input / output behaviour as a result of changes in the environment. Because the activation rule is usually set when building the network and the input / output vector cannot be changed, it is necessary to adjust the input / output behaviour to adjust the behaviour. Learning may be supervised or not in a neural network.

E. Back Propagation Algorithm

Since many years, there was no theoretically correct algorithm for creating artificial, multi-layered neural networks. The creation of the back propagation algorithm played an important role in the renewed interest in artificial neural networks. Backward propagation is a systematic method of creating artificial multi-layer neural networks (Perception). The following figure shows the basic model of the neuron used in reverse propagation networks.

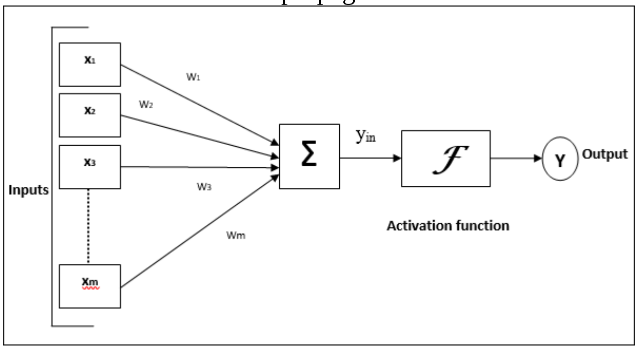


Fig. 4: Basic Model of Neuron Using Back Propagation

Each and every input is multiplied by the appropriate weights, analogously to a synaptic strength, and all weighted input is summed up to determine the level of neuron activation. These summed signals (NETs) are then processed by function of activation (F) to generate a neuron output signal (OUT). In backward propagation, the function used for activation is a logistic or sigmoid function. This function is expressed mathematically by:

$$F(x) = \frac{1}{1+e^{-x}}$$

Thus

$$OUT = \frac{1}{1+e^{-net}}$$

Sigmoid compresses the NET range, so OUT is between zero and one. Because back propagation uses a derivative of the squashing function, it must be differentiable everywhere. . The Sigmoid has this property and the additional advantage of providing a form of automatic gain control (i.e. if the value of NET is large, the gain is small and if it is small the gain is large).

F. Overview of Training

The purpose of network training is to adjust the weights so that the use of a set of inputs (input vectors) generates the desired results (output vectors).Training of the back propagation network means that each and every input vector is matched with the target vector for represent the desired output; together, they are called a training pair. The following figure shows the architecture of a multilayer network of reverse propagation neurons.

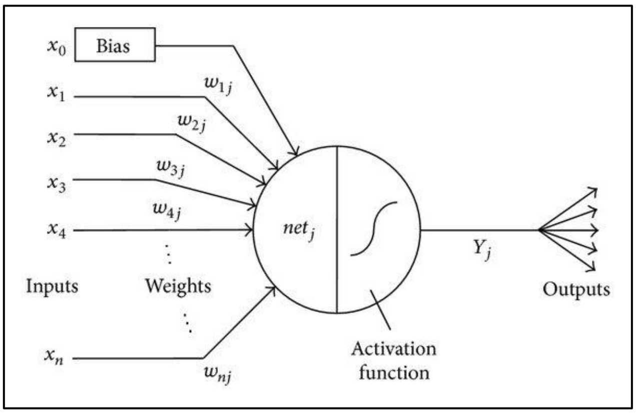


Fig. 5: Multilayer Back Propagation Neural Network

Steps of back propagation training:

1) Select a training pair from the training data and apply the input vector to the network input.
2) Calculate the output of the network, i.e. to each neuron NET=ΣXiWi must be calculated and then the activation function must be applied on the result F (NET).
3) Calculate the error between the network output and the desired output (TARGET – OUT).
4) Adjusting the network weight in a path or way that decreases the ERROR (described below).
5) Repeat step 1 to 4 until no pair produces a larger value than an acceptance level.

V. PROBLEM DEFINITION

We need first to develop an Artificial Neural Network for crankshaft in MATLAB software. Therefore, the objective is to generate an ANN model on the basis of input and output of simulation results. The basic steps adopted in the ANN are as follows: simulation and collection of data; analysis and pre-processing of data; design of the neural network; training and testing of the neural networks; simulation and prediction with the neural networks; analysis and post-processing of predicted result. ANN technique was used to predict the performance of the multi cylinder engine Crankshaft.

VI. RESULTS

The present work was to develop an artificial neural network model that could predict the performance of Crankshaft. The main objective of the current work was to employ neural networks to model the equivalent elastic stress, equivalent elastic strain and total deformation. Neural Network Toolbox of MATLAB (R2016a) was used to design the neural network. The basic steps adopted in the design are as follows: simulation and collection of data; analysis and pre-processing of data; design of the neural network; training and testing of the neural networks; simulation and prediction with the neural networks; analysis and post-processing of predicted result. ANN technique was used to predict the performance of Crankshaft by the parameters; Equivalent Elastic Stress, Equivalent Elastic Strain, Total Deformation & Strain Energy.

TIME	TOTAL DEFORMATION	EQUIVALENT ELASTIC STRESS	EQUIVALENT ELASTIC STRAIN
0.05	3.72E-07	2.58E+05	1.29E-06
0.1	7.44E-07	5.17E+05	2.59E-06
0.15	1.12E-06	7.75E+05	3.88E-06
0.2	1.49E-06	1.03E+06	5.17E-06
0.25	1.86E-06	1.29E+06	6.46E-06
0.3	2.23E-06	1.55E+06	7.76E-06
0.35	2.60E-06	1.81E+06	9.05E-06
0.4	2.98E-06	2.07E+06	1.03E-05
0.45	3.35E-06	2.33E+06	1.16E-05
0.5	3.72E-06	2.58E+06	1.29E-05
0.55	4.09E-06	2.84E+06	1.42E-05
0.6	4.46E-06	3.10E+06	1.55E-05
0.65	4.83E-06	3.36E+06	1.68E-05
0.7	5.21E-06	3.62E+06	1.81E-05
0.75	5.58E-06	3.88E+06	1.94E-05
0.8	5.95E-06	4.13E+06	2.07E-05
0.85	6.32E-06	4.39E+06	2.20E-05
0.9	6.69E-06	4.65E+06	2.33E-05
0.95	7.07E-06	4.91E+06	2.46E-05
1	7.44E-06	5.17E+06	2.59E-05

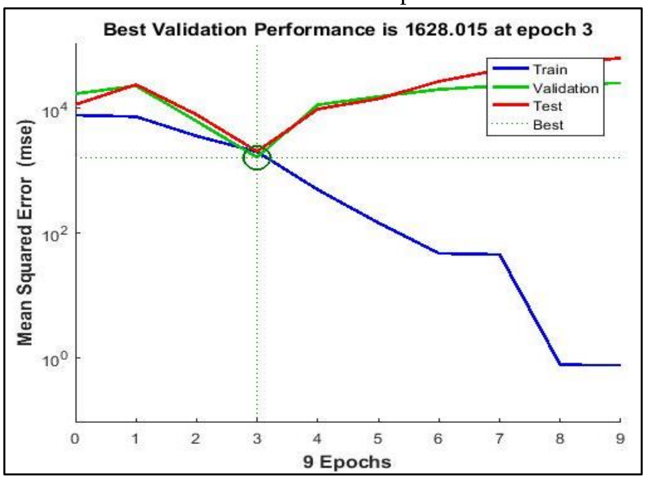
Table 1: Finite Element Analysis–Simulation Results

Neural Network	MLP
Number of Input Variables	4
Number of Hidden Layer	2
Number of Hidden Neuron in First Hidden layer	10
Activation function used in first hidden layer	Straight line

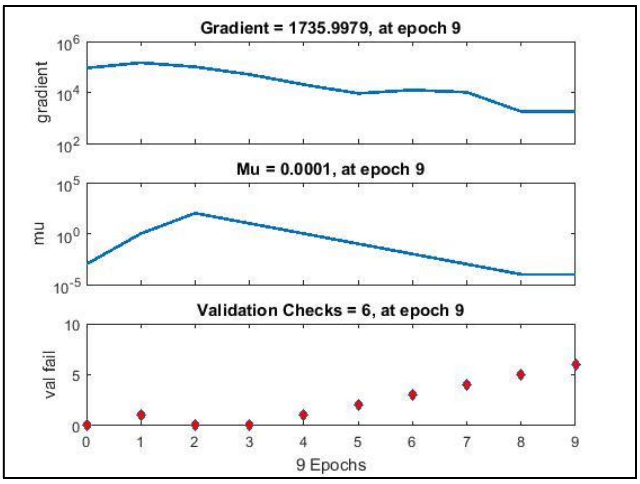
Table 2: Various Elements of Structure

S. No.	Input Data	Range
1	Time	0.05 – 1 Sec
2	Total Deformation	3.72 X 10-07 – 7.44 X 10-06 m
3	Equivalent Elastic Stress	2.58 X 1005 – 5.17 X 1006 Pa
4	Equivalent Elastic Strain	1.29 X 10-06 – 2.59 X 10-05 m/m

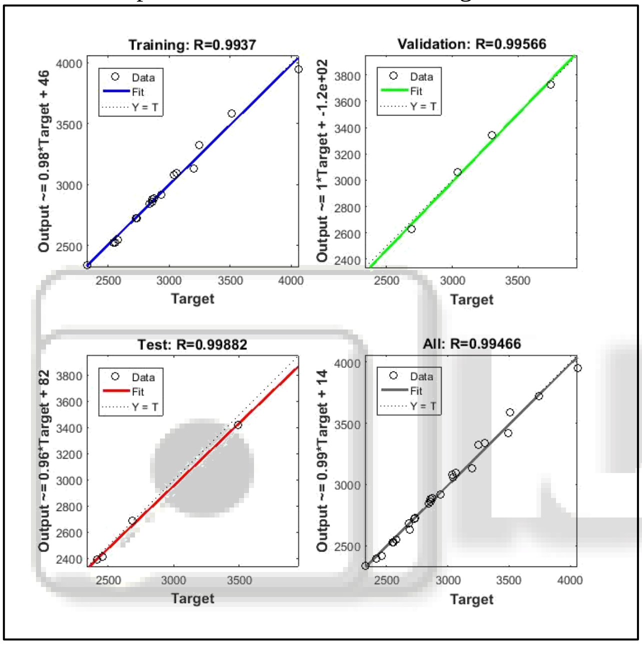
Table 3: Neural Network Input Variables



Graph 1: MATLAB ANN Training Performance



Graph 2: MATLAB ANN Training Status



Graph 3: MATLAB ANN Regression Chart

S. No.	Data set	Value of R
1	Training	0.9937
2	Validation	0.99566
3	Test	0.99882
4	All	0.99466

Table 4: Values of Regression Coefficient

Graph 3 provide the results of all the three data set using training, testing and validation data with whole data considering value of ‘r’ correlation coefficient. Value of ‘r’ indicates similarity between two data series, it value ranges from -1 to +1. A larger value of ‘r’ indicates better correlation. It has been observed from table 5, that value of ‘r’ between output from model and target value, for all the three sets of data is reaching ‘1’ which indicates a good correlation.

From the above graphs, it is found that Equivalent stress, Equivalent Shear Strain, Total Deformation for both Sheet Metal and Ram is well predicted by the regression modal.

Hence, ANN Model is a good tool of MATLAB to predict the Different performance characteristic of any working mechanical model. On the basis of the current work, it is concluded that any Performance parameter can be efficiently predicted by the ANN. The neural model fitted for Equivalent Elastic Strain was obtained using MATLAB software and is represented by the Table 5. The computational Equivalent Elastic Strain is taken as a target value of the programme, whereas the Time, Total Deformation and Equivalent Elastic Stress were taken as Input values of the programme. Hence the Predicted Equivalent Elastic Strain value on the basis of three parameters was arrived.

TIME	PREDICTED ELASTIC STRAIN	ERROR BETWEEN FEM & ANN RESULT
0.05	1.29E-06	-1.00E-09
0.1	2.69E-06	-1.02E-07
0.15	3.58E-06	2.99E-07
0.2	5.18E-06	-4.00E-09
0.25	6.66E-06	-2.00E-07
0.3	7.78E-06	-2.02E-08
0.35	8.05E-06	1.00E-06
0.4	1.05E-05	-2.00E-07
0.45	1.19E-05	-3.00E-07
0.5	1.39E-05	-1.00E-06
0.55	1.45E-05	-3.00E-07
0.6	1.57E-05	-2.00E-07
0.65	1.69E-05	-1.00E-07
0.7	1.71E-05	1.00E-06
0.75	1.98E-05	-4.00E-07
0.8	2.17E-05	-1.00E-06
0.85	2.15E-05	5.00E-07
0.9	2.33E-05	-6.00E-08
0.95	2.47E-05	-1.00E-07
1	2.55E-05	4.00E-07

Table 5: ANN–Simulation Results

The outputs produced by the model have been compared with the target outputs, which are the Equivalent Elastic Strain obtained computationally. Generalization ability of developed network is measured by the mean square error (MSE). Graph 1 presents the Mean square error (MSE) for 9 epochs in all the three runs during training. It has been observed that MSE decreased after each run and the best results found at 3 epochs.

The Predicted Equivalent Elastic Strain is taken as a target value of the programme, whereas the Time, Total Deformation and Equivalent Elastic Stress were taken as Input values of the programme. Hence the Predicted Equivalent Elastic Strain value on the basis of three parameters was arrived for the variable Sample Time. Similarly, we can obtain the Predicted Equivalent Elastic Strain value for variable Time, Total Deformation and Equivalent Elastic Stress. And according to ANN analysis it will be about 99.46% accurate.

VII. CONCLUSION

An empirical model has been developed by using Artificial Neural Network to determine the Equivalent Elastic Strain of Crankshaft. Good validation of results is obtained between computational results and predicted results. ANN prediction would have been more accurate if the computational results were more. This study indicates the ability of the neural network tool as a brilliant technique in order to predict values of Equivalent Elastic Strain with varying input variables. The model implemented satisfactorily in the prediction of Equivalent Elastic Strain of Crankshaft with different variables. The prediction made using proposed model shows a high degree of accuracy for Equivalent Elastic Strain of Crankshaft obtained through models.

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