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Gear fault detection using artificial neural networks with discrete wavelet transform and principal component analysis

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ABSTRACT

The current work aims to develop a classification method devoted to gear defect diagnosis. In this paper, the proposed classification method is based on the Neural Networks, Discrete Wavelet Transform and Principal Component Analysis. A gearbox system with six degrees of freedom (DOF) is simulated in MATLAB and Simulink. Defects are introduced in the model by the meshing stiffness function which is computed by considering in series the bending, shear, axial compressive, fillet foundation and Hertzian stiffness. The signals dataset is collected by changing system or defect parameters. In addition, an experimental data is tested with the proposed method. Signal features are extracted using the Discrete Wavelet Transform with the Principal Component Analysis. This method allows us to classify the extracted features into two classes, healthy and faulty, with a good rate of correct classification. Both simulated and experimental data are tested with the proposed method.

Keywords: Monitoring; Fault; Gears; classification; Neural Networks.

INTRODUCTION

Gears are very widespread equipment in mechanic and in the majority of the industrial fields. They are used to transmit motion and power between two shafts with a constant speed ratio. Unfortunately, gears are subjected to defects during their operating time hence the necessity of the diagnosis and monitoring in order to increase reliability and reduce production losses caused by a failure of the machine components. The early diagnosis of the gear defects, based on vibration analysis, recently arouses more interest in the world of scientific research [1-6].The present work belongs to learning category as application in gear and gearbox defects detection based on Artificial Neural Network, incorporating Discrete Wavelet Transform and Principal component Analysis. Nowadays much attention has been paid to this field, and many studies are conducted to detect defects by artificial intelligence tools [7-10]. Samanta [7] presented a comparative study of two classifiers; artificial neural networks and support vector machine, with genetic algorithm based features selection from time-domain vibration signals. Wuxing et al [8] proposed an effective method for classifying machine faults that exhibit non-linear and noisy signals using the cumulants and the radial basis function network. Lei et al [9] classified the different levels of gear cracks automatically and reliably based on weighted K-nearest neighbour algorithm. Saravanan et al [10] used the fuzzy logic technique to identify defects of the spur bevel gearbox. An artificial neural networks (ANN) based fault detection system to increase reliability is developed in reference [6] where two prominent fault conditions in gears, worn-out and broken teeth are studied. ZhiQiang Chen et al. [11] proposed a deep learning technique based algorithm convolutional neural network (CNN) for the vibration measurements to diagnose the fault patterns of the gearbox.

In the above works, the data is collected by experimentation while in this paper it is by simulation. The main objective of this work is to propose an intelligent method based on gear tooth crack detection and to simulate a six DOF gearbox system. The study of the gears and gearbox system is based on the mesh stiffness function. The presence of defects causes more vibration and noise and a drop in the meshing stiffness [12, 13] . Many research studies were conducted to calculate the gear mesh stiffness and to model defects to evaluate their effects on the Time Varying Mesh Stiffness [14-17].Thus, several models of gear system were developed [18, 19] . The Time Varying Mesh stiffness computation is performed using the potential energy method, taking into account the effects of bending, compression, shear, elastic foundation and Hertz [20, 21]. By changing the gear tooth parameters, the signal data is collected. The proposed system based on Artificial Neural Networks, Discrete Wavelet Transform with Principal Component Analysis is also used with an experimental data. It is shown that both simulated and experimental signals can be used with this method.

METHODS AND MATERIALS

Wavelet Transform

The principle of Wavelet Transform is to decompose signal into wavelets with different scales and positions [22, 23]. These wavelets are obtained by expanding or contracting the mother wavelet and by translating it along the time axis. We have distinguished two types of wavelet transform: continuous and discrete.
The Continuous Wavelet Transform (CWT) of a signal x (t) is as follows [22]:

$$W(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{+\infty} x(t)\psi^*\left(\frac{t-b}{a}\right)d\mathbf{t} \tag{1}$$

where ψ (t) is the mother wavelet, ψ*(t) is the complex conjugate of ψ (t), a and b are the dilation and translation parameters respectively, a∈R+-[1], b∈R.

The Discrete Wavelet Transform (DWT), instead of CWT, is implanted using the Mallat algorithm using the multi-resolution analysis [24]. It is used to introduce the analyzed signal in two filters; low-pass (h) and high-pass (g). At this level, two vectors are obtained, and they are A_1 and D_1. Elements of vector A_1 are called approximation coefficients while the elements of vector D_1 are called detail coefficients. This procedure can be repeated with the elements of vector A_1 and successively with each new obtained vector A_K. During the process of this decomposition the signal x(t) and the vectors A_K undergo undersampling. The signal x (t) reconstruction is by introducing A_K and D_k into two filters $\bar{h}$ and $\bar{g}$ respectively, which are the conjugates of *h* and *g* respectively, preceded by an on sampling. The process of this decomposition and reconstruction is shown in Figure1.

Principal component Analysis

The Principal Component Analysis (PCA) is a linear transformation, which is essentially to project the data on their covariance eigenvectors basis. The correlated variables are replaced by new variables, uncorrelated with maximum variance, established by linear combinations of the original variables [25]. The PCA aims to reduce data in a minimum of components by projecting it in a multidimensional space to a subspace [26]. Indeed, the minimization of the information losses due to projection by maximizing the projected variance is essential. The matrix of eigenvectors used by the PCA is orthogonal and therefore reversible by simple transposition. This characteristic of the PCA allows the reconstruction of the signal.

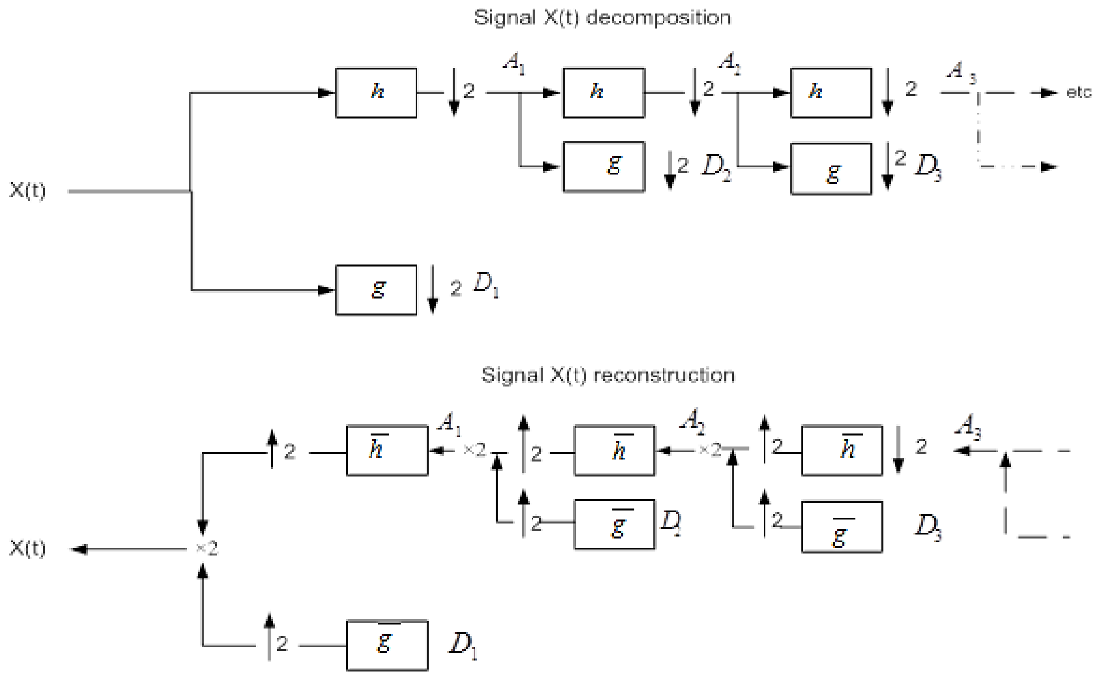
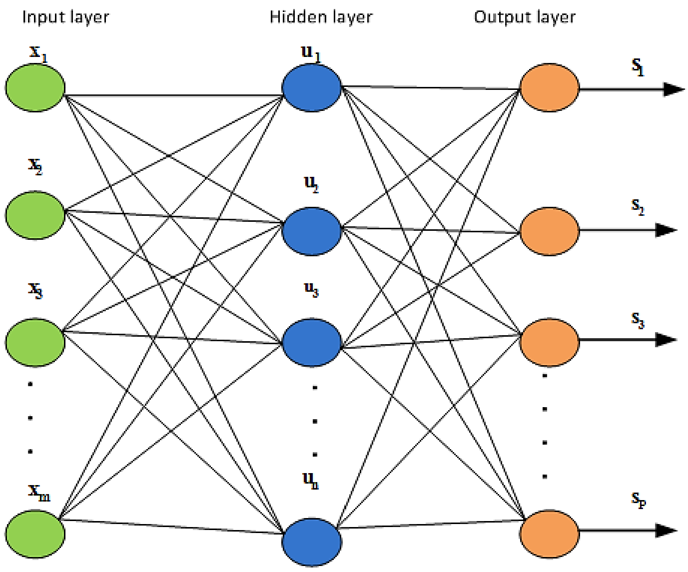


Figure 1. Process of a signal decomposition and reconstruction by the DWT.



where x_m is the input vector, u_n is the hidden layer neurone, s_p is the output vector

Figure 2. Structure of the multilayer perceptron.

Artificial Neural Networks

Artificial Neural Networks (ANNs) are intelligent systems inspired from biological neural networks and composed from simple elements operating in parallel way. The basic neural network is the perceptron that is used to find solution for linear problems[27]. In order to solve non-linear problems, an intermediate layer between the input and the output of the monolayer perceptron is added. This added layer is called 'hidden layer' and the resulting network is called 'multilayer' perceptron (MLP) [28].The MLP consists of an input layer of source nodes, one or more hidden layers of computation nodes called neurons and an output layer as illustrated in Figure 2. The number of nodes in the input and the output layers depends on the number of input and output variables respectively. The number of hidden layers and the number of nodes in each hidden layer affects the generalization capability of the network. The training of an MLP network involves finding values of the connection weights, which minimize an error function between the actual network output and the corresponding target values in the training set. One of the widely used error functions is mean square error (MSE) and the most commonly used training algorithm is back-propagation [29].

MATHEMATICAL MODELLING

Mechanical Model

The gear model used in this study is developed by Bartelmus [18] which is presented in Figure 3. It has six DOFs with time varying mesh stiffness. The equations of motion are as follows [18]:

$$\begin{cases} m_p \ddot{x}_p = -k_{xp} x_p - c_p \dot{x}_p \\ m_g \ddot{x}_g = -k_{xg} x_g - c_g \dot{x}_g \\ m_p \ddot{y}_p = -k_1 y_p - c_1 \dot{y}_p + K_t \left(R_{bp}\theta_p - R_{bg}\theta_g - y_p + y_g \right) + C\left(R_{bp}\dot{\theta}_p - R_{bg}\dot{\theta}_g - \dot{y}_p + \dot{y}_g \right) \\ m_g \ddot{y}_g = -k_2 y_g - c_2 \dot{y}_g + K_t \left(R_{bp}\theta_p - R_{bg}\theta_g - y_p + y_g \right) + C\left(R_{bp}\dot{\theta}_p - R_{bg}\dot{\theta}_g - \dot{y}_p + \dot{y}_g \right) \\ I_p \ddot{\theta}_p = k_p \left(\theta_m - \theta_p \right) + c_p \left(\dot{\theta}_m - \dot{\theta}_p \right) - R_{b1}(\mathrm{K}_t \left(R_{bp}\theta_p - R_{bg}\theta_g - y_p + y_g \right) + C\left(R_{bp}\dot{\theta}_p - R_{bg}\dot{\theta}_g - \dot{y}_p + \dot{y}_g \right)) \\ I_g \ddot{\theta}_g = k_g \left(\theta_g - \theta_l \right) + c_g \left(\dot{\theta}_g - \dot{\theta}_l \right) - R_{b1}(K_t \left(R_{bp}\theta_p - R_{bg}\theta_g - y_p + y_g \right) + C\left(R_{bp}\dot{\theta}_p - R_{bg}\dot{\theta}_g - \dot{y}_p + \dot{y}_g \right)) \\ I_m \ddot{\theta}_m = M_1 - k_p \left(\theta_m - \theta_p \right) - c_p \left(\dot{\theta}_m - \dot{\theta}_p \right) \\ I_l \ddot{\theta}_l = -M_2 + k_g \left(\theta_g - \theta_l \right) + c_g \left(\dot{\theta}_g - \dot{\theta}_l \right) \end{cases} \tag{2}$$

where:

R_p/R_g is the base circle radius of pinion/gear , m_p/m_g is the mass of pinion/gear, I_M/I_L is the mass moment of inertia of the motor/load, I_g/I_g is the masse moment of inertia of the pinion/gear, M_1 is the input motor torque, M_2 is the output torque from load, M_{pk}/ M_{gk} is the, stiffness moment of input/output coupling, M_{pc}/M_{gc} is the damping moment of input/output coupling, k_1/k_2 is the vertical radial stiffness of the input/output bearings, k_{xp}/k_{xg} is the horizontal stiffness of the input/output bearings, c_{xp}/c_{xg} is the horizontal damping coefficient of the input/output bearings, c_p/c_g is the damping coefficient of the input/output flexible coupling, k_p/k_g is the torsional stiffness of the input/output flexible coupling, x_p/x_g is the linear displacement of the pinion/gear in the x direction, y_p/y_g is the linear displacement of the pinion/gear in the y direction.

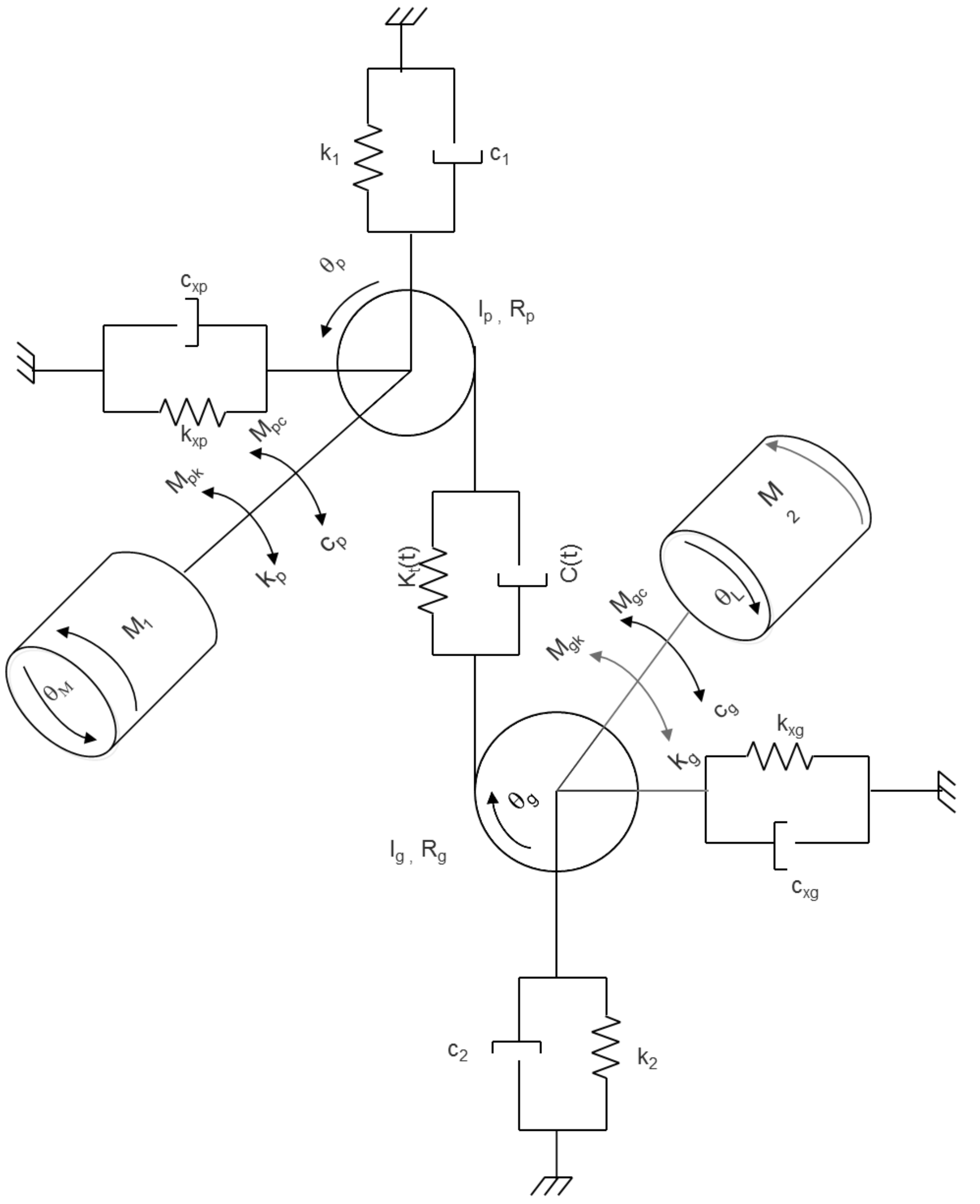


Figure 3. Six DOF gearbox system [18].

Time Varying Mesh Stiffness

The Time Varying Mesh Stiffness (TVMS), Kt, is computed based on the potential energy method [20]. The tooth is considered as a cantilevered beam at the base circle [12] as represented in Figure 4. The TVMS is obtained by calculating the stiffness of bending, compression, shear, elastic foundation and Hertz contact, respectively, k_b ,k_a , k_s, k_f and k_h [16]. For a contact force F, the bending, hertzian, shear, axial compressive and fillet foundation energy are, respectively defined by:

$$U_b = \frac{F^2}{2k_b}, U_h = \frac{F^2}{2k_h}, U_s = \frac{F^2}{2k_s}, U_a = \frac{F^2}{2k_a} \tag{3}$$

where $U_b = \int_0^L \frac{{M_y}^2}{2I_y}$, $U_s = \int_0^L \frac{1.2\,{F_r}^2}{2I_y}$, $U_a = \int_0^L \frac{{F_a}^2}{2EA_y}$

With $G = \frac{E}{2(1+\vartheta)}$, $I_y = (2x)^3 L/12$, A_y=2 x L

The fillet foundation deflection is calculated using ref [21] formula:

$$\delta_f = \frac{F\cos^2\alpha_m}{LE}\left\{L*\left(\frac{u_f}{s_f}\right)^2 + M*\left(\frac{u_f}{s_f}\right) + P*\left(1+Q*\tan^2\alpha_m\right)\right\} \tag{4}$$

The coefficients u_f, s_f, P and Q can be found in [21] and Figure 4 represents the geometrical parameters for the fillet – foundation deflection.

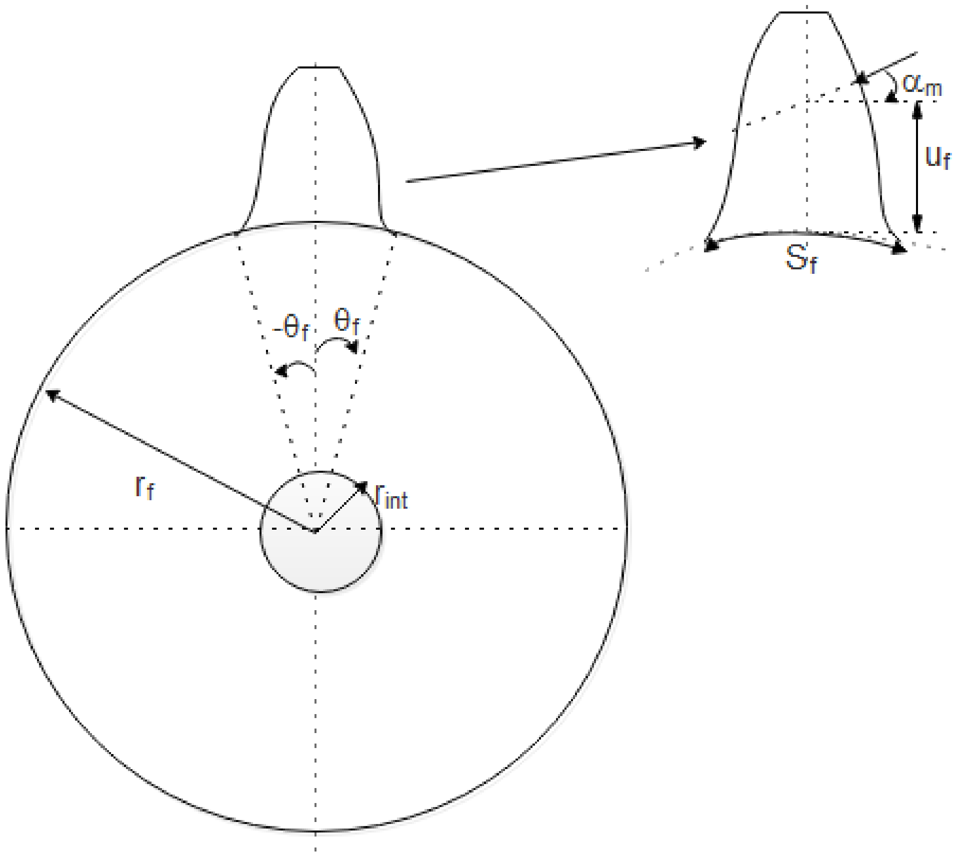


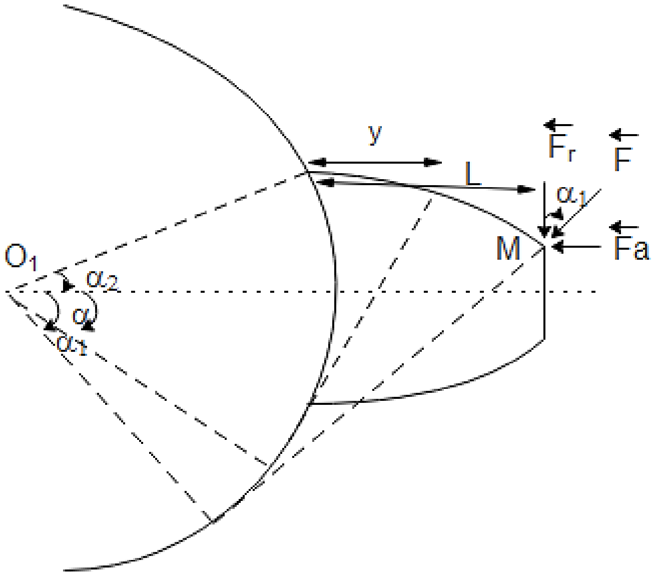
Figure 4. Geometrical parameters for the fillet-foundation deflection [14].

The total mesh stiffness is:

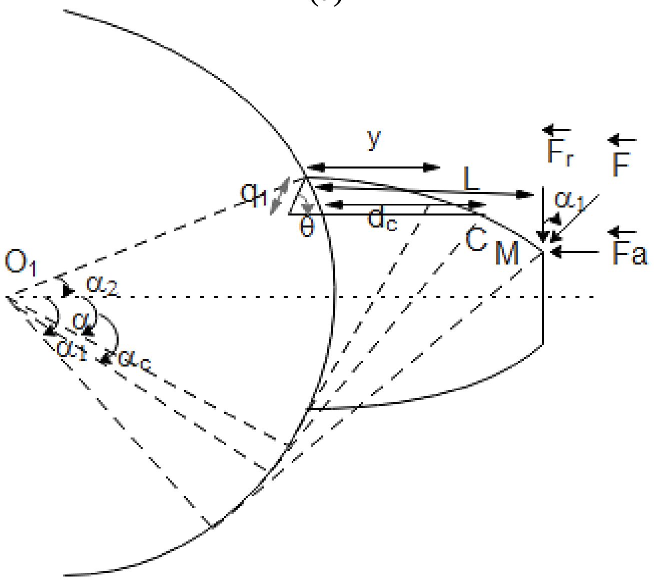
$$K_{t,i} = \sum_{i=1}^{2} \frac{1}{\frac{1}{k_h} + \frac{1}{k_{b1,i}} + \frac{1}{k_{s1,i}} + \frac{1}{k_{a1,i}} + \frac{1}{k_{f1,i}} + \frac{1}{k_{b2,i}} + \frac{1}{k_{s2,i}} + \frac{1}{k_{a2,i}} + \frac{1}{k_{f2,i}}} \tag{5}$$

where i is the number of teeth pair in contact.

In the presence of crack, the tooth is still considered as a cantilevered beam [12]. The crack is defined by its inclination angle ɵ and depth q_1 as represented in Figure 5.



(a)



(b)

where α_2 is the half tooth angle on the base circle, M is the contact point and d_c is the crack length.

Figure 5. Gear tooth modelling [12] (a) for healthy case; (b) for cracked case

RESULTS AND DISCUSSION

The detailed steps of the proposed method are as follows:

Features Extraction

The first step in the pattern recognition approach is the features extraction, which is the transformation of patterns into features considered as a compacted representation. There are several methods for feature extraction in time domain, frequency, time-frequency and statistical approaches. In this work, features are extracted using DWT since it can extract more information from signal.

Features Selection

Before giving the extracted features to the ANNs, we must select the features that represent more information. The method used here is the Principal Component Analysis.

Classification

In order to classify our data into classes; healthy and defected ones, the network used is the MLP. The sigmoid function is used as activation function in the hidden and in the output layers. The ANNs are created, trained and implemented using MATLAB neural network toolbox with back-propagation neural network (BPN). The ANNs are trained iteratively to minimize the performance function of mean square error (MSE) between the network outputs and the corresponding target values. At each iteration, the gradient of the performance function (MSE) is used to adjust the network weights and biases.

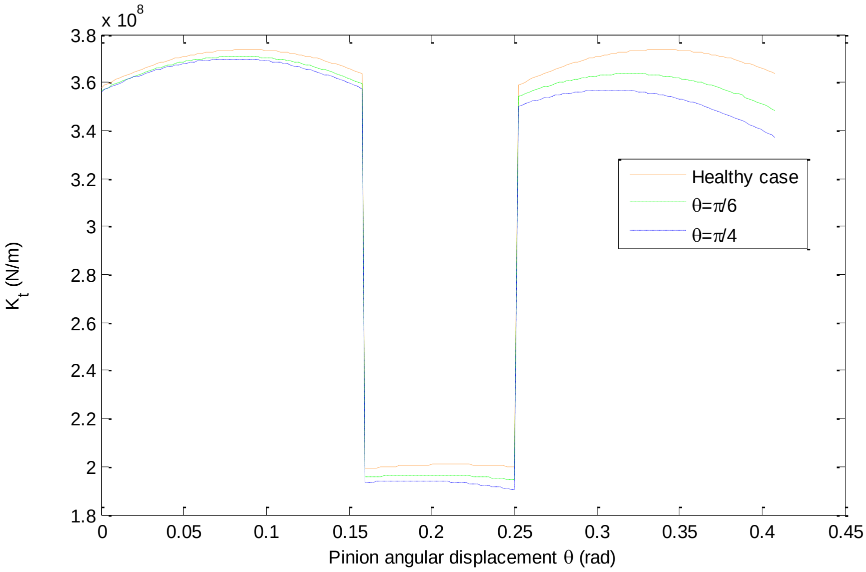
Simulated Data

In this work, the numerical simulation of the mechanical system represented in Figure 3 is made with the parameters of the pinion wheel set given in Table 1. The TVMS obtained is periodic and takes slots form. The presence of crack causes fall in the TVMS value as illustrated in Figure 6. The value of shock in the TVMS depends on the fault severity.

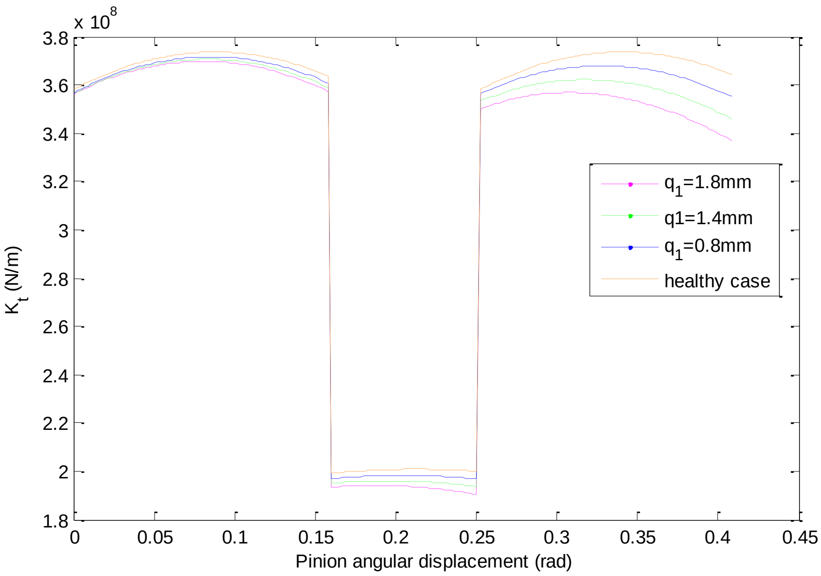
Table 1. Parameters of the pinion wheel set [14].

	pinion	Wheel
Teeth number	Z_1=25	$Z_2 = 30$
Module(mm)	2	2
Teeth width(mm)	20	20
Contact ratio	1.63	1.63
Rotational speed(Rpm)	2400	2000
Pressure angle	20°	20°
Young modulus E(N/mm²)	2.10^5	2.10^5
Poisson ratio	0.3	0.3

The obtained signal y_p, representing the displacement of the pinion in the y direction, is shown in Figure 7. Figure 7 (a) indicates the presence of periodic shocks, equal to the pinion rotation period (0.025s) which contains the cracked tooth, in the signal as shown in Figure 7(a). The used vibratory signal dataset is obtained by changing the gear and crack parameters. The signal dataset consists of 40 signals which are divided into two databases; one for training and the other for the test. The two datasets are composed of 20 signals in the presence and absence of the defect. These signals are obtained by changing the depth, the crack inclination angle, the position and the thickness of the crack as illustrated in Figure 6. Figure 8 shows an example of signals in training data.The mother wavelet and the level decomposition are selected to have a good recognition rate. The mother wavelet used is Daubechies 'db5'at level 4. Figure 9 gives an example of signal decomposition by DWT. By the PCA each vector size of features is reduced into 18 features which are classified using the ANNs. The best value obtained for the MSE is equal to 8.58.10-7 with 29 iterations. The rate of correct classification is 95%, which shows that the proposed method is a powerful classification tool and justifies the choice of the DWT and the PCA for signal features extraction and selection.



(a)



(b)

Figure 6. TVMS versus the pinion angular displacement (a) q_1=1.8mm; (b) $\theta=\pi/4$.

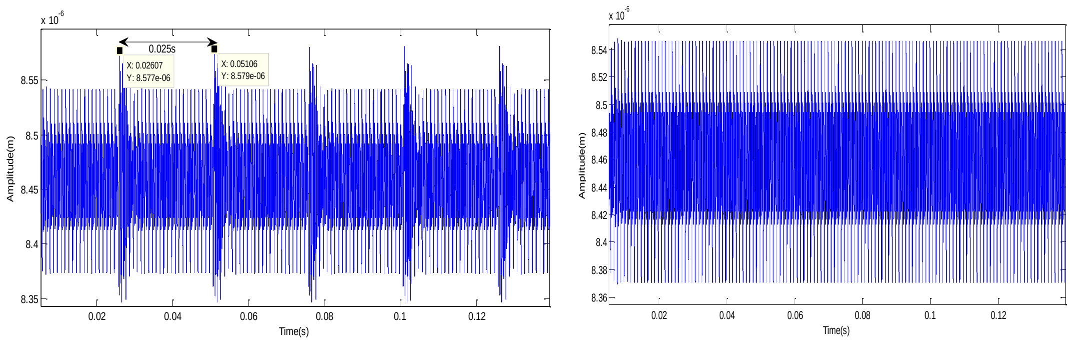


Figure 7. Pinion displacement signal (a) for the cracked case, (b) for the healthy case.

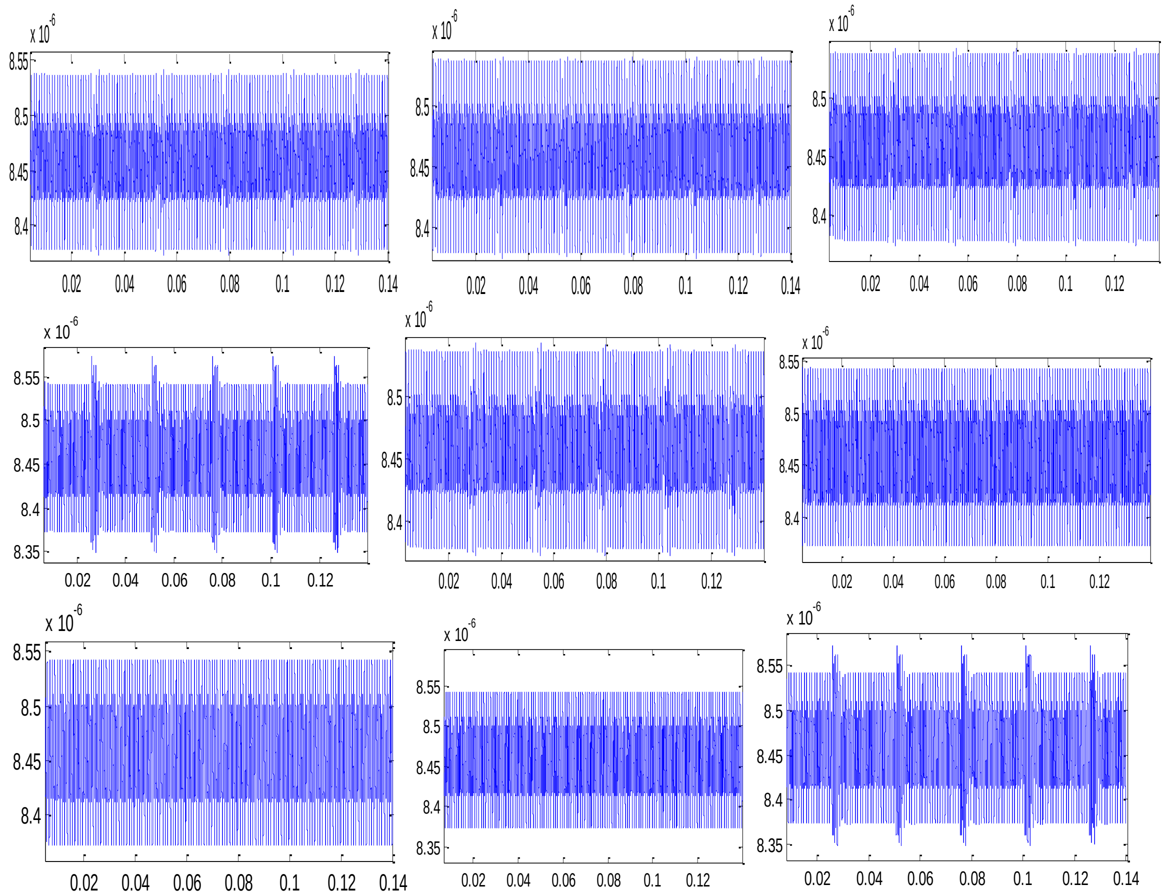


Figure 8. Signals from the training dataset.

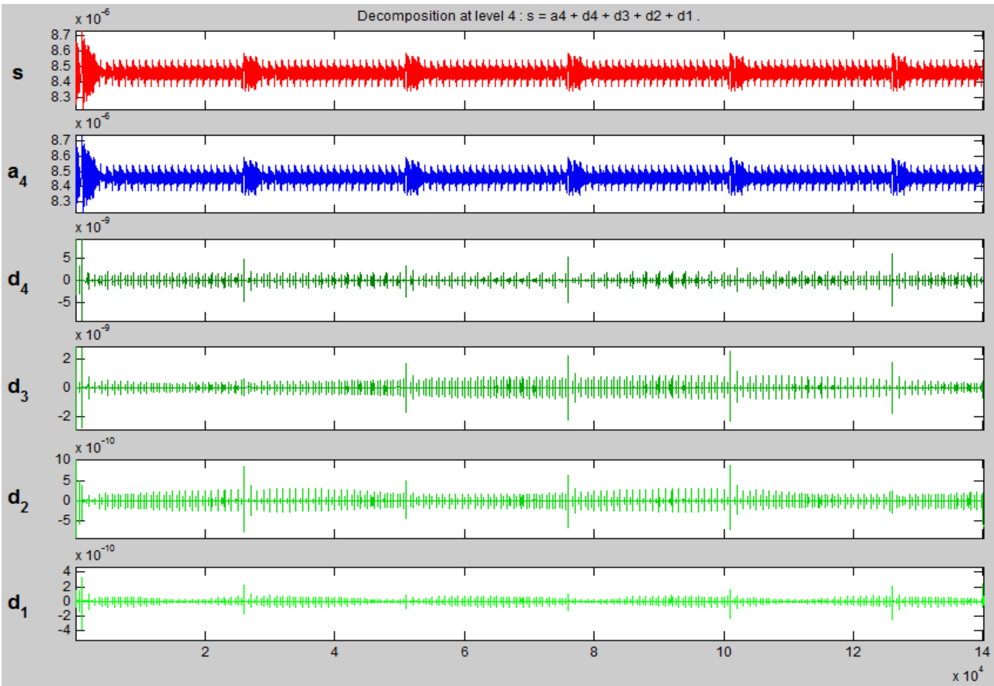


Figure 9. Example of DWT signal decomposition.

Experimental data

In reality, simulated and experimental signals are somewhat different as a simulated signal represents the ideal case. Indeed, the fact is, an experimental signal may contain noise as well as it may have other components dependent on the operating conditions of the machine. The objective of this part is to test the proposed method with an experimental data. The vibratory signal data used in this part comes from the tests carried out on the CETIM gearbox test bench, running 24h/24h, the based gears are with the ratio 20/21 [30, 31] .The dimensioning of the tempered hardened gear wheels and the operating conditions (speed, torques) are fixed to obtain a peeling over the entire tooth length. The test is during 12 days then every day after the acquirement of the vibratory signal, the bench is stopped in order to observe the status of the tooth wheels. The speed of the drive motor is 1000 rpm (16.67 Hz) therefore the rotational speed of the wheel is 952.38 rpm (15.87 Hz) and the meshing frequency is 333.33 Hz. The sampling frequency is 20 Khz and the size of each signal is 60000 in the duration of 3seconds.

Table 2. Signals data test by the artificial neural networks.

Signal day	Vector test	Obtained class	Desired class
2	9.897377862129140e-01 1.132151810515625e-04	1	1
3	9.897377862129140e-01 1.132151810515625e-04	1	1
4	1.632938603652878e-04 9.770642951535482e-01	2	1
5	9.897377862129140e-01 1.132151810515625e-04	1	1
6	9.897377862129140e-01 1.132151810515625e-04	1	1
7	9.897377862129140e-01 1.132151810515625e-04	1	1
8	9.897377862129140e-01 1.132151810515625e-04	1	1
9	1.632938603652878e-04 9.770642951535482e-01	2	1
10	1.632938603652878e-04 9.770642951535482e-01	2	2
11	1.632938603652878e-04 9.770642951535482e-01	2	2
12	1.632938603652878e-04 9.770642951535482e-01	2	2
13	1.632938603652878e-04 9.770642951535482e-01	2	2

where class 1 is for healthy case and class 2 is for the cracked case.

These early defect detection based on this signal data was the subject in many researches [32, 33]. Parey et al [32] showed that the defect can be detected on the 10th day in place of the 11th day, with kurtosis only, by using the Empirical Mode Decomposition and kurtosis values of each IMF are calculated. Elbadoui [33] found that the cepstral peak of the wheel, which develops the fault (A1), increases at the expense of the other. The sum of the first peak is always close to 0.5, which shows that the processed signals are not very noisy. The evolution of the indicator makes it clear that from the 8th day the pinion develops a fault. This result is consistent with the observation made on the expertise of the gearbox system, which is the occurrence of chipping on the top of the tooth 15/16 on the 8th day. In other works, it was possible to detect the occurrence of a very marked fault before the 10th day [31, 33, 34] . Merzoug et al [31] indicated that it is not possible to early detection of the occurrence of a fault with the times signal. They used the decomposition of the experimental signal approximations and evolution of kurtosis, which shows the early fault detection on the 4th day after the approximation 4.This result approves our choice of the DWT for features extraction in order to test the power of the proposed method in the field of the early fault detection in gears and gearbox with experimental signals. After decomposing signal into approximations and details by the DWT, the PCA of approximations is calculated. The MLP is trained by 5 signals and tested by 12 signals with the obtained value for the MSE is equal to 5.97.10-7 with 29 iterations. It is assumed that defects appear only on the 10th day as represented in Table 2.The rate of correct classification is 83.33%, signals of the 4th and 9th day are classified as defected. Indeed in the references [29,31,32] the presence of defect is before the 10^{th} day.

CONCLUSIONS

In this paper the ANNs incorporating DWT with PCA based gear fault detection are developed. The simulated signal data are collected by simulation of a gearbox system. The features extraction is made by the DWT with PCA. The proposed method provides a decision aid in the field of preventive maintenance and able to detect gear defects with a good rate of classification. Two types of signal are tested; simulated and experimental, which show that this classification is not restricted to simulated data. It still uses a big data with different types of defect which is the area of our features research work.

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