SCORING MODELS FOR AUTOMOTIVE MULTISTAGE MECHANICAL TRANSMISSIONS USING PRINCIPAL COMPONENT ANALYSIS

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ABSTRACT

Sophisticated, accurate fault detection and diagnosis of monitoring processes can minimize downtime, increase safety of automotive transmission and gear systems, and reduce costs. To tackle this problem, transmission systems data was studied and analyzed to automatically characterize normal system behavior and anomaly detection and fault diagnosis methods based on multivariate latent techniques. Predictive health monitoring (PHM) systems are currently gaining in popularity due to their effectiveness in providing robust information about the system condition and reducing maintenance costs. However, PHM systems require reliable monitoring techniques, such as vibration, acoustic emission, and oil debris analysis. These techniques have shown the need to apply intelligent algorithms in order to benefit from the advantage of each technique in classifying faults and predicting the onset of failure. This paper presents a soft sensor technique namely Principal Component Analysis (PCA) for monitoring different gear faults using vibration analysis. Experiments were conducted on a multi-stage gearbox under five conditions, normal, external excitation at two positions, high temperature and high temperature with external excitation. The model is verified through additional experimental observations.

KEYWORDS

Mechanical transmission, condition based maintenance, vibration analysis, health monitoring system, Principal Component Analysis.

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INTRODUCTION

One of the main concerns of any automotive equipment is to ensure the health and safety of transmission gear system. The worst case in this circumstance is probably the loss of a mission but the more common interruption of gear functionality can result in compromised task objectives. Condition monitoring soft sensors hold information related to state-of-health (SOH) of its subsystems. Each parameter has information which represents a time-variant property (i.e. a status or a measurement) to be checked. Moreover, the tremendous increase in data volume and its complexity directs the need for more efficient and scalable data processing system. As a consequence, there is a continuous improvement of transmission gear monitoring applications in order to quickly respond to changes in automotive missions.

Also, in some applications there is more demanding aspect such as saving man's life other than reliability [1]. Smith [2], has defined the causes of transmission vibration and its transmission path, including factors such as manufacturing error, design error and gear tooth deflection, which combine to introduce a transmission error (TE), which is the primary source of the vibration.

Over the past decade, vibration analysis proved to be a trustworthy diagnostic technique that can provide reliable information. However, in the last 10 years researchers devoted a much effort to support Condition Based Maintenance CBM actions using vibration information [3-13].

The work focused on the development of reliable features using a suitable signal processing techniques can be grouped in two groups; time domain vibration features including: statistical parameters, time synchronous averaging based methods, filter based methods, stochastic methods and other model based methods. The second group is the frequency domain and time frequency domain features including: first order; (FFT), correlation of spectrum, signal averaging, short time Fourier transform (STFT), continuous wavelet transform (CWT), discrete wavelet transform (DWT), discrete wavelet packet analysis (DWPA), time-averaged wavelet spectrum (TAWS) and time-frequency scale domain (TFS). Second order; power spectrum, Power cepstrum (logarithm of Power spectrum), cyclostationarity, spectrogram Wigner distribution and scalogram. Third order; Bicoherence spectrum, bilinearity and Wigner bi Spectra. Fourth order; Wigner tri Spectra [29].

The authors of this paper developed soft-sensor fusion algorithms to fuse vibration analysis information with other sensory data, such as acoustic emission and oil debris analysis to minimize false alarms that may occur in failure prediction [14-17]. Also, other researchers devoted efforts to build intelligent algorithms based on vibration features including Expert systems, ANN's, Genetic algorithm, and fuzzy logic [18 - 28]. 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" [33]. 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 [33].

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 behavior. Fenton et al [36] 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. The two standard neural network architectures used in transmission diagnostics are the feed-forward back propagation network, and the Kohonen feature map which is also known as the self-organizing map (SOM) [37]. Fuzzy logic was developed by Zadeh in the 1960s to characterize types of knowledge that cannot be represented by classical Boolean algebra to cover approximate knowledge in describing the behavior of systems which are difficult to describe mathematically [33].

Currently, the authors of this paper is devoting their efforts in developing smart CBM systems that can use one analysis technique only such as vibration or acoustic emission analysis along with intelligent algorithms to predict the onset of failures; this is to reduce costs of different sensory requirements [30-32]. This paper builds on the author's previous work to develop an online wireless vibration analysis tool for testing automotive mechanical transmissions. The online operation of this system can lead to the wide spread of using such systems with other rotating machinery.

Parametric methods based on mathematical modelling is to fit measured time series waveform data to a parametric time series model, and then extract features based on this model [34]. Two models are currently in use: the auto regressive (AR) and auto-regressive moving average (ARMA) models. The advantage of mathematical modeling 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 modeled to represent the system [14]. 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.

In Addition, researchers have devoted considerable effort to the application of various different soft computing methods to develop heath monitoring systems HMSs for gear box transmission systems summarized in data mining techniques. These methods can provide important tools for the field of intelligent monitoring which can learn, adapt, and make decisions concerning the system they are in charge of TakehisaYairi et al. [45] evaluating a variety of dimensionality reduction algorithms and compare between them, without using the cross-validation.

Artificial neural networks ANNs in combination with other soft computing methods have been the most predominant to date [42, 43]. However, ANN techniques are characterized as black box approaches which model the relationship between different sensory data and a desired response without giving any information about the process. In addition, issues associated with collinearity and dimensionality needs to be

specifically addressed in these techniques. Solving many of these limitations can be addressed through the use of multivariate statistical analysis, which is a data-driven modelling approach [43]. Iverson et al. [38, 39, 44] discuss several data driven software tools that successfully applied to space mission operations using data mining tool which searches for unusual data points, or outliers, in multivariate data sets in the spacecraft system data that may indicate malfunctioning system components. John MacGregor et al. [45] established the advantages applying of multivariate latent variable monitoring and fault diagnosis methods contrasted with other techniques as Independent Component Analysis (ICA), Artificial Neural Networks (ANN), and Support Vector Machines (SVM).

The simplicity of multivariate statistical analysis approach is that there is no need for a fundamental model of the system and only data from normal operation needs to be used, which is generally available in some form for most machines. Among the approaches used in multivariate analysis are: two projection methods called principal component analysis PCA, projection to latent structure PLS [48, 49, 50]. Many applications of these two techniques have been successfully applied in other fields of process monitoring.

This paper outlines the use of the multivariate latent approach, to develop a framework for monitor heath status of automotive mechanical transmissions gear system under study. Models based on PCA and PLSDA are developed so that automotive mechanical transmissions gear can be monitored using the latent space of these models.

System Configuration

An automotive mechanical transmissions gear test rig is currently being developed for this ongoing research. The rig comprises 130mm centre distance gearbox. Table1 provides the basic geometry specification for the gears. The system is driven by a 7.5Kw variable speed electric motor controlled by an inverter to provide a speed variation of 1750 rpm. The load is applied via a mechanical breaking mechanism.

Table 1. Gears basic geometry.

Specifications	Gear number									
	1		2		3		4		5	
	P	W	P	W	P	W	P	W	P	W
Module (mm)	9.5	9.5	9.5	9.5	8	8	8	8	8	8
Gear Type (H-S)	S	S	H	H	H	H	H	H	H	H
Number of teeth	21	40	19	35	30	33	38	25	43	20
Face Width (mm)	25	25	25	25	25	25	25	25	30	30
Gear Ratio	4.095		3.96		2.365		1.414		1	

The rig can generate a load torque on the test gears in the range of 0 - 200Nm. The torque is measured using calibrated strain gauges installed on the shaft and the measured torque values are transmitted to the control program by telemetry in order to provide torque control of the loading mechanism on the mechanical transmissions. The test rig is shown in Figure 1. 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 the operation can be identified. The advantage of developing the system arises from its ability to enhance online analysis methods for vibration technique to provide robust information about the system's condition. Two temperatures were measured: gearbox oil temperature and bearing temperature using RTD temperature sensors (10mv/C). The input shaft speed and motor current were also monitored as a precaution. The test rig operating conditions were monitored and it is flexibly changed according to the required test conditions using LabVIEW's virtual instrument scalable architecture features.

As shown in figure 1, the process is simply a multistage automotive gearbox. The gearbox is derived   by a 3-phase electrical motor. The system is loaded through a mechanical braking system and controlled with an AC motor inverter. The system is equipped with five sensors, two accelerometers at two different positions (input and output of the gear system), temperature sensor (immersed in the gearbox oiling system), wireless strain gauge for torque measurements (on the output shaft) and a proximity sensor for speed measurement (at the gearbox input shaft).

1. Speed sensor 2. Accelerometer 1 3. Temperature sensor 4. Accelerometer 2 5. Torque sensor

Fig. 1. Multistage gearbox System Scheme.

Fig. 2. 1. Inverter, 2. Electric motor, 3. Fixable coupling, 4. 130 mm center distance Gearbox, 5. Mechanical coupling, 6. Loading Mechanism.

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 DJB Piezotronic constant current source accelerometers (model no. Acc103 -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 sensors 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 30 m for indoor measurements and 100 m for outdoor operation as long as the line of sight of the wireless signal is provided. The system can also provide Ethernet cabling measurements up to a distance of 100 m. The test rig sensor-actuation system layout is shown in Figure 3.

Fig. 3. The test rig sensors - actuation system layout.

MULTIVARIATE LATENT APPROCH (PCA)

Principal component analysis decomposes the variance and covariance structure of a data matrix by defining linear combinations of the columns in the original matrix. Moreover, PCA extracts information from data sets by computing a smaller data set and other summary information that adequately captures most of the underlying features of the larger data set. The point that needs to be stressed is that the data can be reduced to a size which is more manageable but contains the features that are often of interest. PCA extracts a score matrix, T, and a loading matrix, P, from X. These matrices have the following dimensions [10, 13]:

$$X: N \times K \quad T: N \times A \quad P: K \times A \tag{1}$$

The first column of T and P are called by their shorter forms, t_1 and p_1 respectively. The lower case letters indicate that these are vectors, upper case letters indicate matrices. Extracting only one principal component (that is, a single score vector and loading vector) gives:

$$X = t_1 p_1^T + E_1 \tag{2}$$

Extracting a second principal component:

$$X = t_1 p_1^T + t_2 p_2^T + E_2 \tag{3}$$

Principal components are extracted in same manner and then group these score and loading vectors to form matrices T and P:

$$T = [t_1 \ t_2 \ . \ . \ . \ t_A] \text{ and } P = [p_1 \ p_2 \ . \ . \ . \ p_A] \tag{4}$$

The eigenvectors of the real symmetric matrix $X^T X$ give us exactly the loading matrix P. This is the loading matrix obtained by extracting all principal components. P is used to compute T:

$$TP^T = X \quad TP^T P = XP \quad T = XP \tag{5}$$

A more in-depth discussion, which also highlights some geometric concepts of PCA, can be found in [10]. The algorithm used to calculate the PCA is the NIPALS (Nonlinear Iterative Partial Least Squares) algorithm [10, 13].

RESULTS AND DISCUSSION

This section discusses the results of the experimental study, showing the application of the PCA algorithm to real stored sensory data, for normal and anomalous operation periods.

Measurements were driven through five conditions as shown in figure 4. It shows Kurtosis and Crest factors of the input gearbox shaft through the different conditions.

Fig. 4. Kurtosis, Crest factors and Temperature at the input gearbox shaft for 701 samples experiments.

First, the system was run under normal condition (observations 1- 204), then external excitations were applied at two positions (input\ output shaft: 205- 320; 321- 360). The system was then subjected to a high temperature (361-633) and finally, the system was run at high temperature with an external excitation at first position (input shaft: 634-701).

One way of evaluating and clustering database information, such as gearbox data, is the multivariate projection methods such as PCA. The projection aspect has an advantage when dealing with large amounts of collinear variables, noise, missing data and of course provides the reduction of dimensionality. Control charts based on these methods have been outlined by Kresta et al. [69]. Principal component analysis PCA finds latent directions that maximize the variance of the process. First, we must construct a complete system to collect useful information and then fuse them to detect different states of the system. To build such a system, there is a need for a system which can:

• Sense signals describing the multistage automotive gearbox system (Torque, speed, vibration…)
• Interpret incoming sensed information & Facilitate decision making (normal, high temp. and excited system)
• Detect process shifts (General wear, new events)
• Control Charts to monitor important aspects.

A total of 27 features were used to generate the input matrix "X". All these features were obtained from time domain records (length 38000 cycles) of the torque, two positions vibration, temperature and speed. From each time domain record mean, min-max, Kurtosis, crest factor, RMS, peak, exponential, variance, sum and ARMA coefficients values were calculated. Adding up the mentioned features, the final X-matrix is calculated with a total of 27 features. Model configuration for PCA is illustrated in the following sections. All the models were built using SIMCA-P code developed by Umetrics [11].

The multivariate PCA model is a linear model given in matrix form by: $X = TP^T + E_A$ [12, 21]. However, there exist non-linear PCA versions even by augmenting the original matrix with the non-linear factors or by building a non-linear relation between score factors [12]. To build the model using process variables, let X include variables containing the information in the sensory data. Figure 5 illustrates how the score plot is built for a simple case 3-variables and 2-scores. After determining the direction of maximum variation by iterative steps and get the second orthogonal direction by the same way after subtracting the first component, we rotate the new plane determined by the new score variables t_1 and t_2 and then monitor the movement of the process variables in the reduced dimensional space during printing.

Fig. 5: illustrates how the score plot is built for a simple case 3-variables and 2-scores.

The PCA model is based on building classes or clusters using existing information inside the data (unsupervised learning). The model is established using a set of experimental runs called the training set that represents the normal operation of the gearbox system. Finally, regression is made on the matrix X based on NIPALS algorithm. To explore the collected data a first model using PCA was built using all the dataset by cross-validation, now obtaining a two component model, with:R2X(cum): 0.73, Q2(cum) : 0.65. Figure 6 illustrates a scatter plot of the two score vectors (t1 and t2) of the PCA model using a set of 701 observations. These observations represent five states of the multistage gearbox system: *Normal, external excitations at two positions, high temperature and high temperature with an external excitation*. The score plot provides a clear vision of the dispersion of the data, with the normal process data being discriminated against the abnormal data along the first two components. This clustering is indicated by triangle points and manually highlighted with dotted circles in the t1 vs. t2 score plot in figure 6. It can be seen from the figure that the PCA model succeeds in classifying the five states of the system.

More investigation carried out using control charts and contribution plots as shown in figure 7-11 to quickly assess which factors affect these different process shifts. Figure 7 shows the contribution plots for normal state. One can notice that both vibration excitations represented by Kurtosis, Crest factor, RMS, mean, peak and min-max values are low. Also, number of cycles and temperature are low at the beginning of the run.

Fig. 6. illustrates a scatter plot of the two score vectors (t1 and t2) using a set of 701observations.

Fig. 7. Control chart for the contribution plots for normal state.

Figure 8 shows the contribution plots for high temperature state. One can notice that both temperature and number of cycles are high. Also, excitations represented by Kurtosis, Crest factor, RMS, mean, peak and min-max values are still low.

Figure 9 shows the contribution plots for external excitation at the input shaft state. One can notice that excitations represented by Kurtosis, Crest factor, RMS, mean, peak and min-max values at input shaft are higher than at output shaft measurements indicating the external excitation at the first position.

Fig. 8. Control chart for the contribution plots for high temperature.

Fig. 9. Control chart for the contribution plots for external excitation at gearbox input position.

Figure 10 shows the contribution plots for external excitation at the output shaft state. One can notice that excitations represented by Kurtosis, Crest factor, RMS, mean, peak and min-max values at output shaft are higher than at input shaft measurements indicating the external excitation at the second position.

Figure 11 shows the contribution plots for external excitation at the input shaft state with high temperature state. One can notice that both excitations at position one and temperature are high indicating the vibration at the first position and high temperature.

Test 1_All Monitoring Prameters Saving.M1 (PCA-X)
Score Contrib(Obs 334 - Average), Weight=p[1]p[2]

Fig. 10. Control chart for the contribution plots for external excitation at gearbox output position

Test 1_All Monitoring Prameters Saving.M1 (PCA-X)
Score Contrib(Obs 664 - Average), Weight=p[1]p[2]

Fig. 11. Control chart for the contribution plots for external excitation at gearbox input position with high temperature

More analysis is made by examining the loading plot, which shows the relation between the different variables. Figure 12 shows the loading plot clarifying the relation between the 27 variables. In addition, the score and loading plots are superimposed; this means that variables lying in each quarter of the loading plot are contributing to the changes between the observations in the score plot. So, by investigating the loading plot (figure 12), one can detect directly which variables are responsible or more affecting a specified group of data in the score plot.

From these two figures, one can notice, how temperature and number of cycles parameters in the middle lower side of the loading plot contribute to the right lower swarm (high temp. state) of data in the score plot. In addition, vibration excitations

Fig. 12. PCA-X loading plot

represented by Kurtosis, Crest factor, RMS, mean, peak and min-max values for both positions input and output variables are contributing to the external excitation states as lying in the right side. Moreover, one can notice the gradual appearance of the faults, which takes a specific direction in the latent space. This illustrates the power of the proposed method for the early detection of the upcoming events.

A typical form in monitoring processes is to use a priori knowledge about the process by building the model based on normal data. Normal data are data gathered from a specific process under normal behavior including common cause variation. Then, the next step is to examine the model with different conditions (a validation data set). The final step is to detect new events or shifts from the original model using the contribution plots.

An attempt has been made to improve model capability by removing the variables of least important to the model as seen from the loading plot like the torque, rpm, peak, RMS, mean, variance etc.., now obtaining a two component model based on Kurtosis, two Crest factor, temperature and number of cycles using 181 normal observations only as training set. The model parameters are: R2X(cum): 0.85, Q2(cum) : 0.5. Figure 13- 14 shows the score and loading plots of the new model after removing least important factors. It can be noticed the good dispersion of the data in both directions t_1 and t_2.

In this application, out of the 701 observations (181 normal, 520 faulty states), a training set of 181 observations (normal) were chosen to develop the PCA regression model. The developed PCA model was then tested on a test set including some selected observations (290-310) external excitation at position one (input shaft).

It can be seen from figure 15 that the PCA model succeeds in classifying the new observations normal, and vibration at position one.

Test 1_All Monitoring Prameters Saving.M8 (PCA-X)
t[Comp. 1]/t[Comp. 2]

R2X[1] = 0.655073   R2X[2] = 0.193984   Ellipse: Hotelling T2 (0.95)

SIMCA-P+ 12.0.1 - 2013-06-07 01:23:23 (UTC+2)

Fig. 13. Score plot of the normal 181 observations.

Test 1_All Monitoring Prameters Saving.M8 (PCA-X)
p[Comp. 1]/p[Comp. 2]
Colored according to model terms

R2X[1] = 0.655073 R2X[2] = 0.193984   SIMCA-P+ 12.0.1 - 2013-06-07 01:23:50 (UTC+2)

Fig. 14. Loading plot of the normal state.

Test 1_All Monitoring Prameters Saving.M8 (PCA-X), PS-Test 1_All Monitoring Prameters Saving
tPS[Comp. 1]/tPS[Comp. 2]

R2X[1] = 0.655073   R2X[2] = 0.193984   Ellipse: Hotelling T2 (0.95)

SIMCA-P+ 12.0.1 - 2013-06-07 01:56:47 (UTC+2)

Fig. 15. Score plot for prediction of new process events (high Vib. At position one).

Figure 16 shows the contribution plots for high vibration at position one. One can notice that the Kurtosis and crest factors of the first accelerometer data are responsible for this shift, alarming on the occurrence of external excitation at position one.

Test 1_All Monitoring Prameters Saving.M8 (PCA-X), PS-Test 1_All Monitoring Prameters Saving Score ContribPS(Obs {295, 296} - Average), Weight=p[1]p[2]

SIMCA-P+ 12.0.1 - 2013-06-07 01:57:11 (UTC+2)

Fig. 16. Control chart for the test set high Vib at position one.

CONCLUSION

The study has presented the application of a statistical soft sensor PCA to monitor the progression of gear faults in spur and helical gears. Measurements were collected using a wireless vibration measuring system on an automotive gearbox. Sensory system consists of two accelerometers at two different positions (input and output of the gear system), temperature sensor (immersed in the gearbox oiling system), wireless strain gauge for torque measurements (on the output shaft) and a proximity sensor for speed measurement (at the gearbox input shaft). The online information about the transmission condition can provide a solution for PHM systems. The model was tested under different conditions including: normal condition, external excitations at two positions (input/output shaft), high temperature and high temperature with external excitation and was able to successfully differentiate between them.

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