

## Article

# Development of an Advanced Diagnostic System for Automotive Mechanical Transmissions

Helmy, Mohamed, Onsy, Ahmed, Hussein, Wessam and El Sherif, Ibrahim

Available at <http://clock.uclan.ac.uk/18515/>

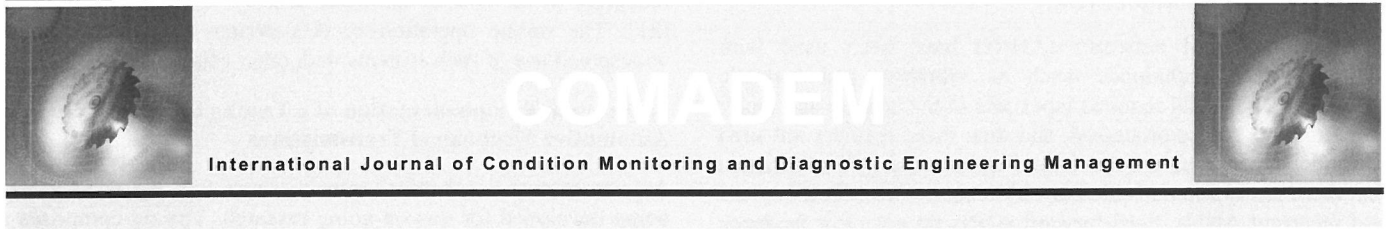
*Helmy, Mohamed, Onsy, Ahmed ORCID: 0000-0003-0803-5374, Hussein, Wessam and El Sherif, Ibrahim (2014) Development of an Advanced Diagnostic System for Automotive Mechanical Transmissions. International Journal of Comadem, 17 (2). pp. 39-44. ISSN 1363-7681*

It is advisable to refer to the publisher's version if you intend to cite from the work.

For more information about UCLan's research in this area go to <http://www.uclan.ac.uk/researchgroups/> and search for <name of research Group>.

For information about Research generally at UCLan please go to <http://www.uclan.ac.uk/research/>

All outputs in CLoK are protected by Intellectual Property Rights law, including Copyright law. Copyright, IPR and Moral Rights for the works on this site are retained by the individual authors and/or other copyright owners. Terms and conditions for use of this material are defined in the <http://clock.uclan.ac.uk/policies/>



## Development of an Advanced Diagnostic System for Automotive Mechanical Transmissions

Helmy Mohamed<sup>a</sup>, Ahmed Onsy<sup>b\*</sup>, Wessam M. Hussein<sup>c</sup> and Ibrahim A. El Sherif<sup>d</sup>

<sup>a,b,c,d</sup> MTC, Cairo, Egypt

\* Corresponding author. Tel.: +2-01278505159; E-mail: tiphms@gmail.com

### ABSTRACT

Automotive transmission is one of the most important parts of any vehicle power train system, and in order to achieve reliable operation, effective health monitoring must be used. Predictive health monitoring (PHM) systems are currently gaining in popularity due to their effectiveness in reducing maintenance costs; however, reliable monitoring techniques are required such as the analysis of vibration, acoustic emissions and oil debris. In this paper different monitoring techniques and their features are studied in order to develop an advanced monitoring system able to track the condition of an operating transmission system, classify faults, and detect the onset of failure. The study presents an online PHM system utilising autoregressive (AR) parametric algorithms, time and frequency analysis based on wireless transmission of vibration data. The online monitoring algorithm can support CBM and PHM of automotive multistage manual transmissions. The design, operation and validation of the online system are described and demonstrated. The results of the experimental test prove the system's capability and support the recent trend of using CBM and PHM strategies.

*Keywords: Mechanical Transmission, CBM, PHM, Vibration Analysis, Health Monitoring System, Autoregressive, AR, Time - Frequency Analysis.*

### 1. Introduction

Monitoring the condition of in-service mechanical transmission systems is an important issue for reliability, since their components deteriorate over time and are greatly affected when subjected to varying loads. This has led to the continuous improvement of maintenance strategies, from breakdown and periodic maintenance to CBM and predictive maintenance in order to maintain reliability and reduce periodic maintenance costs. Also, in some applications there are more demanding requirements, such as saving life, in addition to reliability [1]. Smith [2] has defined the causes and paths of transmission vibration, including factors such as manufacturing and design error and gear tooth deflection, which combine to introduce a transmission error (TE) which is the primary source of vibration.

Over the past decade, vibration analysis has proved to be a trustworthy diagnostic technique that can provide reliable information. However, researchers have devoted much effort to supporting CBM actions using vibration information [3-9]. Onsy et al. [3] and Tan et al. [4] used vibration data to monitor the progression of surface fatigue failures in spur gears, while Onsy et al [5, 6] monitored the progression of both surface and bending fatigue failures in helical gears. Surveys of the different features used in vibration analysis and suitable signal processing techniques [7-10] categorised them in two groups. The first includes time domain vibration features, such as: statistical parameters, time synchronous averaging based methods, filter based methods, stochastic methods and other model based

methods. The second group includes frequency domain and time frequency domain features, such as, at the first order: (FFT), correlation of spectrum, signal averaging, the short time Fourier transform (STFT), continuous wavelet transform (CWT), discrete wavelet transform (DWT), discrete wavelet packet analysis (DWPA), time-averaged wavelet spectrum (TAWS) and the time-frequency scale domain (TFS); at the second order: power spectrum, power cepstrum (logarithm of power spectrum), cyclostationarity, spectrogram Wigner distribution, and scalogram; at the third order: bicoherence spectrum, bilinearity and Wigner bi Spectra; and at the fourth order: Wigner tri Spectra [11].

Onsy et al. [12-14] have continued their research by developing multi-sensor fusion algorithms to fuse vibration analysis information with other sensory data, such as acoustic emission and oil debris, to minimise false alarms that may occur in failure prediction. The work utilised adaptive fuzzy logic algorithms to predict both surface and bending fatigue failures. Also, other researchers have devoted effort to building intelligent algorithms based on vibration features, including expert systems, ANN's, genetic algorithm, and fuzzy logic [15-20]. Intelligent health monitoring systems incorporate AI algorithms, where AI can be defined as "the science of making machines do things that would require intelligence if done by humans" [20]. To develop an IHMS, the running system condition must be recognized and classified. Researchers have devoted considerable effort to the application of various different soft computing methods to develop IHMSs, and have shown that this can be achieved using

methods such as neural networks, fuzzy logic and mathematical modelling based on parametric approaches. All of these methods can provide important tools in the field of intelligent systems, which can learn, adapt, and make decisions concerning the system they are in charge of [20].

Artificial neural networks (ANNs) have been used with different HMS techniques, such as vibration and acoustic monitoring. An ANN requires input data of the healthy and faulty conditions to be pre-processed, and then these features are used to model the system's behaviour. Fenton et al [19] mentioned that there are two main basic network architectures: feed-forward and recurrent ANNs. Feed-forward ANNs do not have feedback between layers, and previous inputs are not remembered, whereas recurrent ANNs involve feedback between layers and previous inputs are remembered and can be used to reconstruct correlative memory. Fuzzy logic was developed to characterize nonlinear behaviour to cover approximate knowledge in describing the behaviour of systems, which are difficult to describe mathematically [20].

Parametric methods based on mathematical modelling are used to fit measured time series waveform data to a parametric time series model, and then extract features based on this model [8]. Two models are currently in use: the auto regressive (AR) and auto-regressive moving average (ARMA) models. The advantage of mathematical modelling based on parametric methods over the neural networks model-based method is its ability to deal with time series data directly without the need for a signal pre-processing step to extract useful features that can be modelled to represent the system [8]. However, they can only be used to model a time series signal such as a vibration signal, and cannot be applied to combined information from several techniques (vibration, AE and ODA) such as in the case of fuzzy logic. Onsy et al. [21] successfully utilised auto-regressive (AR) algorithms to monitor the progression of surface fatigue failure in a single stage gearbox.

This paper builds on previous research achievements [21], utilising the advantage of mathematical modelling based on parametric methods over other methods to build an online model

for multi-stage automotive mechanical transmissions under healthy and faulty conditions. The work in this paper is based on the development of an online wireless vibration analysis tool for testing automotive mechanical transmissions resulting in reduction in the cost of the other sensory requirements used in [21]. The online operation of this system could lead to the widespread use of such systems with other rotating machinery.

**2. Design and Implementation of a Testing System for Automotive Mechanical Transmissions**

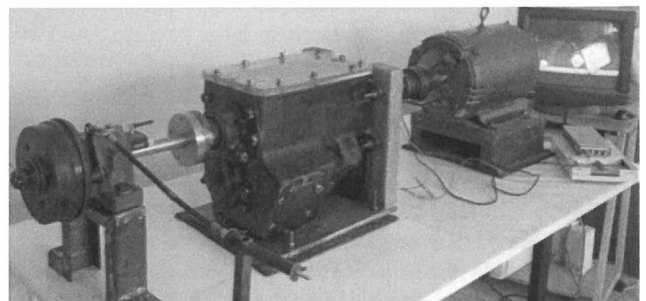
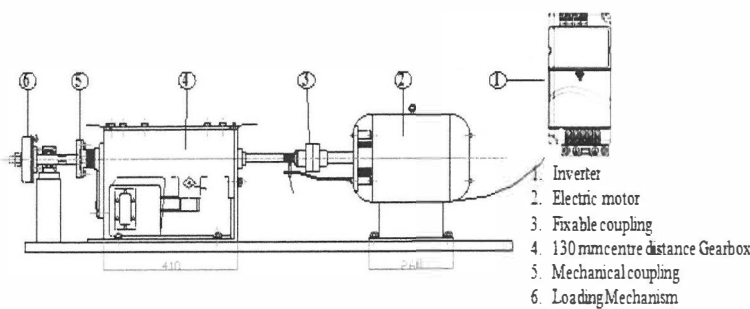
An automotive mechanical transmissions test rig is currently being developed for this on-going research. The rig comprises a 130mm centre distance gearbox. The gearbox is used in a rear-wheel drive vehicle, and the gearbox contains three shafts with five forward gear-shifts (all synchronesh) and one reverse. Table 1 provides the basic geometry specifications for the gears. The system is driven by an AC electric motor with maximum speed of 1765 rpm and output power of 10 Hp. The AC motor is controlled by an inverter model 'Delta VFD-E' to provide its variable speed operation. The load is applied via a mechanical brake drum equipped with tension mechanism.

The rig can generate a load torque on the test gearbox in the range of 0-200Nm using the mechanical drum brake. The torque is measured using calibrated 120ohm strain gauges (model KFG-2-120-D31-11) installed on the shaft at 45° and the measured torque values are transmitted to the control program using the SG-LINK telemetry system in order to provide torque control of the loading mechanism on the mechanical transmissions.

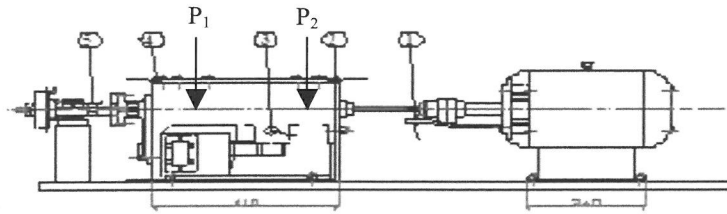
Gearbox oil and bearing temperatures were measured using three RTD temperature sensors (10mv/C). The input shaft speed was measured using an inductive speed sensor (model LM8-3002NA), and the motor current was also monitored as a precaution. The NI USB-6221 DAQ (16 bits - 250 kS/s) was used to acquire the sensor signals, and the test rig operating conditions were monitored and flexibly changed according to the required test conditions using NI LabVIEW's virtual instrument scalable architecture features. The test rig is shown in Figure 1.

**Table 1.** Basic Gear geometry

Specifications					
Gear No.:	1	2	3	4	5
Pinion/Wheel:	P/W	P/W	P/W	P/W	P/W
Module (mm)	9.5	9.5	8	8	8
Number of teeth	21/40	19/35	30/33	38/25	43/20
Face Width (mm)	25	25	25	25	30



**Figure 1.** Test Rig Layout



- 1.Speed sensor
- 2.Accelerometer 1
- 3.Oil temperature sensor
- 4.Accelerometer 2
- 5.Torque sensor

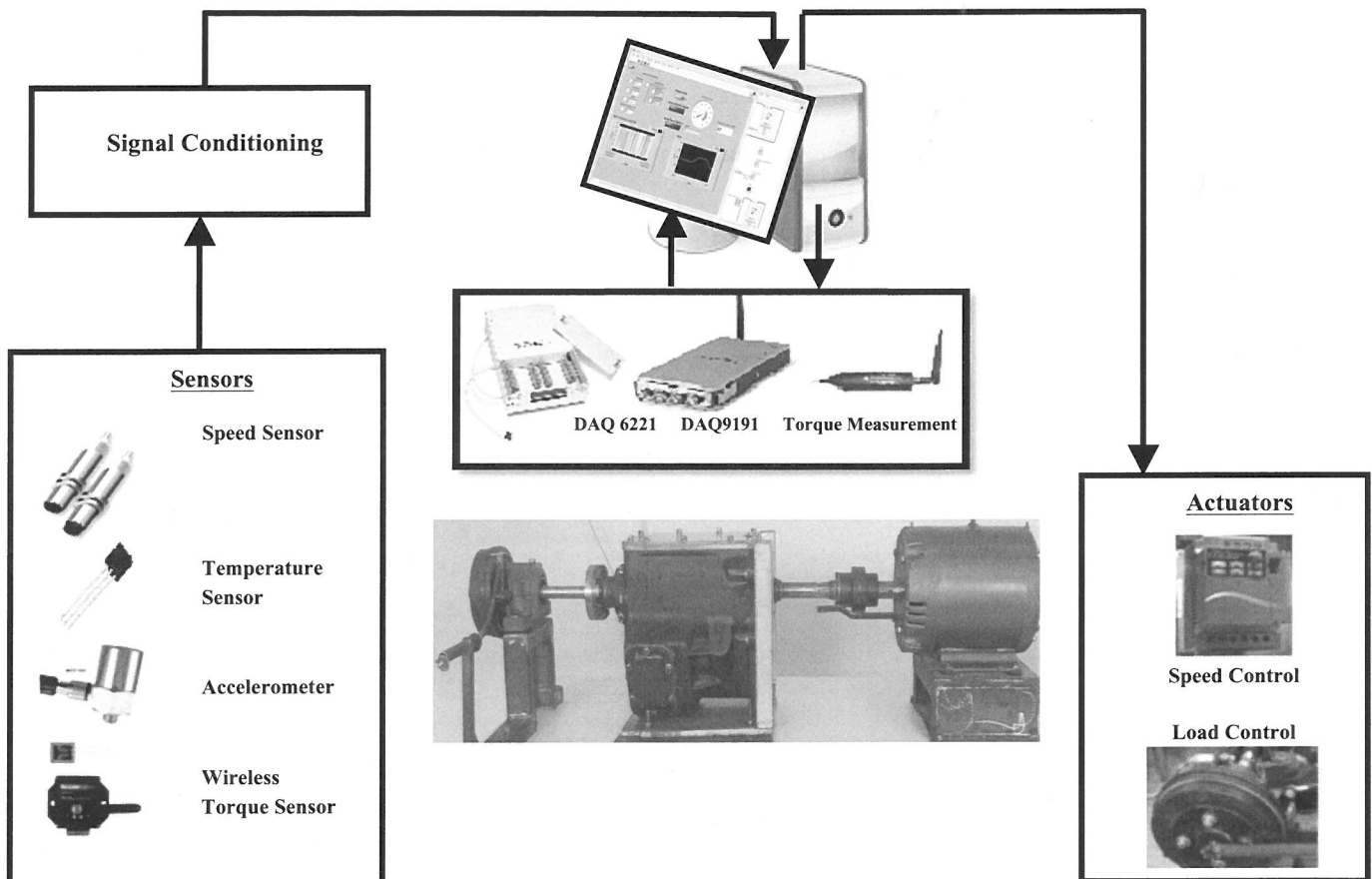
**Figure 2.** Sensors Location Layout

The vibration analysis system incorporated a 24-bit NI wireless DSA data acquisition card (NI 9234 with cDAQ-9191) to acquire the vibration signal, speed and temperature. The vibration signals were acquired using two ICP Piezotronic constant current source accelerometers (10mV/g) mounted adjacent to the tested gear bearings transversely to the gearbox casing, and a shaft speed sensor was used to acquire the shaft rotation reference. The sensor location diagram over the test rig is shown in Figure 2.

The vibration signals are then acquired continuously and transmitted to the base unit using an IEEE 802.11b/g (Wi-Fi) wireless communication interface (frequency range 2.412–2.462 GHz). The system can send the data from a range up to 30m for

indoor measurements and 100m for outdoor operation as long as the line of sight for the wireless signal is provided. The system can also provide Ethernet cabling measurements up to a distance of 100m. The test rig sensor-actuation system layout is shown in Figure 3.

The testing system has been developed for this research work, and is capable of on-line monitoring, automatic measurement, and analysis. Also, any changes in the gears and bearing conditions due to degradation during operation can be identified. The advantage of the development of the system arises from its ability to enhance online analysis methods for vibration techniques to provide robust information about the system's condition.



**Figure 3.** Test Rig Sensors - Actuation System Layout

### 3. Design and Implementation of Advanced Diagnostic System for Automotive Mechanical Transmissions Testing

#### 3.1. Online Time / Frequency Analysis

The advanced vibration analysis system software is developed in the NI LabVIEW environment to provide continuous online system monitoring using vibration features including time and

frequency: such as the RMS, crest factor, and kurtosis features (Equations 1-3), for the different frequency bands. Blocks of 12600 discrete samples were continuously received at the base unit and analysed, and these features were then processed using several algorithms and logged continuously in order to build up the data history. All the analysis, feature extraction, and data logging processes of the vibration features are achieved at the base unit.

$$V_{RMS} = \sqrt{\frac{1}{n} \sum_{i=0}^{n-1} |x_i|^2} \quad (1)$$

where  $n$  is the number of elements in  $x_i$ .

$$V_{Ku} = \frac{\frac{1}{n} \sum_{i=0}^{n-1} (x_\tau(i) - \mu)^4}{\sigma^4} \quad (2)$$

where  $n$  is the number of samples of the input time series  $x_\tau$ ,  $\mu$  is the arithmetic mean, and  $\sigma$  is the standard deviation of  $x_\tau$ .

$$V_{CF} = \frac{V_{pk}}{V_{RMS}} \quad (3)$$

where  $V_{pk}$  is the peak value of the DTS signal

### 3.2. Online AR Monitoring Algorithms

The method is based on matching the model to a specific data type, such as data from a healthy transmission, and any change in the signal characteristics due to failure will change the statistical properties of the output [24]. Samuel and Pines [8] discussed the differences between various types of parametric method, explaining the AR and ARMA models as follows.

The AR model for a time series  $X$  can be represented by a linear regression of  $X$  on itself plus an error series which is assumed to be noise having a Gaussian distribution. The AR model is given in Equation (4).

$$x_i = -\sum_{k=1}^p a_k x_{i-k} + e_i \quad (4)$$

where  $p$  is the model order and provides the number of past inputs required to model the signal (which is determined experimentally),  $a_k$  are the AR coefficients,  $i$  is the sample index, and  $e_i$  is the Gaussian error series [8].

### 4. Testing and Validation of the Automotive Mechanical Transmissions Test Rig and the Advanced Diagnostic System:

System validation comprised a series of tests designed to achieve the proposed aim of developing and validating the behaviour of the advanced diagnostic system, including the AR algorithms, and investigating its capability to provide information to users about the system status.

The group of tests were carried out on a new gearbox under three different conditions: normal and externally excited at two different positions 1 and 2 ( $P_1$  and  $P_2$  shown in Figure 2) on the gearbox external casing while the transmission is running at 200 rpm. Tests were done at a constant speed of 200 rpm, with no load, and operating at different temperatures (35°C, 60°C and 85°C). Further publications will follow to provide the results of the other series of tests including for healthy, in-service, and faulty gears that are working in real applications in which failure

under accelerated conditions was brought about by introducing artificial errors to the gear flanks. All three tests will be carried out at the same speed and torque until the tests end.

Figure 4 shows online screen shots of the output of the AR models for accelerometers 1 and 2, where Figure (4-a) is at the normal running condition of the gearbox, while Figure (4-b) is at the externally excited condition. The AR model provided values for the 'a<sub>1</sub>' and 'a<sub>2</sub>' coefficients as follows: when the gearbox was running at normal condition, accelerometer 1 (a<sub>1</sub>, a<sub>2</sub>) coefficient values of (-0.3, -0.06), accelerometer 2 (a<sub>1</sub>, a<sub>2</sub>) coefficient values of (-0.04, 0.16), while accelerometer 1 (a<sub>1</sub>, a<sub>2</sub>) coefficient values of (0.65, 0.65), accelerometer 2 (a<sub>1</sub>, a<sub>2</sub>) coefficient values of (0.67, 0.57) when the gearbox was continuously excited at P<sub>1</sub> and running at 200 rpm. It is worth noting that the repeated excitation of the gearbox case provided almost the same output as long as the excitation force is kept at the same average level.

Figure 4 provides the online screen shots for the AR models output for accelerometers 1 and 2, where Figure (4-a) is at the normal running condition of the gearbox, while Figure (4-b) is at the externally excited condition. The AR model provided values for the 'a<sub>1</sub>' and 'a<sub>2</sub>' coefficients as follows: when the gearbox was running at normal condition accelerometer 1 (a<sub>1</sub>, a<sub>2</sub>) coefficient values of (-0.3, -0.06), accelerometer 2 (a<sub>1</sub>, a<sub>2</sub>) coefficient values of (-0.04, 0.16), while accelerometer 1 (a<sub>1</sub>, a<sub>2</sub>) coefficient values of (0.65, 0.65), accelerometer 2 (a<sub>1</sub>, a<sub>2</sub>) coefficient values of (0.67, 0.57) when the gearbox was continuously excited at P<sub>1</sub> and running at 200 rpm. It is worth noting that the repeated excitation of the gearbox case almost provided the same output as long as the excitation force is kept at the same average level.

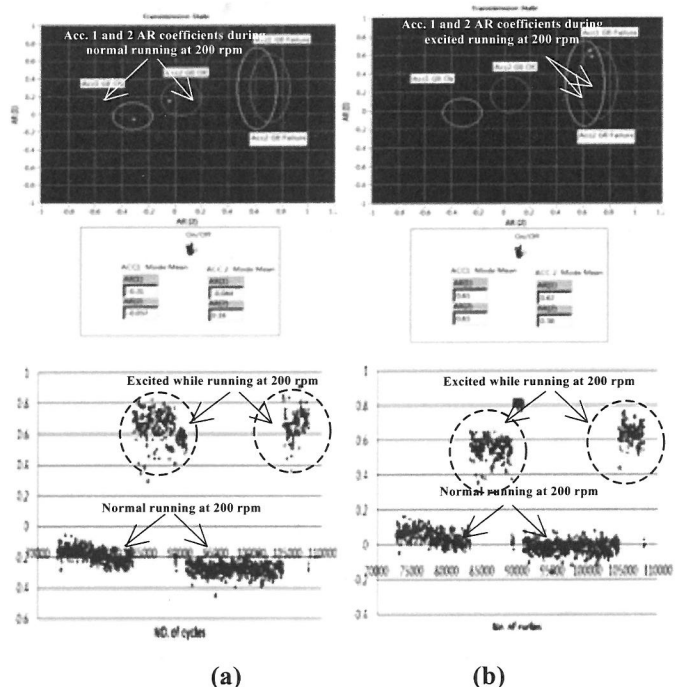
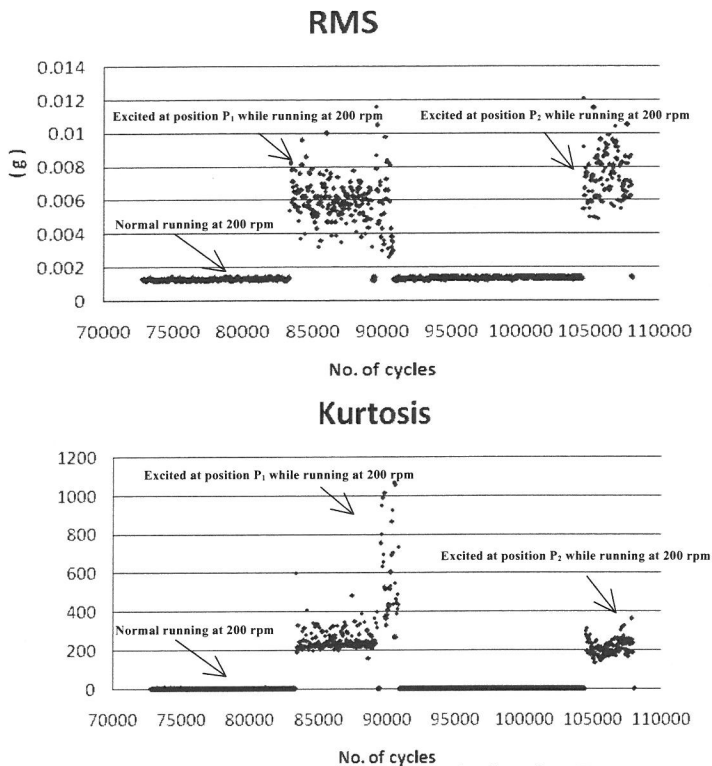


Figure 4. Screen Shots for Online Output of the AR Models for Accelerometers 1 and 2

Further tests were carried out on the gearbox under the same conditions; normal, and externally excited at P<sub>1</sub> and P<sub>2</sub> positions while the transmission was running at 200 rpm. Figure 5 shows the kurtosis and RMS features of the vibration signal at a selected frequency band, and it is evident that the selected features can provide an online warning indication in the case of the failure of the automotive mechanical gearbox.



**Figure 5.** Logged Kurtosis and RMS of Vibration Features Over a Selected Frequency Band

## 5. Conclusions

The study has presented a new advanced diagnostic system for automotive mechanical transmissions based on wireless vibration measurement that was able to detect different conditions of the automotive gearbox and can clearly identify the condition using only one accelerometer placed on the gearbox casing. The study has focused on monitoring three different conditions; normal, and externally excited at two different positions 1 and 2 on the gearbox external casing while the transmission is running at 200 rpm; using model-based parametric method AR algorithms based on vibration data only and also the kurtosis and RMS features of the vibration signal. The online information about the transmission condition can provide a solution for PHM systems. The system solved a major problem for applications where sensing points are far from the sites of acquisition and analysis. The system is being developed for use on 130mm automotive manual transmissions, but could be adapted for other transmission or machinery systems with rotating machinery. Further publications will follow to provide the results of surface fatigue tests. The advanced HMS system was able to provide an online prediction output for gearbox failure using two AR algorithms.

## References

- SCHEFFER, C. and GIRDHAR, P. (2004) *Machinery Vibration Analysis and Predictive Maintenance*, Newnes Press; ISBN 0750662751.
- SMITH, J.D. (1983) *Gears and their Vibration: A Basic Approach to Understanding Gear Noise*, New York: M. Dekker; London: Macmillan Press.
- ONSY, A., SHAW, B.A. & JISHAN, Z. (2011) Monitoring the Progression of Micro-Pitting In Spur Geared Transmission Systems Using Online Health Monitoring Techniques. *SAE International Journal of Aerospace*, 2014, 1301-1315.
- TAN, C.K., IRVING, P. & MBA, D. (2005) Diagnostics and Prognostics with Acoustic Emission, Vibration and Spectrometric Oil Analysis For Spur Gears: A Comparative Study. *Insight: Non-Destructive Testing and Condition Monitoring*, 47, 478-480.
- ONSY, A., BICKER, R., SHAW, B.A., ROWLAND, C.W. & KENT, T. (2008a) Monitoring the Progression of Micro-Pitting in Helical Gears: Towards an Intelligent Health Monitoring System. Paper presented at the AEWG-51 & International Symposium on AE, USA, Memphis, Tennessee.
- ONSY, A., BICKER, R., SHAW, B.A., ROWLAND, C.W. & KENT, T. (2008b) Monitoring Bending Fatigue Failure in Helical Gears Using Acoustic Emission, Vibration, and On-Line Oil Debris Analysis: A Comparative Study. *Proceedings of the Fifth International Conference on Condition Monitoring & Machinery Failure Prevention Technologies*, UK, Edinburgh.
- JARDINE, A.K.S., LIN, B., & BANJEVIC, D. (2006) A Review On Machinery Diagnostics And Prognostics Implementing Condition-Based Maintenance, *Mechanical Systems and Signal Processing*, 20, 1483-1510.
- SAMUEL, P.D. & PINES, D. J. (2005) A Review of Vibration-Based Techniques for Helicopter Transmission Diagnostics. *Journal of Sound and Vibration*, 282, 475-508.
- YANG, H., MATHEW, J. and MA, L. (2003) Vibration Feature Extraction Techniques For Fault Diagnosis of Rotating Machinery-A Literature Survey, Paper presented at Asia-Pacific Vibration Conference, Gold Coast, Australia, School of Mechanical Manufacturing and Medical Engineering, Australia.
- DALPIAZ, G., RIVOLA, A. and RUBINI, R. (2000) *Gear Fault Monitoring: Comparison of Vibration Analysis Techniques*, Department of Mechanical Design Engineering University of Bologna, Italy.
- AL-GHAMD, A.M. & MBA, D. (2006) A Comparative Experimental Study on the Use of Acoustic Emission and Vibration Analysis for Bearing Defect Identification and Estimation of Defect Size. *Mechanical Systems and Signal Processing*, 20, 1537-1571.
- ONSY, A., BICKER, R. & SHAW, B.A. (2010) A Novel Intelligent Health Monitoring System for Gear Fatigue Failure Prediction. *23<sup>rd</sup> International Congress on Condition Monitoring and Diagnostic Engineering Management; COMADEM 2010*, Japan, Nara, ISBN 978-4-88325-419-4.
- ONSY, A., BICKER, R. & SHAW, B.A. (2010) Intelligent Diagnostic Health Management of Power Transmission Systems: An Experimental Validation, *International Journal of COMADEM*, 13(2), 46-58.
- ONSY, A., BICKER, R., SHAW, B.A., ROWLAND, C.W. & KENT, T. (2009) Intelligent Health Monitoring Of Power Transmission Systems: An Experimental Validation. *Proceedings of the 2009 Conference of the Society for Machinery Failure Prevention Technology*, USA, Dayton, Ohio, 499-518.
- DEMPSEY, P.J. & AFJEH, A.A. (2002) *Integrating Oil Debris and Vibration Gear Damage Detection Technologies Using Fuzzy Logic*, NASA/TM—2002-211126, National Aeronautics and Space Administration Glenn Research Center, USA.
- T.H. Loutas, G. Sotiriades, I. Kalaitzoglou, V. Kostopoulos, (2009) Condition Monitoring of A Single Stage Gearbox with Artificially Induced Gear Cracks Utilizing On-line Vibration and Acoustic Emission Measurements, *Applied Acoustics*, 70, 1148–1159.
- SARAVANAN, N., CHOLAIRAJAN, S. & RAMACHANDRAN, K.I. (2009) Vibration-based Fault Diagnosis of Spur Bevel Gear Box Using Fuzzy Technique, *Expert Systems with Applications*, 36, 3119–3135.
- CZECH, P., LAZAR, B., MADEJ, H. & WOJNAR, G. (2010) Classification Of Tooth Gear Wheel Faults of Gearbox Working In the Circulating Power Test Rig By Multilayer Perceptron and Continuous Wavelet Transform, *ACTA Technica Corviniensis – Bulletin of Engineering* ISSN: 2067-3809.
- FENTON, W.G., MCGINTY, M.C. & MAGUIRE, L.P. (2001) Fault Diagnosis Of Electronic Systems Using Intelligent Techniques: A Review. *IEEE Transactions on Systems, Man and Cybernetics, Part C: Applications and Reviews*, 31, 269-281.
- JAIN, L. C. & SILVA, C. W. (1999) *Intelligent Adaptive Control, Industrial Applications*.
- HUSSEIN, W., ONSY, A., & EL SHERIF, I. (2014) Health Monitoring of Electro-Pneumatic Controlled Systems using Multivariate Latent Methods: An Experimental Validation, *SAE International Journal of Materials and Manufacturing*, Vol 7, Issue 1.
- ONSY, A., BICKER, R. & SHAW, B.A. (2013) Predictive Health Monitoring of Gear Surface Fatigue Failure Using Model-based Parametric Method Algorithms; An Experimental Validation. *SAE International Journal of Aerospace*, Vol 6, Issue 1.

23. ONSY, A., BICKER, R., SHAW, B. A. & FOUAD, M. (2012) Application of Image Registration Techniques in Monitoring the Progression of Surface Fatigue Failures in Geared Transmission Systems. Paper presented at *The AeroConf 2012 IEEE Aerospace Conference*, USA, Big Sky.
24. BRAUN, S. (1986) *Mechanical Signature Analysis: Theory and Applications*. London: Academic Press Inc.

ISSN 1363 – 7681

# International Journal of Condition Monitoring and Diagnostic Engineering Management

*COMDEM*

VOL.17 NO.2  
April 2014



# INTERNATIONAL JOURNAL OF COMADEM

Volume 17    Number 2    2014    ISSN 1363 – 7681

## CONTENTS

Invitation to participate in COMADEM 2014 in Brisbane	2
Integrated Network Topology Control and Key Management for Wireless Sensor Networks <i>D.Satish kumar , N.Nagarajan; India</i>	3
Digital Image Processing Technique for Microstructure Analysis of Spheroidal Graphite Iron <i>P.B. Shetty,, A. Shetty, A. K Murthy, H.Sarojadevi, P.G Mukunda; India</i>	11
Numerical Simulation and Experimental study on Plate Valve Transient Motion and Fatigue Fracture Principles <i>J. Zhang, Z. Jiang, Y. Wang, F. Xu; PRC</i>	17
Condition monitoring of combined fault scenarios in rotating machinery by integrating vibration based analysis and design of experiments <i>J. Majumdar and V.N.A. Naikan; India</i>	29
Development of an Advanced Diagnostic System for Automotive Mechanical Transmissions <i>H. Mohamed, A. Onsy, W. M. Husseinand and I. A. El Sherif; Egypt</i>	39

### **This Journal is indexed in**

**Elsevier Bibliography Index (SCOPUS INDEX H), INSPEC, Acoustics Abstracts, Engineering  
Index Monthly, International Aerospace Abstracts, etc.**

### **Published by**

COMADEM International, 307 Tiverton Road, Selly Oak, Birmingham B29 6DA, UK  
Tel/Fax: +44(0)121 472 2338    E-mail: rajbknrao@btinternet.com    Website: www.comadem.com