A Study on Vibration Intelligence Control Technology Concept of Integrated Automotive Transaxle System

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ABSTRACT

An active internal vehicle transaxle unit structure is developed and evaluated experimentally to suppress gear pair vibration due to gear transmission error excitation. The main objective of the vibration controller for a vehicle transaxle unit system is to reduce the discomfort sensed by passengers which arises from gear transmission error excitation resulting from tooth profile errors, misalignment and elastic deformation (meshing stiffness). This paper deals with an artificial intelligence the adaptive neuro-fuzzy inference system (ANFIS) controller technique to design a robust controller to meet the control objectives. The advantage of this controller is that it can handle the nonlinearities faster than other conventional controllers. The approach of the proposed model monitoring index (FMI) can be used to allocate the exiting faults which need to be controlled by the suggested controller which is to minimize the rotational vibrations acceleration on each side (offside and nearside) of vehicle by supplying control forces to transaxle unit system. The results show that ANFIS controller has improved the dynamic response measured by decreasing the cost function. In addition, the analytical results showed that the maximum feedback control voltage required in the proposed method was further reduced as compared to existing methods for similar vibration control.

Keywords: Nonlinear transaxle system, ANFIS, control design, input selection, transmission error.

NOMENCLATURE

RMS	Root-mean-square of the signal in its time history
ANFIS	Adaptive Neuro Fuzzy Inference System
X	The input signal of the X-direction rotational vibration acceleration
Y	The input signal of the Y-direction rotational vibration acceleration
Z	The input signal of the Z-direction rotational vibration acceleration
M	The input signal of the modulus (M) - rotational vibration acceleration
CX	The output (controlled) signal of the X-direction rotational vibration acceleration
CY	The output (controlled) signal of the Y-direction rotational vibration acceleration
CZ	The output (controlled)signal of the Z-direction rotational vibration acceleration
CM	The output (controlled) signal of the modulus (M) - rotational vibration acceleration
MM	The output (model signal) of the modulus (M) - rotational vibration acceleration
CMd	The output (controlled signal) of the modulus (M) - rotational vibration acceleration
Ei	The cost function error
RMSE	Root mean squared error
K	The membership functions for each input
R	The number of fuzzy rules
Ni	Adaptive Neuro Fuzzy Inference Scheme inputs data

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1. Introduction

A novel algorithm was proposed which is based upon the narrowband simultaneous equation's adaptation. It requires no offline identified secondary path model and belongs to the class of direct adaptive feed forward control algorithms. The investigation reveals that a phase exact implementation in which an incremental encoder was used to generate synthetical reference signals was required. No feedback between algorithm output and reference measurement occurs [1]. Performance and robustness of the proposed algorithm was compared to the common model-based FXLMS algorithm in simulation and experiment. It achieves comparable convergence speeds and vibration reductions. However, in contrast to FXLMS it was able to compensate for changes in the secondary path. A test rig for small planetary gearboxes was presented. Internal forces caused by gear meshing can be measured. In one of the experiments 112 vibration orders were controlled with a mean reduction of 72%. The proposed active vibration control setup consumes 22 W of electric power and thereby degrades the planetary gearbox efficiency by only 0.2% for the experimentally examined operating point.

The presence of damages and diagnose the damaged component in automotive gearboxes were identified by comparing the vibration signals of the damaged and undamaged systems. The vibration signals were obtained in the gearboxes test bench taking into account ten samples approved by subjective method (based on human hearing) and three gearboxes damaged (two with bearing damaged and one with gear tooth damaged). The signals were obtained through five accelerometers positioned in the samples and each test comprises ten different steps with different coupling configurations of the gears [2]. Different signal analysis techniques based on wavelet transform, mathematic morphology and energy (entropy) were used to verify the presence of damage in the systems. The presence of damage to the systems is verified directly by comparing the energy levels and entropy of the signals of the damaged and undamaged systems for the ten steps tests. A signal processing technique combining pattern spectrum and selective filtering in certain frequencies ranges was used for identification of component failures.

Practical techniques and procedures employed were reviewed to quiet gearboxes and transmission units. The gearbox noise problem solution was focused on the improvement of gear design. On the verification of its effect on the radiated noise and the determination of the gears' contribution to the truck's or car's overall noise levels and on the analytical and/or numerical computer-based tools needed to perform the signal processing and diagnostics of geared axis systems [3]. All of the analytical methods are based on the time and frequency domain approach. The progress in technique of the gear angular vibration analysis and its effect on gear noise due to the self-excited vibration was reviewed. This presentation will include some examples of the use of such approaches in practical engineering problems.

A model allows us to simulate gear transmission dynamics was presented including most of these features usually neglected by the state of the art models. This work presents a model capable of considering simultaneously the internal excitations due to the variable meshing stiffness (including the coupling among successive tooth pairs in contact, the non-linearity linked with the contacts between surfaces and the dissipative effects), and those excitations consequence of the bearing variable compliance (including clearances or pre-loads) [4]. The model can also simulate gear dynamics in a realistic torque dependent scenario. The proposed model combines a hybrid formulation for calculation of meshing forces with a non-linear variable compliance approach for bearings. Meshing forces were obtained by means of a double approach which combines numerical and analytical aspects.

An active internal gearbox structure control approach was developed experimentally to suppress gear pair vibration due to transmission error excitation. The approach was based on an active shaft transverse vibration control concept that was theoretically analyzed in an earlier study and determined to be one of the most feasible methods [5]. The experimental results yield to 8–13 dB attenuation in the gearbox housing vibration levels and correspondingly 5–8 dB reduction in measured gear whine noise levels at the first and second operating gear mesh frequencies.

Four actuation concepts were modelled and compared for the active suppression of gearbox housing mesh frequency vibrations due to transmission error excitation from the gear pair system by computing the required actuation forces and amplifier power spectra. The proposed designs studied consisted of (1) active inertial actuators positioned tangentially on the gear body to produce a pair of reactive force and moment, (2) semi-active gear–shaft torsional coupling to provide tuned vibration isolation and suppression, (3) active bearing vibration control to reduce vibration transmissibility, and (4) active shaft transverse vibration control to suppress/tune gearbox casing or shaft response [6]. Numerical simulations that incorporate a transmission error term as the primary excitation were performed using a finite element model of the geared rotor system constructed from beam and lumped mass/stiffness elements. Several key comparison criteria including the required actuation effort, control robustness and implementation cost were examined. Based on the simulated data, the active shaft transverse vibration control scheme was identified as the most suitable approach for this application.

The non-linear vibration of a gear pair including shaft flexibility was simulated. Backlash is included because of the clearance between the teeth and the periodic variation in the stiffness of the mesh produces a parametric excitation [7]. The different behaviour that may be observed when the additional degree of freedom was added to the single degree of freedom model previously analyzed.

Some efficient strategies for the active control of vibrations of a beam structure using piezoelectric materials were described. The control algorithms have been implemented for a cantilever beam model developed using finite element formulation. The vibration response of the beam to an impulse excitation had been calculated numerically for the uncontrolled and the controlled cases. The essence of the method proposed was that a feedback force in different modes be applied according to the vibration amplitude in the respective modes i.e., modes having lesser vibration may receive lesser feedback [8]. This weighting may be done on the basis of either displacement or energy present in different modes. This method was compared with existing methods of modal space control, namely the independent modal space control (IMSC), and modified independent modal space control (MIMSC). The method was in fact an extension of the modified independent space control with the addition that it proposed to use the sum of weighted multiple modal forces for control. The analytical results showed that the maximum feedback control voltage required in the proposed method was further reduced as compared to existing methods of IMSC and MIMSC.

A similar approach using a pair of magneto-strictive actuators with an adaptive digital controller tried to treat the responses at the first three mesh harmonics simultaneously [9]. A reduction of 20–28 dB was reported at the fundamental mesh frequency, while reductions of only 2–10 dB were achieved at the higher harmonics. In that piece of work, they used a conventional filtered-X least mean square (LMS) algorithm that required a relatively accurate estimation of the secondary path transfer function over a wide frequency range. Note that this secondary path represents the dynamic characteristic between the control input and error signal. The level of accuracy needed will generally require a large-order finite impulse response (FIR) model of the secondary path and thus lead to fairly high computational load requirement.

An active shaft transverse vibration control technique was proposed. This technique uses a piezoelectric linear stack actuator to deliver control forces to the rotating shaft close to the gear pair via a rolling element bearing. Although the conventional filtered-X LMS algorithm was one of the most widely used techniques, it required the availability of a relatively accurate secondary path transfer function over a wide frequency range. Moreover, the computational load can be quite high especially for large and complicated applications. Since the target signals in the gearbox vibration problem were the discrete gear mesh harmonics, it was more appropriate to apply a simplified delayed-X LMS version [10]. Because the simplified approach aims only at the specific harmonic responses of interest, less computational effort was needed. The same linear behavior was expected in the active gearbox structure considered here especially if the piezoelectric stack actuator operates only within a small driving voltage range. Accordingly, the use of a more complex nonlinear controller such as the frequency domain adaptive harmonic controller was not necessary in the present application.

A neuro-fuzzy ensemble (NFE) model for machinery health diagnosis was investigated. The proposed diagnosis system was illustrated by discriminating between various gear health conditions of a motorcycle gearbox. Four different health scenarios were considered in this work: normal, slight-worn, medium-worn and broken-teeth gear [11]. Experimental results show the NFE model performs better than single neuro-fuzzy (NF) model with respect to classification accuracy, sensitivity and specificity, while the computational complexity is not increased significantly. In addition, the NF-based models are able to interpret their reasoning behavior in an intuitively understandable way as fuzzy if-then rules, which allow users to gain a deep insight into the data.

A method presented A study demonstrates by which these vibrations produced due to the primary forcing function originating from the mesh points can be controlled. Hence, to deal with both the meshing stiffness generation and vibration transmissibility processes more effectively, the control system must be applied close to the gear's connection [12]. This close proximity will allow the application of a single controller. The results presented showed that the outputs take less time to stabilize. Moreover, due to incorporation of the ANFIS controller with the gearbox, it was observed that the gearbox reaches the desired vibration very quickly in relatively shorter time.

The above mentioned works have shown that almost the efforts which had been done based on the artificial intelligence techniques in the field of the human knowledge applications were established, while in the engineering application, their contributions were limited due to the biggest expression of the success of these techniques. In addition, electrical machines have received the biggest attention, particularly with the use of neuro-fuzzy system, whereas mechanical rotating machinery such as gearboxes which have been given little considerations, because only traditional techniques (such as LMS and adaptive FXLMS controllers) are used. The modern techniques of artificial intelligence such as ANFIS have not been considered in this sector particularly in vehicle transaxle units. The objective of this study is to use the adaptive neuro-fuzzy inference system (ANFIS) to control vehicle transaxle unit vibration active control rotational vibration response measured by accelerometers at the unit end bearing casing and produced due to transmission error excitation and is to reduce the discomfort sensed by passengers which arises from gear transmission error excitation resulting from tooth profile errors, misalignment and elastic deformation (meshing stiffness originating from the mesh points), while the vehicle transaxle unit rotates up to 1400 rpm, at different gear shifts and torque loads up to 100 Nm.

2. Measurement Technique and Experimental Procedure

This section deals with the description of the instrumentation and experimental procedure used in this study. The vehicle transaxle unit vibration parameters were measured when the vehicle transaxle unit driven by electric motor in the laboratory. Furthermore, the description of the tools and instrumentation system used in the measurements, modern approaches for analysis the way of carrying out the tests and test procedure.

2.1 Tested Vehicle Manual Transaxle Unit

A transaxle is a major automotive mechanical component that combines the functionality of the transmission, axle, and differential into one integrated assembly. Transaxles are near universal in all automobile configurations that have the engine placed at the same end of the vehicle as the driven wheels: the front-engine/front-wheel drive; rear-engine/rear-wheel drive; and mid-engine/rear-wheel drive arrangements. In this work, the front-engine/front-wheel drive is used, where the gearbox mounted in block at the rear differential; also inboard brakes to reduce unspring mass and is shown in Fig. 1 while Fig. 2 displays the front wheel layout of the vehicle manual transaxle unit.

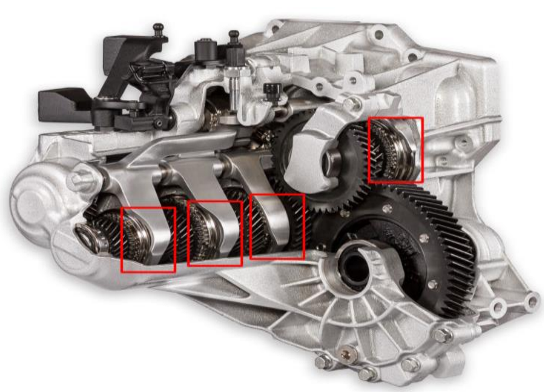


Fig.1 Manual Transaxle unit layout, with gearbox mounted in block

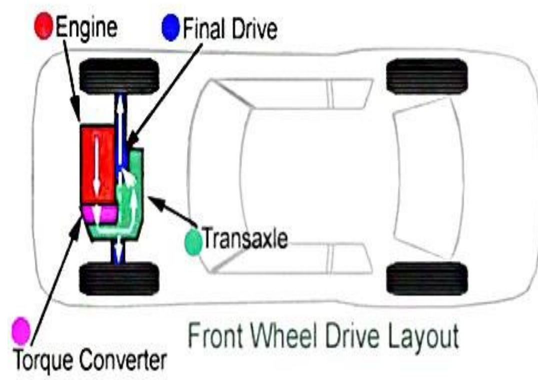


Fig. 2 A typical transaxle designed for a front-engine, front-wheel-drive vehicle

2.2 Description of Test Rig

The manual vehicle transaxle unit is powered by the electric motor and consumes its power on a hydraulic disc brake. A short shaft of 20 mm diameter is attached to the shaft of the motor through a flexible coupling. This is to minimize effects of misalignment and transmission of the vibration from the motor. The shaft is supported at its ends through two ball bearings and then the motion is transmitted directly to the transaxle unit. The manual transaxle unit gear shifts are also tabulated in Table 1. The entire system is settled in an oil basin in order to ensure proper lubrication. SAE 75W90 oil (shell Gear Oil GX) was used as a standard lubricant.

Table 1 Vehicle manual transaxle unit technical specifications and gear shafts

S/N	Parameter		
	Model		M5EF2
1	Type		Forward 5 speed, reverse 1 speed
2	Engine displacement		1.1 MPI engine
3	Gear ratio	First	3.545
		Second	1.894
		Third	1.192
		Forth	0.853
		Fifth	0.719
		Reverse	3.636
4	Final gear ratio		4.437

2.3 Measurement Methodology and Test Procedure

One non-destructive technique has been employed to monitor the vehicle manual transaxle unit, namely vibration generation. A significant effort was dedicated to the signal processing of the vibration waveforms acquired during the tests. The goals set a priori were to control and calculate a number of parameters-features extracted by the signals in its rotational phase and check their behavior during the tests in order to identify the most promising ones. Fig. 3 shows photograph of the experimental setup the test rig of the vehicle manual transaxle unit along with the establishment of the experimental methodology and the smart phone sensors positions which are illustrate in Appendix, where the measuring of acceleration has been done at three directions (X, Y, Z).

Prior to testing, the manual transaxle unit had been separated from its vehicle and put on a heavy steel stand made and mounted on it. The reason for doing this is to measure the translation vibration responses for the transaxle unit output sides (namely offside and nearside) at points 1, 2, 3, and 4 as shown in Fig. 4 away from other vehicle elements (tire/road interface, engine, etc) not only, but also to allow the transaxle unit points, to be tested with and without loads at different torque loads, rotational speeds and gear shift conditions. The translation vibration acceleration responses for the transaxle unit points 1, 2, 3, and 4 were measured which had been mounted on the center of each panel and element surfaces of the four. The accelerometer signals were recorded via software and were converted and passed to the excel Microsoft. The motor speed was measured by photoelectric tachometer probe which placed in front of the gearbox input shaft. using the oil pressure measured on vehicle wheel and transferred to the gearbox through the reduction ratio for the differential and gearbox. The speed is measured by a photo electric probe. Recordings were carried out at constant speeds Many tests were conducted in order to calibrate the sensor configuration and insure the repeatability of the recordings and the proper operation with minimum system vibrations as well as the various cables and connections.

Fig. 3 Test rig schematically layout

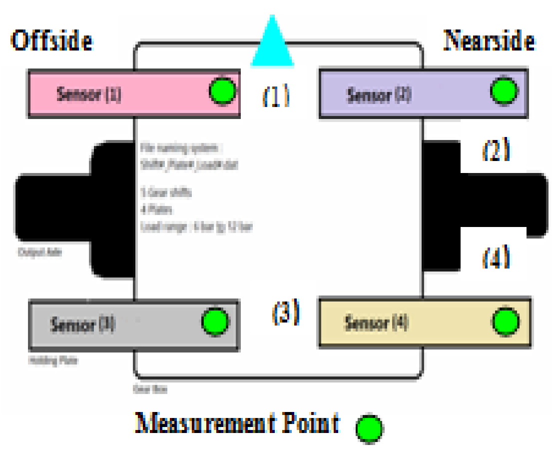


Fig. 4 Transaxle unit measuring points

3. ROTATIONAL VIBRATION ACCELERATION

It is well known that most of the motions in the gearbox are rotational motion. On the other hand, it is a fact that 50% of all coordinates are rotational (as opposed to translations) and 75% of all frequency response functions (FRFs) involve rotational coordinates. However, it is extremely rare to find enough references to describe the methods used for the measurement of rotational responses. This situation arises from a considerable difficulty which is encountered when trying to measure either rotational response and /or when trying to apply rotational excitation, i.e., an excitation torque. There are basically two problems to be tackled; the first is that of measuring rotational responses and the second is concerned with the generation of the rotational excitations. The first of these is the less difficult, and a number of techniques have been evaluated, which use a pair of matched accelerometers placed a short distance (ℓ) apart on the gearbox's structure to be measured [13]. The principle of operation is to measure both accelerometers signals from which, the responses of rotational vibration acceleration ($\ddot{\theta}_o$) can be deduced by taking the difference of ÿA and ÿB as:

$$\ddot{\theta}_o = \left(\ddot{y}_A - \ddot{y}_B \right) / \ell \qquad (1)$$

4. VEHICLE TRANSAXLE UNIT CONTROL PERFORMANCE PARAMETERS

4.1 ADAPTIVE NEURO FUZZY INFERENCE SCHEME TECHNIQUE

The final output is the weighted average of each rule's output. Adaptive Neuro Fuzzy Inference Scheme (ANFIS) is functionally equivalent to a Takagi-Surgeon (T-S) fuzzy inference system. By using stipulated input-output training data pairs, ANFIS tunes the membership functions and other associated parameters by back propagation gradient descent and least square type method, respectively. Such methodologies make the ANFIS modeling more systematic and less reliant on expert knowledge, thus more objective. The corresponding equivalent ANFIS structure and learning process can be found in details in [14, 15].

4.2 TRAINING PROCESS FOR ANFIS MODEL

The ANFIS model mainly consists of the NF network placed in series with the vehicle. The training process for obtaining the model of the vehicle is shown in Fig. 5, where the input and output data set is used to reflect input-output characteristics of the vehicle. The training data set is used based on: X, Y, Z, M and MM d, where X is the X-direction vibration acceleration, Y is the Y-direction vibration acceleration, Z is the Y-direction vibration acceleration, M is the modulus vibration acceleration, MM d, is the desired vehicle transaxle unit vibration acceleration. The ANFIS network can be trained by least square estimation method to minimize the cost function error (E i) defined by:

$$E_1 = \sum_{i=1}^{N} (M - MM_d) \qquad (2)$$

M is the input signal and MM $_d$ the corresponding actual (desired) output of the component's ANFIS. The iterative learning tuner is designed to improve the tracking performance of inverse-control which repeats the desired task over a finite interval.

4.3 INPUTS SELECTION

Prior to training the individual ANFIS model, the number of input membership functions is determined, which is an important factor in the initial condition. In the case of ANFIS which has Ni inputs and K membership functions for each input, the number of fuzzy rules R is:

$$\boldsymbol{R} = \boldsymbol{K}^{N_1} \qquad (3)$$

It is seen from equation (3) that too many inputs and input membership functions will lead to substantial increase of inference rules and thus increase training time and computer memory space consumption. Therefore, it is necessary to do input selection that finds the priority of each candidate inputs and uses them accordingly. A quick and straightforward way of input selection for neuro-fuzzy modeling is to use ANFIS. The proposed input selection method is based on the assumption that the ANFIS model with the smallest RMSE (root mean squared error) after one epoch of training has a greater potential of achieving a lower RMSE when given more epochs of training. In this study, five models have been tried with different combinations of two inputs and train them with a single pass of the least square method [16]. After several trials, the smallest training error was achieved when the inputs were X, Y and Z at the current time step and M from previous time step to produce output MM $_d$ at the current time step. Then the selected inputs were trained using the hybrid learning rule to tune the membership functions as well.

4.4 Vehicle Transaxle Faults Monitoring Index

The health condition monitoring (FMI) of a vehicle transaxle unit is conducted one condition at a time. To get a reliable fault detection, the features to be monitored should be sensitive to the vibration trend of the system. According to the discussion presented in [17], these requirements can be reached using selected signal processing techniques such as RMS. Usually more than one feature should be used for machine health. As an example, the RMS value based on overall residual signal is used here to demonstrate how to employ a feature for machine condition monitoring. The forecasting process includes the following relation:

$$FMI,(\%) = \frac{(RMS)_{model} - (RMS)_{measured}}{(RMS)_{model}} \quad (4)$$

Where:

$FMI,(\%)$ = Component vibration signature

$(RMS)_{measured}$ = RMS value measured

$(RMS)_{model}$ = RMS value predicted

4.5. Adaptive Neuro-Fuzzy Inference Scheme Controller Design

In this study, Adaptive Neuro Fuzzy Inference Scheme (ANFIS) technique is used to design a controller to reduce the vibration of the vehicle seat pan by control the vibration response transmitted from both engine and road surface. The design process is as follows: A neuro-fuzzy model for the vehicle seat pan is built to represent the relation between the variation of the vibration acceleration transmitted through to driver seat pan i.e. (obtain outputs given the inputs).

4.5.1 Training Neuro-Fuzzy Vehicle Seat Pan Controller

Given input/output data sets, ANFIS constructs Fuzzy Inference System (FIS) whose membership function parameters are adjusted using a back propagation algorithm. The size of input-output data must be large enough and cover all ranges to fine time the membership function. The X-direction vibration acceleration (X), the Y-direction vibration acceleration (Y), the Z-direction vibration acceleration (Z), the M is the modulus vibration acceleration (M), at previous step were used as inputs and controlled (desired) vehicle transaxle unit vibration acceleration (CM $_d$) from current step as output as seen in Fig. 6.

ANFIS controller is developed using MATLAB software based on the experimental data sets. 3048 data samples were collected corresponding to vehicle speed of 10 km/h).. These data was divided to 1524 points (odd number, where an odd number is number that cannot be divided evently by 2) for training and 1524 points (even number) for checking [18-21].

(4)

Fig. 5 ANFIS model for the vehicle inputs

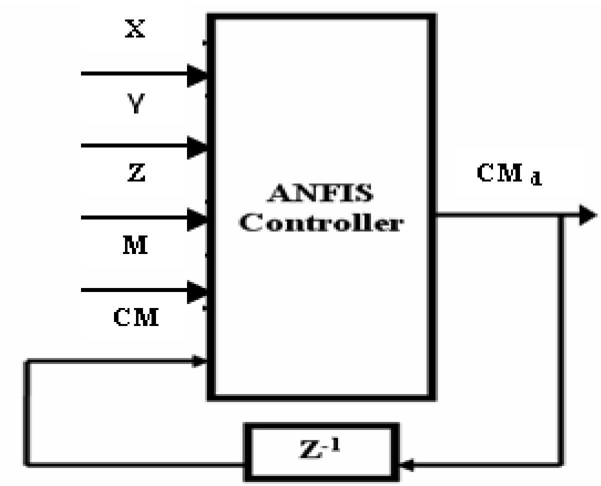
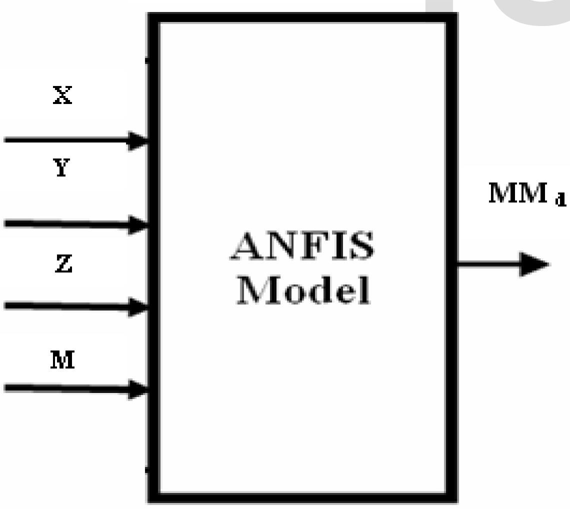


Fig. 6 ANFIS controller for the output

4.5.2. Development of Simulink model

Simulink model for the control of the vehicle transaxle unit vibration acceleration was developed using MATLAB software. This Simulink model with the ANFIS controller was developed using the various toolboxes available in the Simulink library such as the power system, power electronics, control system, signal



processing toolboxes and from its basic functions. The entire system modeled in Simulink is a closed loop feedback control system consisting of the NF forward model and the inverse ANFIS controller. The developed Simulink model for the control of various parameters of the NF controller is shown Fig. 7

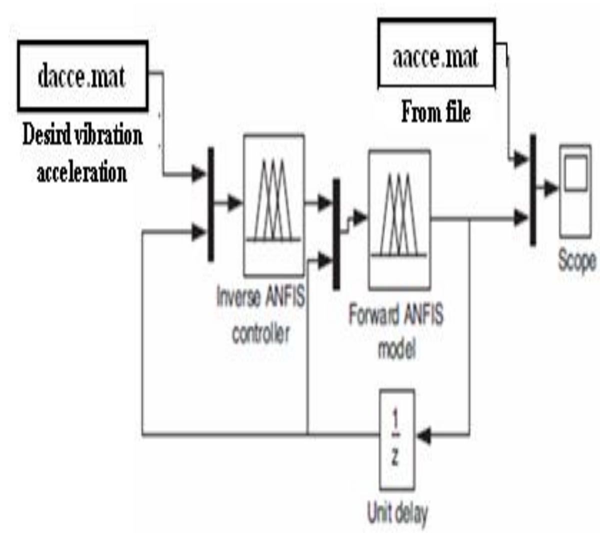


Fig. 7 Block diagram of the Simulink of Neuro-Fuzzy controller

4.6 Building the controller

Having now a database with the best control decisions, inputs and outputs, a controller needs to be constructed that mimics these best decisions. Obviously running this algorithm instead of the controller or storing the data set of a run through all possible values and then referencing it whenever needed would always yield the best control output. Nevertheless such a solution is infeasible in a real time system, especially the vehicle transaxle unit, where the speed of decision taking is very crucial. Here a feasible solution is proposed by Adaptive Neuro-Fuzzy Inference System (ANFIS) where data are obtained through the algorithm, the learning is made offline and then using the generalization and pattern recognition ability of the Artificial Neural Network (ANN), the optimum performance can be learned and a new Fuzzy Logic System (FLS) can be constructed to mimic that optimum performance. In this study, the controller is built using the Mat lab ANFIS toolbox.

4.7 Integration of the Controller in the Vehicle Transaxle Unit

Once the ANFIS auto-learning system constructs, the new Fuzzy Logic Control from the learned parameters. The controller is ready to be integrated in the vehicle transaxle unit. To do so, the controller is imported as a Simulink block and is connected to the vehicle transaxle unit. Also an observer that provides the controller with the offside rotational vibration data is measured from the test rig and is connected to the vehicle transaxle unit sensors and the proposed controller. Once the modules are connected to the vehicle transaxle unit, the transaxle unit becomes ready to be tested on the different testing condition.

4.8 Verification of the Presented Controller Effectiveness

To verify the effectiveness of the presented controller, the testing conditions were completely different from the designing measurement conditions. Unlike the control systems from the literature that uses the same measurement conditions to design the controller as the measurements to test the controller, which makes their controllers reliability and predictability questionable. For a fair judgment of the obtained results, the presented controller results were compared to that of a uncontrolled results.

5. Results and Discussion

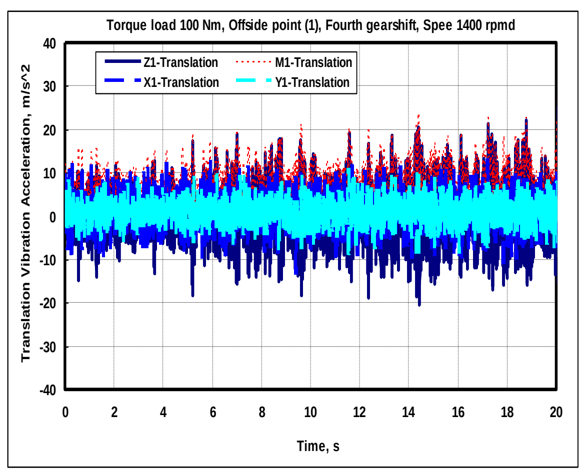
5.1 Transaxle Unit Model Prediction and Active Control

5.1.1 Translation and Rotational Vibration Responses

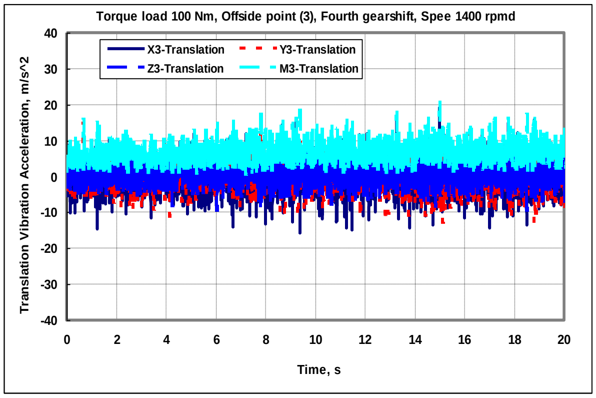
Figures 8 (a, b) shows samples from the translational acceleration vibration responses in terms of time-domain at points (1) and (3). Points (1) and (3) are two points located on the offside of the transaxle unit (Fig. 4) and have distance of 300 mm apart respectively. The gear shift is being fourth (4^{th}) and torque load is being 100 Nm. Samples from the computed rotational acceleration vibration responses for the the transaxle unit based on equation (1) for both time-history and frequency domain are shown in Figs. 9 (a, b) respectively. The conditions during the tests are illustrated in the figures. Perhaps the most powerful analysis technique is the frequency-domain analysis (FFT), see Fig. 9 b, for the following reasons:

(1) Changes in minor spectral components which may be the first indication of incipient failure will not always affect the overall vibration level, but can be picked up by spectrum monitoring.

(2) A rise in overall level indicates that something has changed but not gives any information as to the source, whereas this will often be indicated by the frequency at which the change occurs.

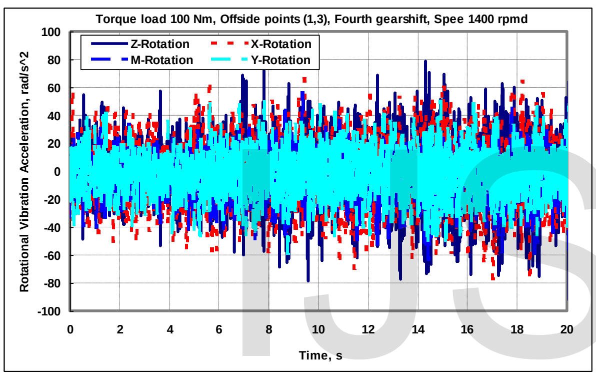


a) Point No. (1)

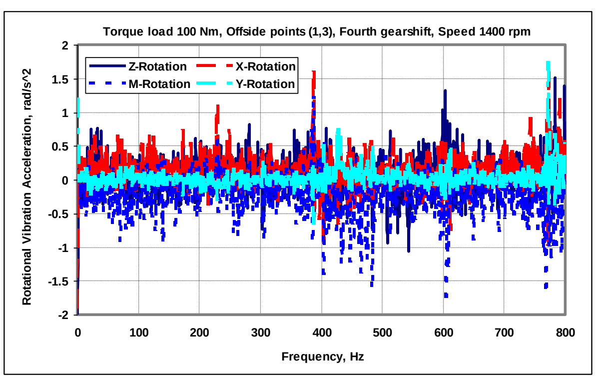


b) Point No. (3)

Fi g. 8 Translation vibration acceleration responses measured for X, Y, Z, M in transaxle unit offside



a) Point (1,3) – Time history



b) Point (1,3) – Frequency domain

Fig. 9 Rotational vibration acceleration responses predicted for X, Y, Z, M in vehicle transaxle unit offside

5.1.2 Transaxle Unit Model Evaluation and Detection Faults

The developed ANFIS model structure with two input neurons and one output neuron along with four hidden layers (input membership function, rule base, membership function, and aggregated output) are used. 16384 data points from measured data are used to validate the accuracy of the forward model. Fig. 10 (a, b) shows comparison between measured and predicted rotational vibration accelerations in terms of time-history. It can be seen that the predicted force can track the target force very well. The measured data are belong to torque load of 100 Nm and 20 Nm respectively as an example. The same validation procedure is done for all the cases considered in this work.

To confirm the model performance, the second dataset is employed as the input and output of the model developed from the first set. To measure the quality of the model in fitting the second data and to detect abnormalities from new datasets is computed based on equation (4). Table 2 tabulates fault monitoring index (FMI) results which are computed the model using the second part of data measured. It can be seen that most of the errors obtained by subtraction between the model data predicted and the measured values are within the threshold which indicates that the model fits the data with high accuracy. On the other hand, it also indicates that the data reflecting the process is healthy However, there are some data points exceeding the threshold. These data points are regarded as outliers arising from the load transient periods. Table 2 illustrates the monitoring index (FMI) for the fault detection in the vehicle transaxle unit due to gear transmission error excitation resulting from tooth profile errors, misalignment and elastic deformation (meshing stiffness originating from the mesh points), where the value of FMI is equal to 1.0 (the unit is healthy), while the value of FMI is equal to 0.0 (the unit is Fully defected) was induced. It can be seen clearly from the data presented in the table that the predicted model have a large differences from the measured ones. However, many measurements are

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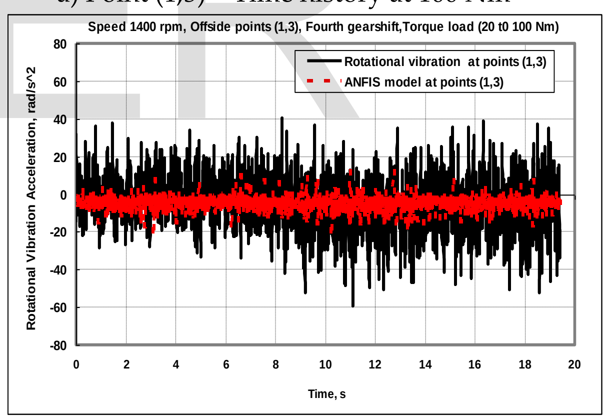
observed to have a large difference from the predicted (model) one. To perform detection , the residual data which is the difference between the predicted model and measured results and the details of the data points exceeding the threshold can be seen more clearly .Compared data, many successive data points exceed the thresholds and indicate there is a fault in the unit. To confirm the model performance, the second dataset is employed as the input and output of the model developed from the first set. To measure the quality of the model in fitting the second data and to detect abnormalities from new datasets is computed based on equation (4). Table 2 tabulates faults monitoring index (FMI) results which are computed the model using the second part of data measured. It can be seen that most of the errors obtained by subtraction between the model data predicted and the measured values are within the threshold which indicates that the model fits the data with high accuracy. On the other hand, it also indicates that the data reflecting the process is healthy However, there are some data points exceeding the threshold. These data points are regarded as outliers arising from the load transient periods when the temperature measurements have delayed responses to current increases The examination of the FMI data presented in Table 2 describe that there faults due to the transmission loss which needs to be active controlled. However, the training of the neural network by using the fuzzy rule base for selection of proper and optimal rule is considered in the next section (designed ANFIS controller).

Table 2 Monitoring index (FMI) values

S/N	Model input data group	RMS	Measurements input data group	RMS	Monitoring index (FMI), %
1	Torque load 100 Nm Speed of 1400 rpm 1st , 2nd, 3rd and 4th gearshifts	10.70	Torque load 100 Nm Speed of 1400 rpm Fourth gearshift	115.8	32.28
2	Torque load (20 t0 100) Nm Speed of 1400 rpm Fourth gearshift	7.81	Torque load 20 Nm Speed of 1400 rpm Fourth gearshift	16.71	53.26
3	Torque load 100 Nm Speed of (600 to1400) rpm Fourth gearshift	6.00	Torque load 100 Nm Speed of 1400 rpm Fourth gearshift	15.13	60.34
4	Torque load 80 Nm Speed of (600 to 1400) rpm Fourth gearshift	14.52	Torque load 80 Nm Speed of 1400 rpm Fourth gearshift	19.57	25.80
5	Torque load 0.0 Nm Speed of (600 to 1400) rpm Fourth gearshift	3.57	Torque load 0.0 Nm Speed of 1400 rpm Fourth gearshift	7.63	53.21

a) Point (1,3) – Time history at 100 Nm

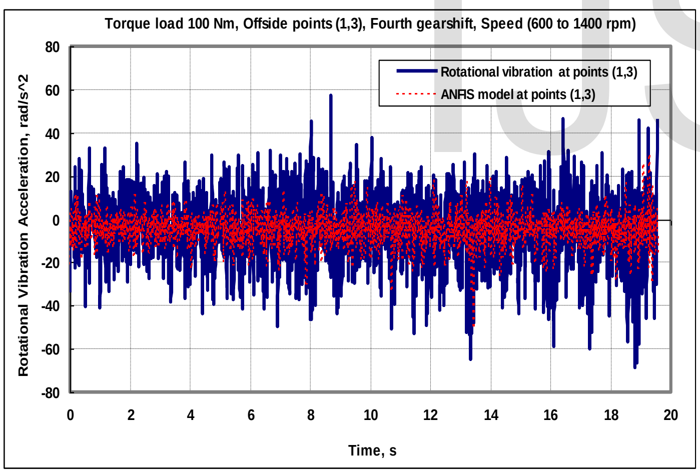


b) Point (1,3) – Time history at 20 Nm

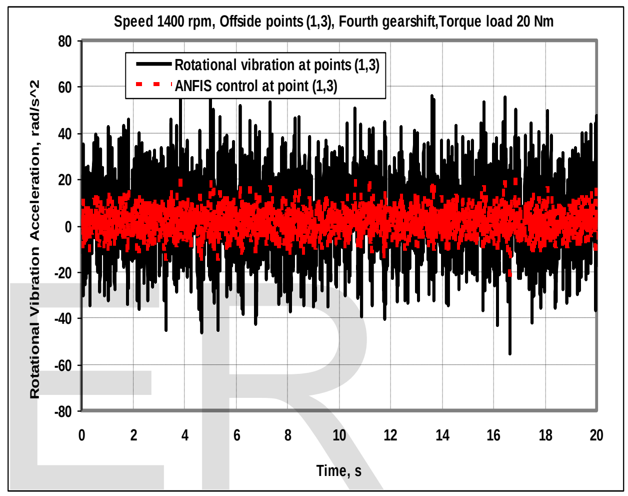
Fig. 10 Comparison between measured and ANFIS model predicted for rotational vibration acceleration.

5.1.3 Transaxle unit ANFIS controller establishment

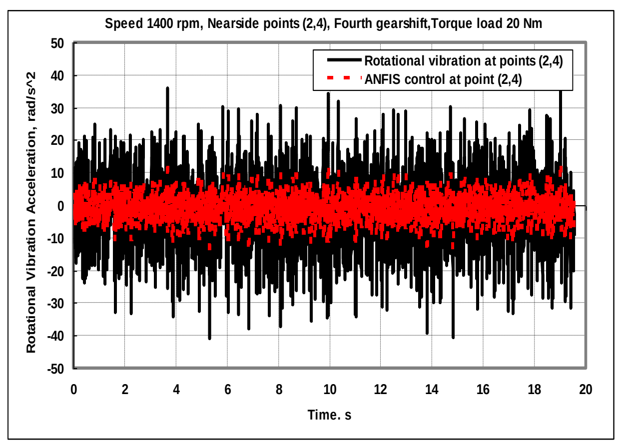
Figures 11 (a, b) shows a comparison between the measured and controlled rotational vibration accelerations in terms of time-history at rotational speed of 1400 rpm and torque load of 20 Nm at point (1,3) and (2,4) respectively. It is observed from the analysis of results in the figures that using the ANFIS control that the measured rotational vibration acceleration reached an acceptable error values. It is also observed that with the designed neuro-fuzzy controller, the measured rotational vibration acceleration characteristics curves take less time to settle with the system stabilization because of the training process of the ANN used and the proper selection of the rule base. The estimated RMSE between the measured and ANFIS controlled data. It can be seen that predicted force can track the target force very well. To prove that using ANFIS for controlling the vehicle transaxle unit rotational vibration acceleration takes a very small time to be stabilized As an example, take the results



shown in Fig. 11 an to indicate the effectiveness of the ANFIS controller to manipulate the rotational vibration acceleration generated from the vehicle transaxle unit structure in order to increase its life time when operates within the range of the torque loads and rotational speeds for points (1,3) and (2,4) as shown in Figs. 11 a and 11 b respectively, the root mean square (RMS) of rotational vibration accelerations values (RMS) for time-history were calculated for measured and controlled curves and are 18.4126 (measured) and 6.0815 (controlled) for point (1,3); 12.5902 (measured) and 4.1977 (controlled). Based on equation (1), the values of RMSE for the cases presented in Fig. 11 are 12.33 and 8.39, the same can be estimated for the cases considered in this work. The percentage effectiveness of the ANFIS controller is evaluated by divided the value of RMSE by the value of RMS for the measured data which reflect the effectiveness of the ANFIS controller. The percentage effectiveness for the controller used in this study is found to be almost 66.82%.



a) Point (1,3) – Time history at 20 Nm



b) Point (2,4) – Time history at 20 Nm

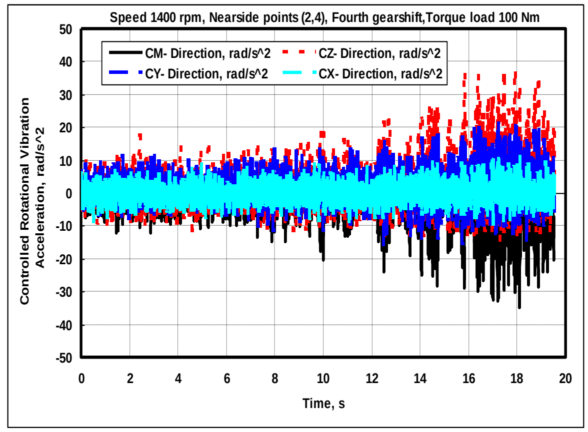
Fig. 11 Comparison between experimental and ANFIS controlled for rotational vibration acceleration

5.2 Transaxle Unit Performance Parameters

5.2.1 The Effect of Measurements Side and Direction

The transaxle unit rotational vibration acceleration was measured by the above-described method and was controlled by the designed controller. The results presented are an outcome of a series of testing and calculations that were made on different transaxle unit sides (offside, point (1,3) and nearside, point (2,4)) measurement sides and directions. Figs 12 a (offside) and Fig. 12 b (nearside) depict the controlled rotational vibration acceleration values (CX, CY, CZ) with modulus (CM) in the three directions (X, Y, Z) with modulus (M) in narrow bands respectively. The torque loading condition is 100.0 Nm and the fourth gearshift. It is observed from the results that the rotational controlled vibration responses measured in Y and Z directions are higher than those measured in X direction. On the other hand, the observation is extended to include the influnces of transaxle unit the controlled rotational vibration responses measured in Y and Z directions were made on different transaxle unit sides (offside, point (1,3) and nearside, point (2,4)), where the controlled rotational vibration acceleration responses for were measured and calculated (CX, CY, CZ) in narrow bands. It is observed that the rotational controlled vibration responses created at offside point (1, 3) are slightly higher than those created for nearside point (2, 4) in terms of time and frequency domains. The torque loading condition is 120.0 Nm and the fourth gear shift. It is observed that the rotational vibration responses created at offside point (1, 3) are slightly higher than those created for nearside point (2, 4) in terms of time history.

a) Point (1,3) – Time history at 100 Nm

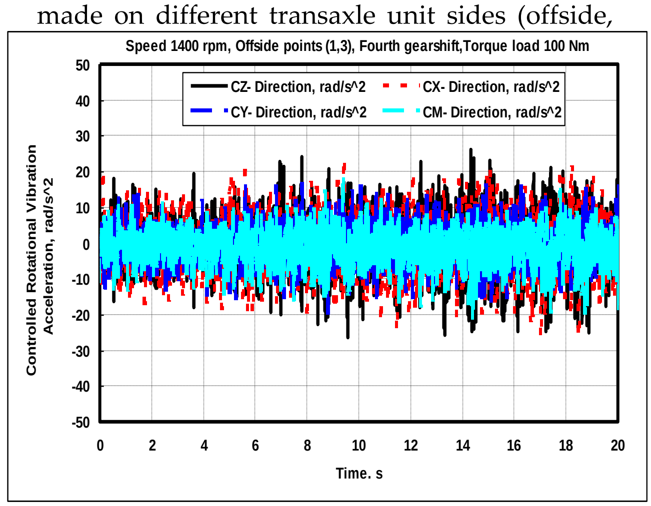


b) Point (2,4) – Time history at 100 Nm

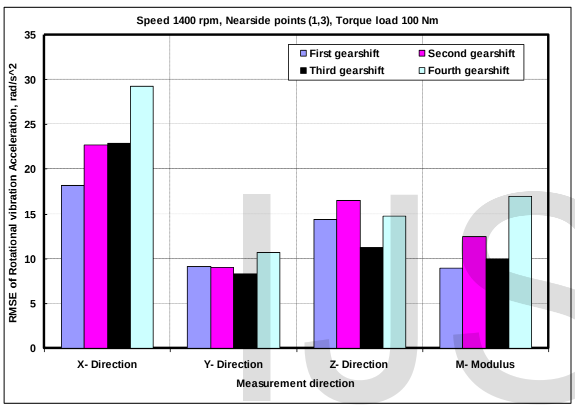
Fig. 12 Time history of the controlled rotational vibration acceleration of offside and nearside

5.2.2 The Effect of Gearshift

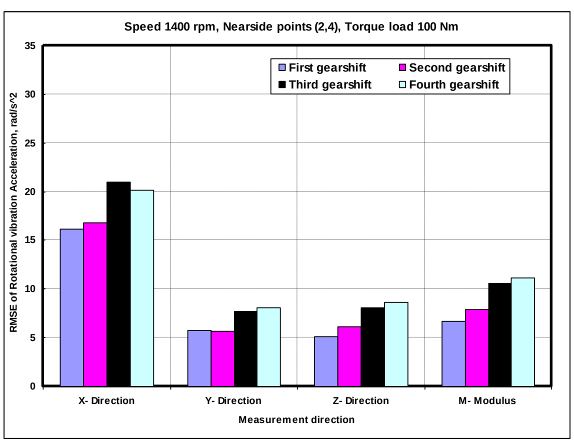
The transaxle unit was tested by the above-described method. The results presented are an outcome of a series of experiments that were made on different transaxle unit sides (offside,



point (1,3) and nearside, point (2,4), where the RMSE values were calculated based on equation (2) for the controlled rotational vibration responses measured in X,Y, Z directions, M modulus and are shown in **Fig. 13 (a, b)**. The torque loading condition is 100.0 Nm and 1400 rpm at offside point (1,3) , Fig. 13 a and nearside point (2,4), Fig. 13 b for different gearshifts in the vehicle transaxle unit, it can be seen that RMSE estimated for nearside point (2,4) are lower than those estimated for offside point (1,3) in all the measurements directions (X, Y, Z) with the M (modulus). Move rover, either in offside point (1,3) or nearside point (2,4), the X-direction performs the highest RMSE level. The reason of this is attributed to the nature of the ends design of the vehicle transaxle unit component.



a) Point (1,3) – Time history at 100 Nm

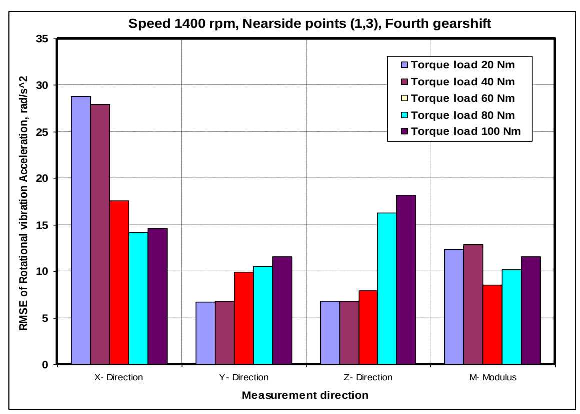


b) Point (2,4) – Time history at 100 Nm

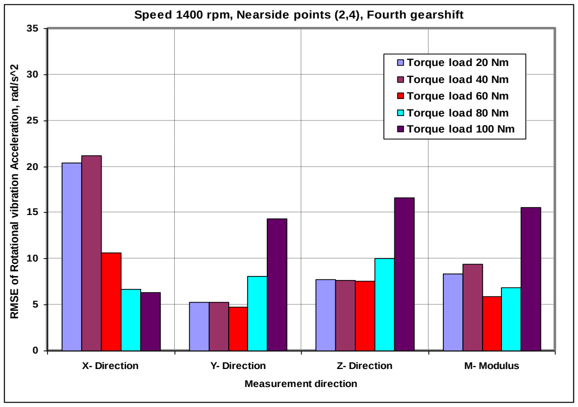
Fig. 13 Time history of the controlled rotational vibration acceleration for different gearshifts

5.2.3 THE EFFECT OF TORQUE LOAD

The transaxle unit was tested by the above-described method. The results presented are an outcome of a series of experiments that were made on different transaxle unit sides (offside, point (1,3) and nearside, point (2,4), where the RMSE values were calculated based on equation (2) for the controlled rotational vibration responses measured in X,Y, Z directions, M modulus and are shown in Fig. 14 (a, b). The torque loading condition is 1400 rpm at offside point (1,3) , Fig. 14 a and nearside point (2,4), Fig. 14 b for different torque load in the vehicle transaxle unit, it can be seen that RMSE estimated for nearside point (2,4) are lower than those estimated for offside point (1,3) in all the measurements directions (X, Y, Z) with the M (modulus). move rover, either in offside point (1,3) or nearside point (2,4), the X-direction performs the highest RMSE level particularly at 20 and 40 Nm. The reason of this is attributed to the nature of the ends design of the vehicle transaxle unit component.



a) Point (1,3) – Time history at 1400 rpm

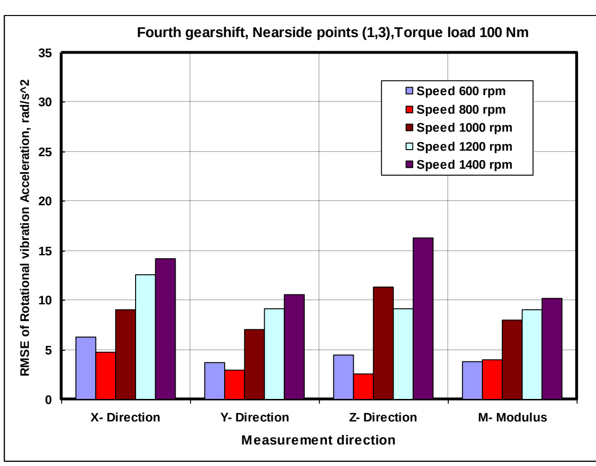


b) Point (2,4) – Time history at 1400 rpm

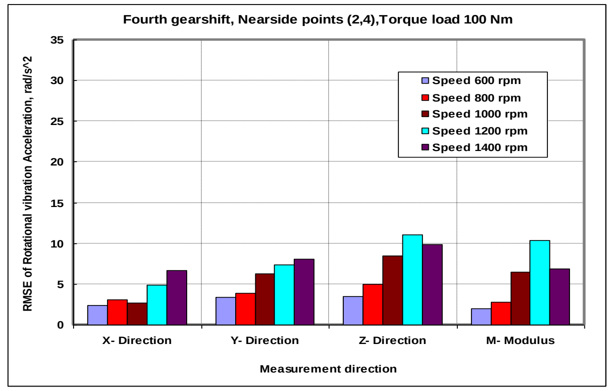
Fig. 14 Time history of the controlled rotational vibration acceleration for different torque load

5.2.4 The Effect of Rotational Speed

The transaxle unit was tested by the above-described method. The results presented are an outcome of a series of experiments that were made on different transaxle unit sides (offside, point (1,3) and nearside, point (2,4), where the RMSE values were calculated based on equation (2) for the controlled rotational vibration responses measured in X,Y, Z directions, M modulus and are shown in Fig. 15 (a, b). The torque loading condition is 100.0 Nm at offside point (1,3) , Fig. 15 a and nearside point (2,4), Fig. 15 b for different gearshifts in the vehicle transaxle unit, it can be seen that RMSE estimated for nearside point (2,4) are lower than those estimated for offside point (1,3) in all the measurements directions (X, Y, Z) with the M (modulus). move rover, either in offside point (1,3) or nearside point (2,4), the X-direction performs the highest RMSE level particularly at 1400 rpm. The reason of this is attributed to the nature of the ends design of the vehicle transaxle unit component.



a) Point (1,3) – Time history at 100 Nm



b) Point (2,4) – Time history at 100 Nm

Fig. 15 Time history of the controlled rotational vibration acceleration for different rotational speeds.

6. Conclusions

This paper presents an auto-generated controller, that could be automatically constructed through artificial intelligence techniques. Such that, an intelligent algorithm is developed to search for the optimum control decision in the control variables space and store it in a database that contains control inputs and their correspondent optimum output. This database is then passed to an Artificial Neural Network that is trained on these data, and from what it has learned, it constructs a Fuzzy Logic Controller that mimics these optimum control decisions. This FLC is the final controller that is used to control the vehicle.

A systematic approach of achieving the rotational vibration acceleration control of vehicle transaxle unit drive by means of adaptive neuro fuzzy inference control strategy has been investigated in this paper. Simulink model was developed in Matlab software with the ANFIS controller for the vibration control of low speed planetary gearbox. The control strategy was also developed by writing set of fuzzy rules according to the ANFIS control strategy with the back propagation algorithm in the back end.

The presented automated-approach have various advantages over the others in literature. The most important of which are the minimization of the human-intervention that cannot be reliable in a safety critical system. It guarantees the inclusion of the dynamic performance that a vehicle transaxle unit can go through. It can be easily auto-construct and auto-adapt and therefore can be easily adapted to any vehicle transaxle unit model or any changes in the vehicle transaxle unit characteristics. It almost fully exploits the available control hardware. The use of the ANNs together with the FLCs helps to combine the advantages of both techniques were the first have auto-learning and adaption capability while the other provides a smooth control performance.

To test the proposed controller, an experimental test rig containing a real vehicle transaxle unit was designed. By controlling this vehicle unit through the rotational vibration acceleration produced from the transmission loss, the controller performance was evaluated with effectiveness of 66.82%. The experimental data model was predicted which allows the faults to be monitored through monitoring index. The influences of vehicle unit rotational speed, torque load and vehicle gearshifts are evaluated.

The ANFIS also can be used with systems handling more complex parameters. Another advantage of the ANFIS is that its speed of operation is much faster than the other control strategies; the tedious task of training of membership functions is done in ANFIS. Collectively, these results show that the ANFIS controller provides faster settling times, has very good dynamic response and good stabilization. From practical point of view, the experience gained from this application will help to install such system on rotary machines containing vehicle transaxle unit. This will help to better quantify the true value of these systems.

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Appendix

Smart phone sensors

The smart phone sensors are software-based (ICM-20608-G) offers lower power consumption, lower noise, and a thinner package. Software-based sensors are not physical devices, although they mimic hardware-based sensors. Software-based sensors derive their data from one or more of the hardware-based sensors and are sometimes called virtual sensors or synthetic sensors. The linear acceleration sensor and the gravity sensor are examples of software-based sensors. In general, the sensor coordinate system is shown in Figure A1, where the sensor framework uses a standard 3-axis coordinate system to express data values. For most sensors, the coordinate system is defined relative to the device's screen when the device is held in its default orientation. When a device is held in its default orientation, the X axis is horizontal and points to the right, the Y axis is vertical and points up, and the **Z axis points toward the outside of the screen face. In this system, coordinates behind the screen have negative Z values. This coordinate system is used by the following sensor.**

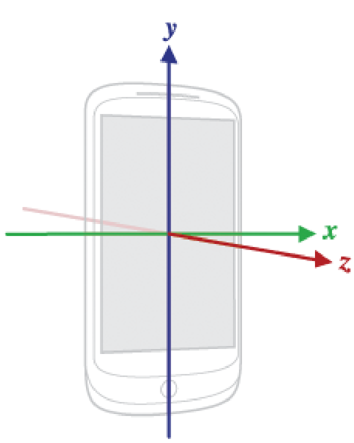

Fig. A1 Coordinate system (relative to a device)