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A COMPREHENSIVE INTELLECTUAL FREE VIBRATION ANALYSIS OF COMPOSITE DERIVE SHAFT

AZHAR UDDIN SHEIKH, DR SATYENDRA SHARMA

azharsheikh760@gmail.com satyendra.sage@gmail.com

DEPARTMENT OF MECHANICAL ENGINEERING, SAGAR INSTITUTE OF RESEARCH AND TECHNOLOGY

SAGE UNIVERSITY – INDORE-DEWAS BYPASS, INDORE MP

ABSTRACT-

The overall objective of this work is to analyze a composite drive shaft for power transmission. Substituting composite structures for conventional metallic structures has many advantages because of higher specific stiffness and strength of composite materials. This work deals with the replacement of conventional steel drive shafts with an epoxy composite drive shaft for an automotive application. The intention of work is to minimize the weight of drive shaft. In this present work an attempt has been made to estimate the deflection, stresses, and natural frequencies under subjected loads using FEM (CATIA). Further comparison carried out for both (cyclic and dynamic) loads using FEM. Further comparison carried out for both optimized and stress intensity factor found for both Steel and composite drive shafts.

Keywords: Conventional shaft, drive shaft, composite shaft, composite material, FEM etc

I. INTRODUCTION

Nowadays there is a heavy requirement for lightweight materials in automotives. The conventional steel material is replaceable by advanced composite materials. Composite materials are favored by most of the scientist in the design of automobiles due to its higher specific strength and stiffness. Composite materials can be tailored to efficiently meet the design requirements of strength, stiffness and composite drive shafts weightless than steel or aluminum of similar strength. Also, composite materials typically have lower modulus of elasticity. As a result, when torque peaks occur in the driveline, the driveshaft can act as a shock absorber and decrease stress on part of the drive train extending life. Many researchers have been investigated about hybrid drive shafts and joining methods of the hybrid shafts to the yokes of universal Joints. But this project provides the analysis of the design in many aspects [1].

II. MERITS OF COMPOSITE DRIVE SHAFT

1. They have high specific modulus and strength.

2. Reduced weight.

3. The fundamental natural frequency of carbon fiber composite drive shaft can be twice as high as that of steel because the carbon fiber composite material has more than

4 times the specific stiffness of steel, which makes it possible to manufacture the drive shaft of cars in one piece. A one piece composite shaft can be manufactured so as to satisfy the vibration requirements. This eliminates all the assembly, connecting the two piece steel shafts and thus minimizes the overall weight, vibrations and the total cost.

5. Due to the weight reduction, fuel consumption will be reduced.

6. They have high damping capacity hence they produce less vibration and noise.

7. They have good corrosion resistance.

8. Greater torque capacity than steel shaft.

9. Longer fatigue life than steel shaft.

10. Lower rotating weight transmits more of available power [2].

III. DRIVE SHAFT VIBRATION

Vibration is the most common drive shaft problem. Small cars and short vans and trucks (LMV) are able to use a single drive shaft with a slip joint at the front end without experiencing any undue vibration. However, with vehicles of longer wheel base, the longer drive shaft required would tend to sag and under certain operating conditions would tend to whirl and then setup resonant vibrations in the body of the vehicle, which will cause the body to vibrate as the shaft whirls. Vibration can be either transverse or torsional. Transverse vibration is the result of unbalanced condition acting on the shaft. This condition is usually by dirt or foreign material on the shaft, and it can cause a rather noticeable vibration in the vehicle.

FINITE ELEMENT METHOD (FEM)

The finite element method (FEM) is a widely used method for numerically solving differential equations arising in engineering and mathematical modeling. Typical problem areas of interest include the traditional fields of structural analysis, heat transfer, fluid flow, mass transport, and electromagnetic potential [3].

The FEM is a general numerical method for solving partial differential equations in two or three space variables (i.e., some boundary value problems). To solve a problem, the FEM subdivides a large system into smaller, simpler parts that are called finite elements. This is achieved by a particular space discretization in the space dimensions, which is implemented by the construction of a mesh of the object: the numerical domain for the solution, which has a finite number of points. The finite element method formulation of a boundary value problem finally results in a system of algebraic equations. The method approximates the unknown function over the domain. [4] The simple equations that model these finite elements are then assembled into a larger system of equations that models the entire problem. The FEM then approximates a solution by minimizing an associated error function via the calculus of variations.

APPLICATION

A variety of specializations under the umbrella of the mechanical engineering discipline (such as aeronautical, biomechanical, and automotive industries) commonly use integrated FEM in the design and development of their products. Several modern FEM packages include specific components such as thermal, electromagnetic, fluid, and structural working environments. In a structural simulation, FEM helps tremendously in producing stiffness and strength visualizations and also in minimizing weight, materials, and costs.[5]

FEM allows detailed visualization of where structures bend or twist, and indicates the distribution of stresses and displacements. FEM software provides a wide range of simulation options for controlling the complexity of both modeling and analysis of a system. Similarly, the desired level of accuracy required and associated computational time requirements can be managed simultaneously to address most engineering applications. FEM allows entire designs to be constructed, refined, and optimized before the design is manufactured. The mesh is an integral part of the model and it must be controlled carefully to give the best results. Generally the higher the number of elements in a mesh, the more accurate the solution of the discretized problem. However, there is a value at which the results converge and further mesh refinement does not increase accuracy.[6]

IV. INTRODUCTION OF ARTIFICIAL NEURAL NETWORKS

Artificial neural networks (**ANNs**), usually simply called **neural networks** (**NNs**), are computing systems inspired by the biological neural networks that constitute animal brains.

Neural computing is an information processing paradigm, inspired by biological system, composed of a large number of highly interconnected processing elements(neurons) working in unison to solve specific problems. Artificial neural networks (ANNs), like people, learn by example. An ANN is configured for a specific application, such as pattern recognition or data classification, through a learning process. Learning in biological systems involves adjustments to the synaptic connections that exist between the neurons. This is true of ANNs as well.

An ANN is based on a collection of connected units or nodes called artificial neurons, which loosely model the neurons in a biological brain. Each connection, like the synapses in a biological brain, can transmit a signal to other neurons. An artificial neuron receives a signal then processes it and can signal neurons connected to it. The "signal" at a connection is a real number, and the output of each neuron is computed by some non-linear function of the sum of its inputs. The connections are called *edges*. Neurons and edges typically have a *weight* that adjusts as learning proceeds. The weight increases or decreases the strength of the signal at a connection. Neurons may have a threshold such that a signal is sent only if the aggregate signal crosses that threshold. Typically, neurons are aggregated into layers. Different layers may perform different transformations on their inputs. Signals travel from the first layer (the input layer), to the last layer (the output layer), possibly after traversing the layers multiple times.

The scope of this teaching package is to make a brief induction to Artificial Neural Networks (ANNs) for people who have no previous knowledge of them. We first make a brief introduction to models of networks, for then describing in general terms ANNs. As an application, we explain the backpropagation algorithm, since it is widely used and many other algorithms are derived from it. The user should know algebra and the handling of functions and vectors. Differential calculus is recommendable, but not necessary. The contents of this package should be understood by people with high school education. It would be useful for people who are just curious about what are ANNs, or for people who want to become familiar with them, so when they study them more fully, they will already have clear notions of ANNs [7].

Also, people who only want to apply the backpropagation algorithm without a detailed and formal explanation of it will find this material useful. This work should not be seen as "Nets for dummies", but of course it is not a treatise. Much of the formality is skipped for the sake of simplicity. Detailed explanations and demonstrations can be found in the referred readings. The included exercises complement the understanding of the theory. The on-line resources are highly recommended for extending this brief induction [7].

ARTIFICIAL NEURON MODEL

An artificial neuron is a mathematical function conceived as a simple model of a real (biological) neuron.

· The McCulloch-Pitts Neuron This is a simplified model of real neurons, known as a Threshold Logic Unit.

· A set of input connections brings in activations from other neuron.

· A processing unit sums the inputs, and then applies a non-linear activation function (i.e. squashing/transfer/threshold function).

· An output line transmits the result to other neurons.

BASIC ELEMENTS OF ANN

Neuron consists of three basic components –weights, thresholds and a single activation function. An Artificial neural network (ANN) model based on the biological neural systems is shown in Figure 4.1.

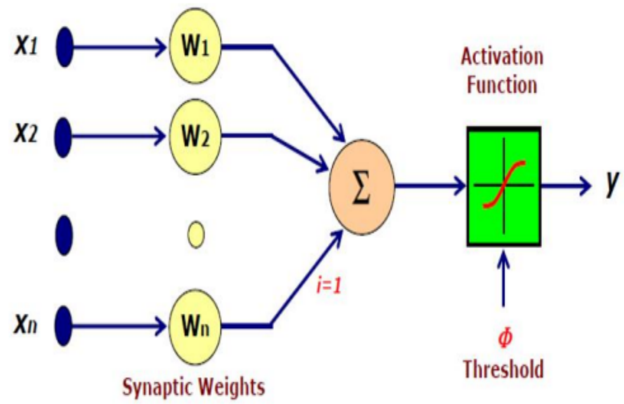

Fig. 4.1: Basic Elements of Artificial Neural Network.

DIFFERENT LEARNING RULES

A brief classification of Different Learning algorithms are as follow.

- Training: It is the process in which the network is taught to change its weight and bias.
- Learning: It is the internal process of training where the artificial neural system learns to update/adapt the weights and biases.

Different Training /Learning procedure available in ANN are

- Supervised learning
- Unsupervised learning
- Reinforced learning
- Hebbian learning
- Gradient descent learning
- Competitive learning
- Stochastic learning

REQUIREMENTS OF LEARNING LAWS

• Learning Law should lead to convergence of weights

• Learning or training time should be less for capturing the information from the training pairs

• Learning should use the local information

• Learning process should able to capture the complex non linear mapping available between the input & output pairs

• Learning should able to capture as many as patterns as possible

• Storage of pattern information's gathered at the time of learning should be high for the given network.

NETWORKS

One efficient way of solving complex problems is following the lemma “divide and conquer”. A complex system may be decomposed into simpler elements, in order to be able to understand it. Also simple elements may be gathered to produce a complex system (Bar Yam, 1997). Networks are one approach for achieving this. There are a large number of different types of networks, but they all are characterized by the following components: a set of nodes, and connections between nodes. The nodes can be seen as computational units. They receive inputs, and process them to obtain an output. This processing might be very simple (such as summing the inputs), or quite complex (a node might contain another network...) The connections determine the information flow between nodes. They can be unidirectional, when the information flows only in one sense, and bidirectional, when the information flows in either sense. The interactions of nodes though the connections lead to a global behaviour of the network, which cannot be observed in the elements of the network. This global behaviour is said to be emergent. This means that the abilities of the network supercede the ones of its elements, making networks a very powerful tool.

TRAINING

Neural networks learn (or are trained) by processing examples, each of which contains a known "input" and "result," forming probability-weighted associations between the two, which are stored within the data structure of the net itself. The training of a neural network from a given example is usually conducted by determining the difference between the processed output of the network (often a prediction) and a target output. This difference is the error. The network then adjusts its weighted associations according to a learning rule and using this error value. Successive adjustments will cause the neural network to produce output which is increasingly similar to the target output. After a sufficient number of these adjustments the training can be terminated based upon certain criteria. This is known as supervised learning.

Such systems "learn" to perform tasks by considering examples, generally without being programmed with task-specific rules. For example, in image recognition, they might learn to identify images that contain cats by analyzing example images that have been manually labeled as "cat" or "no cat" and using the results to identify cats in other images. They do this without any prior knowledge of cats, for example, that they have fur, tails, whiskers, and cat-like faces. Instead, they automatically generate identifying characteristics from the examples that they process.

V. RESULT AND ANALYSIS

CATIA V5 supports multiple stages of product development, including conceptualization, design (CAD), engineering (CAE) and manufacturing (CAM). CATIA facilitates collaborative engineering across disciplines around its 3DEXPERIENCE platform, including surfacing & shape design, electrical fluid & electronics systems design, mechanical engineering and systems engineering.

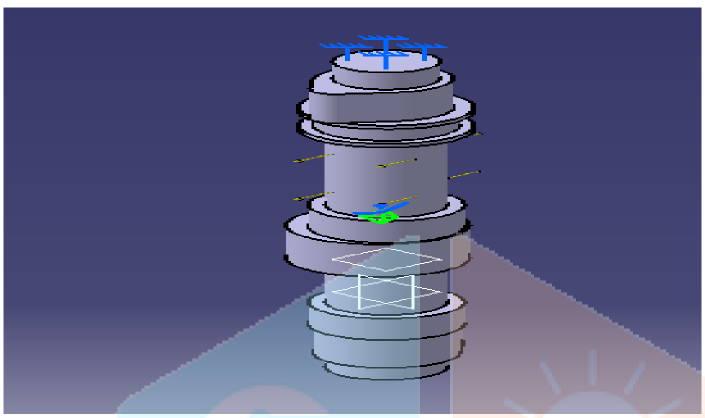

Fig.5.1. Design Module.

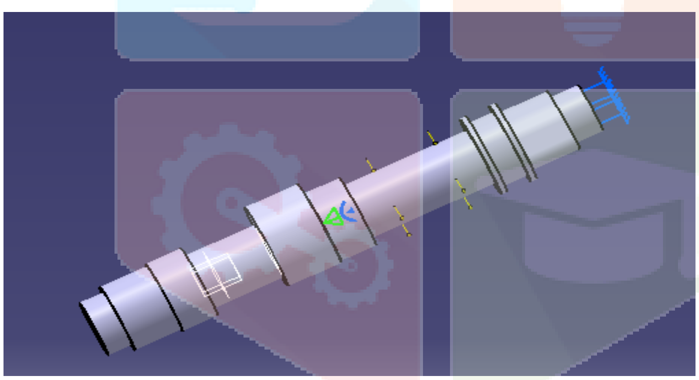

Fig.5.2. Design Module side view.

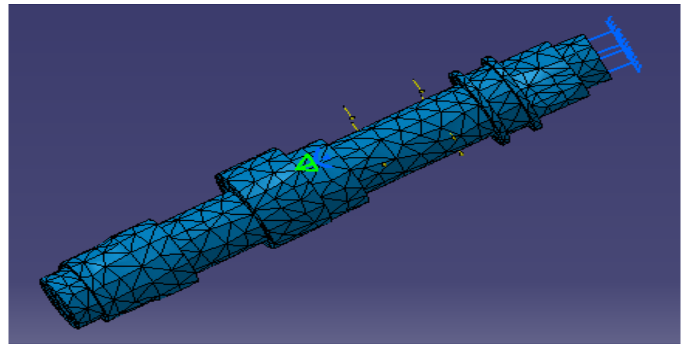

Fig.5.3 Meshing.

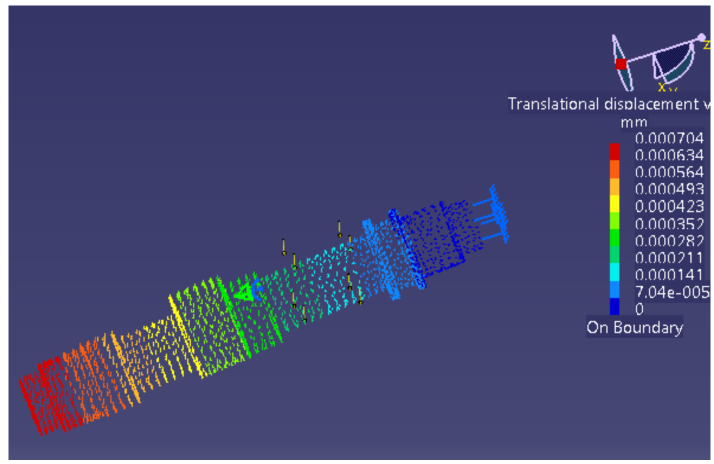

Fig.5.4. Design Module rotary load distribution.

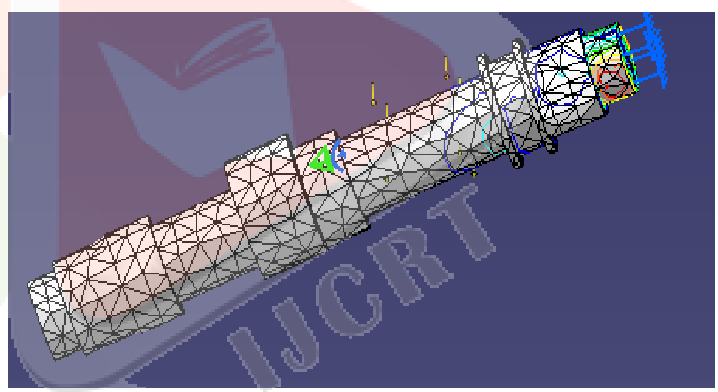

Fig.5.5.mesh with load criteria.

Table 5.1.Stretch and Aspect Ratio relation.

Criterion	Good	Poor	Bad	Worst	Avg.
Stretch	2882 (100.00 %)	0 (0.00%)	0 (0.00%)	0.319	0.614
Aspect Ratio	2538 (88.06%)	344 (11.94 %)	0 (0.00%)	4.873	1.969

Table 5.4 Translational pivot distribution

Value	Percentage
10.E6 --> 10.E7	1.2965e-002
10.E7 --> 10.E8	0.0000e+000
10.E8 --> 10.E9	5.1601e+000
10.E9 --> 10.E10	9.4775e+001
10.E10 --> 10.E11	5.1860e-002

Table 5.2 Min. and Max. pivot

Value	Dof	Node	x (mm)	y (mm)	z (mm)
5.4662e+006	Ty	5184	7.5303e+000	-1.6256e+001	-9.3326e+001
1.4898e+010	Ty	3714	-1.6879e+001	5.8286e+000	1.2360e+002

Table 5.3 Minimum pivot

Value	Dof	Node	x (mm)	y (mm)	z (mm)
6.7673e+006	Ty	5185	3.3148e+001	1.2534e+001	7.0345e+001
1.4982e+008	Tz	5183	3.6782e+001	2.3010e+000	7.0852e+001
1.7508e+008	Tz	848	-2.1852e+001	-1.2145e+001	-1.0412e+002
2.2036e+008	Tx	756	2.9790e+000	-1.6253e+001	2.1763e+002
2.2538e+008	Tz	1436	-4.9344e-001	-3.1768e+001	2.5588e+002
2.4857e+008	Tz	960	1.9990e+001	1.5014e+001	4.5000e+001

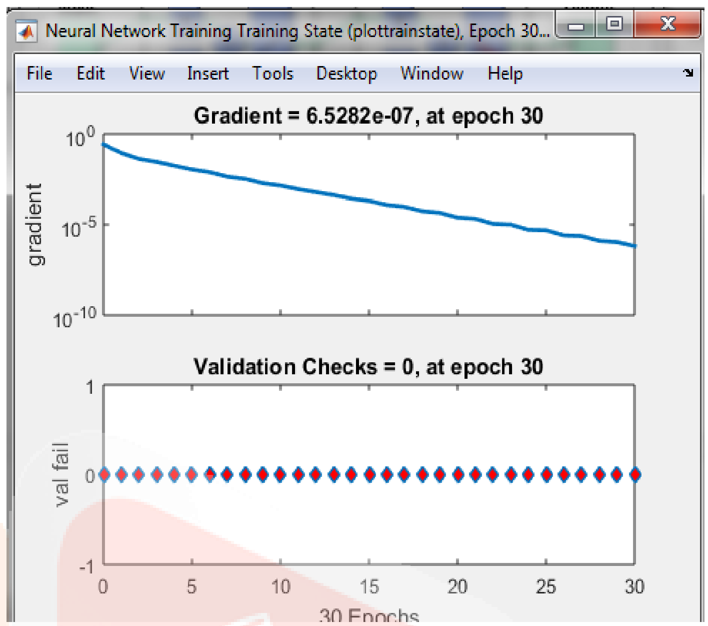

Fig.5.5 Correlation factors.

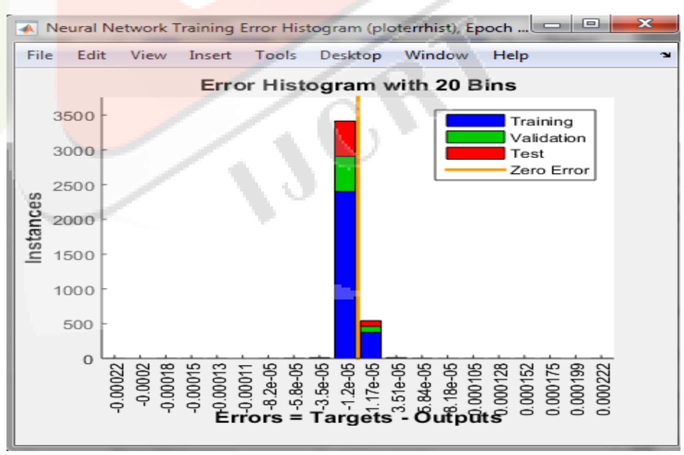

Fig.5.6 Error Histogram of ANN.

VI. CONCLUSION AND FUTURE SCOPE

CONCLUSION

When study has been carried out for different fiber angles for composite layers, it has been observed that 90o angle of fibers is providing better fundamental frequency compared to other angles. In present work, main aim in concentrated towards reducing overall weight of shaft with same strength, which ultimately results in less fuel consumption. Moreover by using composite drive shaft we can avoid using two piece drive shaft, since composite materials are providing much better natural frequency compared to the steel material. Moreover use of composite as replacement of the steel drives shaft, results in less noise and vibration.

For this study, a dataset with vibration data for the classification of unbalance on a rotating shaft with variable speed and unbalance strength was created. Various approaches to solve the associated classification task were tested. The largest unbalance could be detected by all algorithms with almost perfect prediction accuracy, even if only 3 characteristic values per sample were used for the classification. With the smaller unbalances, on the other hand, wider variations between the different approaches were found.

The best way to classify the dataset was to use an ANN with two hidden layers, which received the scaled FFT-transformed vibration data as input. Measured on the entire evaluation dataset, 98.6 % of the cases could be classified correctly. In addition, the examined models showed a very different behavior regarding the dependence on the speed. In future studies, this behavior could be exploited by building ensembles of different models to further increase the prediction accuracy. Strengths and weaknesses of individual models in the different speed ranges would then at least partially compensate each other.

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