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Gear Fault Diagnosis and Classification Based on Fisher Discriminant Analysis

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Abstract

Gears are the most essential parts in rotating machinery. So gear fault modes diagnosis and levels classification are very important in engineering practice. This paper present a novel method in gear fault recognition and identification using Fisher discriminant analysis (FDA) due to FDA can reduct dimension when analyse signal. The real data collected from a gearbox test rig is used to validate the method this paper proposed. And the effectiveness of the methodology was demonstrated by the results obtained from the analysis. Three kinds of fault modes and levels were identified. And energy was selected as feature parameter. The fault modes (normal, breaktooth and crack) were diagnosed at first, then the fault levels of breaktooth and crack are classified. The accurate rate of the method is approximate 89%.

Keywords: *gear, fault diagnosis, dimension reduction, Fisher discriminant analysis*

1. Introduction

Gears are important components of rotating machinery. Typical faults of gears include pitting, chipping, and more seriously, crack [1]. Failures of gears usually cause significant loss. Therefore, it is badly need to reduct the numbers of gear breakdown and maintenance costs. To this end, many techniques have been used in early fault diagnosis and classification to monitor the condition of these systems. Su etc. [2] proposed an improved method of gear fault identification based on Hilbert-Huang transform (HHT) to overcome the problem of reconstructing a feature matrix of singular value decomposition. In the paper, HHT technique was utilized to acquire instantaneous frequency and amplitude matrices from faulted gear signals. The adaptive variable step-length natural gradient blind source separation (BSS) algorithm was used in [3] to analyse the vibration signal to implement fault diagnosis on helicopter gearbox. Lei and Zuo [4] proposed a new algorithm in classifying the different levels of gear cracks based on weighted K nearest neighbor. This enabled the fault characteristic frequency of gears can be detected effectively. In addition, some other techniques are all utilized in this aspect, such as Hidden Markov Model (HMM) [5, 6], support vector machine (SVM) [7, 8], wavelet packet transformation (WPT) [9] and artifical neural network (ANN) [10] and so on.

Sometimes the problem can not be solved by using only one technique as the equipments becoming more and more complicated. Hereby, the combination of two or three of methods may be utilized. A fault detection method that combines Hilbert transform and wavelet packet transform was proposed [11] to extract modulating signal and help to detect the early gear fault. Wu etc [12] developed an intelligent diagnosis for fault gear identification and classification based on vibration signal using discrete wavelet transform and adaptive neuro-fuzzy inference system (ANFIS) for solving the problem of abnormal transient signals.

As described above, the accurate rate of early fault diagnosis and classification is very important when implement condition monitoring on systems. It must be more accuracy that consider the complete signal than a part if adopt a appropriate method. However, some of these methods mentioned above take a section of vibrate signal into account (i.e. WPT and EMD) and some of them reject a lot information that these methods think useless,for instance, SVM. No matter select a part or reject some information, some useful data that could reveal real condition of a equipment may be left out [9, 13]. If separate the frequency spectrum into many sections to

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consider, it will be more accuracy the number of the sections larger. But this will produce another problem, the procedure of calculation will be hard to implemented. In order to solve the dillema, this paper proposed a gear fault diagnosis and classification method based on Fisher discriminant analysis (FDA) [14]. The objective is to present a novel method which can diagnose gear faults and classify fault levels exactly by taking the total signal into consideration at first than dimension reduction. The performance of this method has been validated by real data.

The remaining sections of this paper are organized as follows. In Section 2, the methodology of the method this paper proposed is introduced. Section 3 describes the experiment, the procedure of fault diagnosis and classification. Meanwhile, the results analysis is implemented in this section. Finally, the conclusions are drawn in section 4.

2. Methodology

The method this paper proposed is based on Fisher discriminant analysis (FDA). “Dimension disaster” is a challenge which often confront when solve problems of pattern recognition, some methods are applicative when in high dimension space but they do not work in below dimension space. However, many methods are more accurate in high dimension space than below. This moment dimension reduction can achieve very good results and it is the objective that utlize FDA in this paper.

If project the dots in dimensions space to a line, the space can be reduce to one dimension. But some samples that are simple to be separated in high dimension space will be mixed after reduce the dimension, as Figure 1 (a) shows. In this situation, maybe project the samples to a line which rotated around the origin will obtain a better result, as depicted in Figure 1(b). So select the line is very important, it is the result vector ***W**** FDA need.

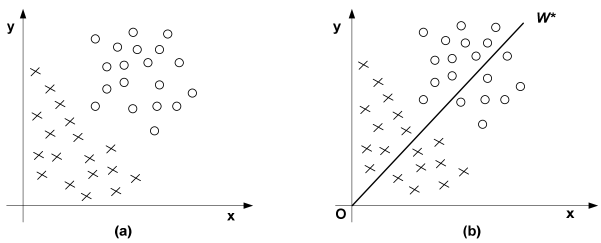

Figure 1. The Sketch Map of FDA Principle

How to calculate the result vector ***W**** and classify the samples, the specific procedures are as follows:

(1) Compute the mean value vector $\boldsymbol{m_i}$ of every sample:

$$m_i = \frac{1}{N} \sum_{X \in \omega_i} X \qquad i = 1,2 \tag{1}$$

Where N_i is the amount of the sample ω_i.

(2) Calculate the discrete level vector $\boldsymbol{S_i}$, $\boldsymbol{S_w}$ of every sample and among all samples, respectively.

$$S_i = \sum_{X \in \omega_i} (X - m_i)(X - m_i)^T \qquad i = 1,2 \tag{2}$$

$$S_w = S_1 + S_2 \tag{3}$$

(3) Compute the discrete level vector $\boldsymbol{S_b}$ which between two samples.

$$S_b = (m_1 - m_2)(m_1 - m_2)^T \tag{4}$$

(4) Calculate the vector ***W****.

The ideal result after projection is the distances among all samples in one dimension *Y* space are as far as possible. Namely, the mean value difference $(\tilde{m}_1 - \tilde{m}_2)$ of two samples is as large as possible. Meanwhile, a below discrete level of one sample is very well. So, the Fisher function can be defined as:

$$J_F(W) = \frac{W^T S_b W}{W^T S_w W} \tag{5}$$

To make the value of $J_F(\boldsymbol{W})$ maximum, ***W**** should be:

$$W^* = S_w^{-1}(m_1 - m_2) \tag{6}$$

(5) All the samples project to ***W****.

$$y = (W^*)^T X \tag{7}$$

(6) Compute the threshold value in projective space. Where the mean value of every sample in one dimension *Y* space and the discrete level vector $\tilde{s}_i^2$, $\tilde{s}_w$ are:

$$\tilde{m}_i = \frac{1}{N_i}\sum_{y\in\omega_i} y \qquad i = 1,2 \tag{8}$$

$$\tilde{s}_i^2 = \sum_{y\in\omega_i}\left(y - \tilde{m}_i\right)^2 \qquad i = 1,2 \tag{9}$$

$$\tilde{s}_w = \tilde{s}_1^2 + \tilde{s}_2^2 \tag{10}$$

The selection of threshold value y_0 has some different methods, one kind of the usually used is:

$$y_0 = \frac{\tilde{m}_1 + \tilde{m}_2}{2} + \frac{ln\left(P(\omega_1)/P(\omega_2)\right)}{N_1 + N_2 - 2} \tag{11}$$

Another is also this paper utilized:

$$y_0 = \frac{N_1\tilde{m}_1 + N_2\tilde{m}_2}{N_1 + N_2} \tag{12}$$

(7) To the test sample ***X***, the projective dot *y* to ***W**** can be computed as follows:

$$y = (W^*)^T X \tag{13}$$

(8) Classify on the basis of decision regulation (i.e. if $y>y_0$, than the test sample ***X*** belong to the class1. Otherwise, it belongs to class2).

$$\begin{cases} y > y_0 \Rightarrow X \in \omega_1 \\ y < y_0 \Rightarrow X \in \omega_2 \end{cases} \tag{14}$$

Two classes FDA should be implemented at first when identify a test sample, it will give out the nearest class which the test sample belong to. Then the nearest class and another new class could constitute a conference samples and conduct the two classes FDA, A new nearest class can be obtained, continue carry out the procedure above until all the classes are considered. At last, the class which the test sample belong to will be classified. This is the procedure this paper used.

3. Experiment Specifications and Results Analysis

3.1. Experiment Specifications

In engineering practice, gear breaktooth and crack are the most serious fault modes [1]. They are often the reasons that lead to breakdown of a machine. Figure 2(a) is a real photo of gear breaktooth in practice.Other kinds of fault modes are also common, such as the gear wear, gluing or fatigued. But due to gear breaktooth and crack are more serious than them, so in this approach, the two fault modes are mainly analyzed. The diagram of them can be seen in Figure 2(b).

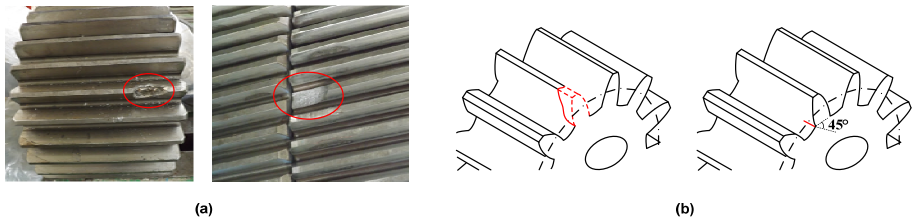

Figure 2. Fault Modes: (a) real photo of fault gears in engineering practice, (b) the diagram of the fault modes in this experiment: breaktooth and crack

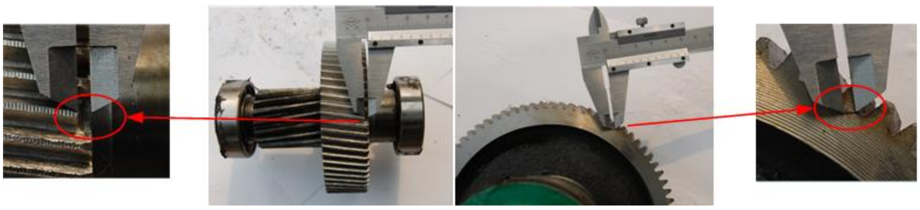

Figure 3. The Fault Gears uesd in this Study

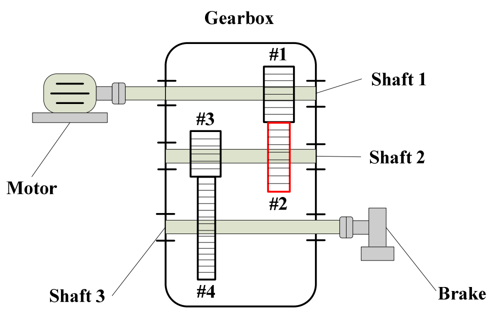

Figure 4. The Structure of Gearbox the Experiment used

The experiment data this study used is obtained from the RCM laboratory of Mechanical Engineering College. The Electro-Discharge Machining (EDM) method is used to introduce faults to the test gears. And two faults modes (breaktooth and crack) were designed with different levels, the diameters of breaktooth and crack are 2mm, 5mm, 10mm and 2mm, 5mm, 8mm, respectively. Figure 3 shows the fault gears uesd in this study. The sampling frequency of this experimental system is 20kHz and sampling time is 6s. Each fault mode has 60 samples, the 1-3 samples are selected as the reference sets and the 4-13, 24-33, 44-53 samples are choosen as the test samples. The load generated by brake is 10N•m and the input rotary speed of motor is 800rpm. The structure of the gearbox used in this experiment is shown as Figure 4. The #2 gear is test gear.

3.2. Results Analysis

The method this paper proposed choose three kinds of fault modes and levels to discuss. And select energy as feature parameter. First of all, normal, breaktooth and crack should be diagnosed. As Figure 5 shows, the red line is the threshold value y_0 (as same as the follows). For example, y_0 is -7.47*10^{16} and -3.90*10^{16} in (a) and (b). On the basis of the theory in Section 2, select breaktooth and normal as class1 and class2, respectively. So if the projective value y of one sample greater than y_0, the sample belong to class1, otherwise the sample belong to class2. Namely, after the first comparison, the black and pink samples belong to class1 (i.e. breaktooth) and the blue samples belong to class2 (i.e. normal). Than the neareat class and crack constitute the reference sets. Similarly, (b), (c) are breaktooth-crack and normal-crack. The conclusion could be given out. Blue belong to normal, black belong to breaktooth and pink belong to crack. All the 90 samples, there are 10 samples are mistake. So the accurate rate of this method is approximate 89%. It is a number taht can be accepted.

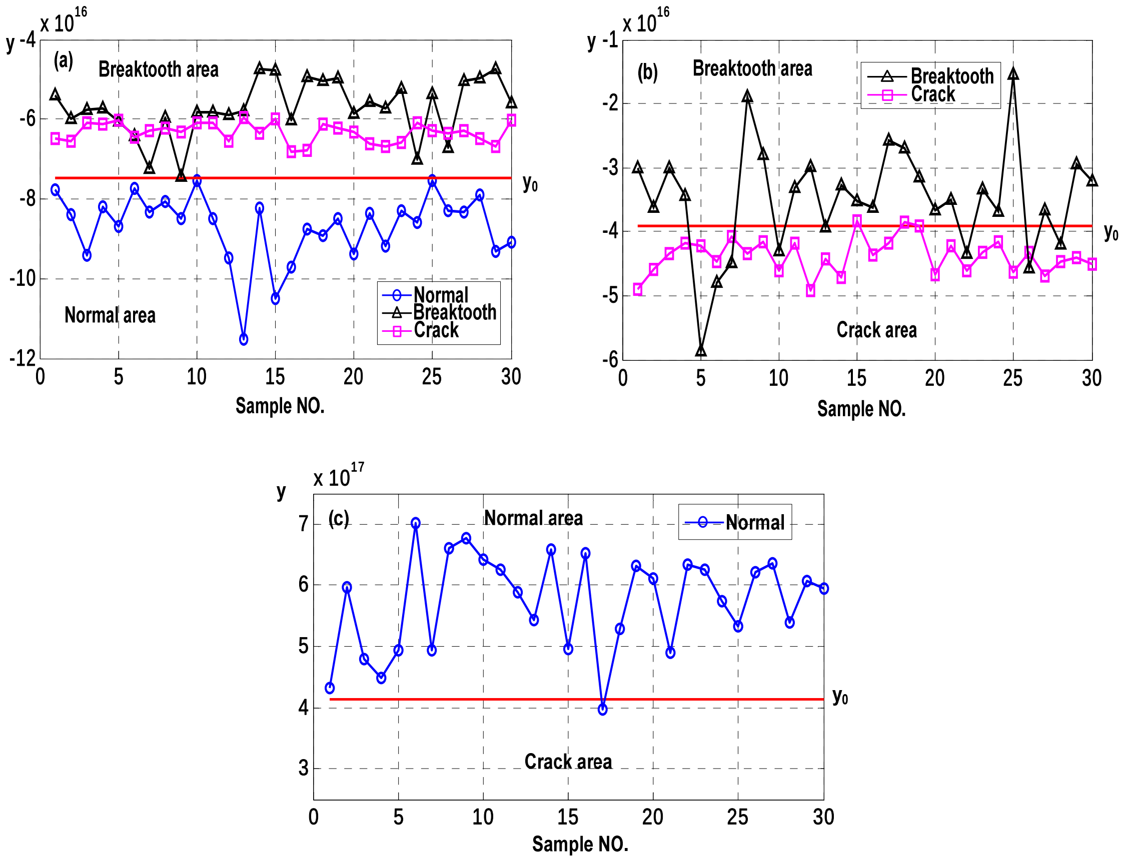

Figure 5. The Result Figures of Gear Fault Modes Diagnosis

After the fault modes of the samples are known, the next step is classify the fault levels. Due to the procedures of classify breaktooth and crack levels are the same, so this paper take the former as an example. Similar to the fault modes diagnosed above, blue, black and pink stand for the diameters of breaktooth are 2mm, 5mm, 10mm. Figure 6(a), (b) and (c) are the comprison of 5-10mm, 2-10mm and 2-5mm. After first comparison, black belong to 5mm and the other two belong to 10mm. When (b) and (c) are implemented, the final results are the same as the assumption before and the accurate rate is also 89%. So the effectiveness of this method is validated.

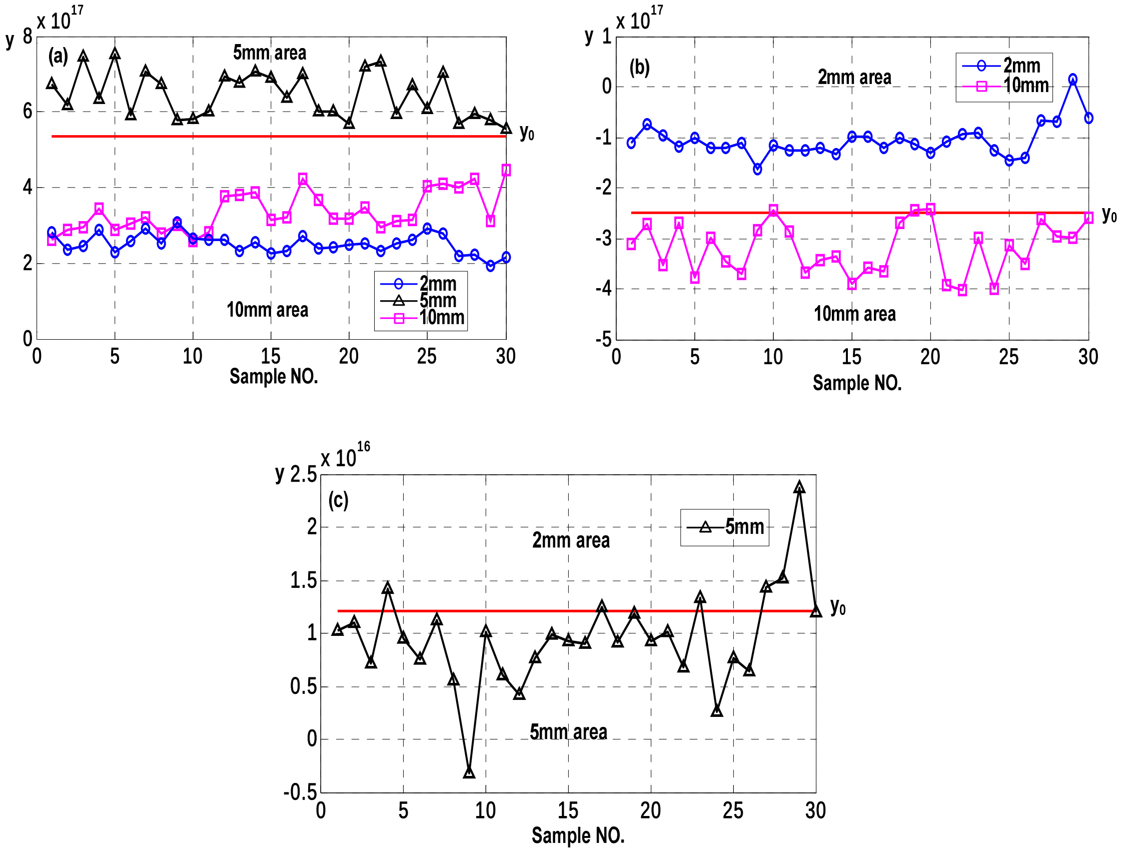

Figure 6. The Result Figures of Gear Fault Levels Classification

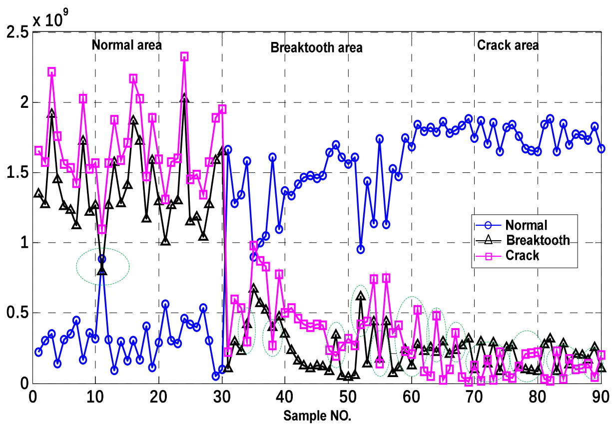

Figure 7. The Result Figures of Gear Fault Modes Diagnosis using Euclidean Distance

To demonstrate the effectiveness of the method this paper proposed, the Euclidean Distance [15] method was utilized to process the experiment data. The procedure of using it is the same as utilizing the FDA. The normal, breaktooth and crack condition were diagnosed at first. The result is as Figure 7 shows. To the normal condition, the result is pretty good. However, to the breaktooth and crack codition, the result are unsatisfactory. The accurate rate of the Euclidean Distance method is only 78%. So it has no need to classify the fault leves due to the error of the first stage. Furthermore, this result prove the significance of dimension reduction which the Euclidean Distance method does not have and validate the approach of this paper.

4. Conclusion

This paper present a novel method in gear fault recognition and classification using Fisher discriminant analysis (FDA). The real data collected from a gearbox test rig is used to validate the method this paper proposed. And the effectiveness of the methodology was demonstrated by the results obtained from the analysis. First of all, three kinds of fault modes (normal, breaktooth and crack) were diagnosed, then the fault levels of breaktooth and crack are classified. Both of the two stages were based on FDA. Two classes FDA were implemented at first when identify a test sample, the nearest class which the procedure give out and another new class could constitute a conference samples to continue conduct the two classes FDA until all the classes are considered. At last, the fault modes and levels are all classified. Meanwhile, the accurate rate of the method is approximate 89% which is superior to the value 78% of using the Euclidean Distance method.

References

[1] Fan XF, Zuo MJ. Gearbox fault detection using Hilbert and wavelet packet transform. *Mechanical Systems and Signal Processing*. 2006; 20(4): 966-982.
[2] Su ZY, Zhang YM, Jia MP, Xu FY, Hu JZ. Gear fault identification and classification of singular value decomposition based on Hilbert-Huang transform. *Mechanical Science and Technology*. 2011; 25(2): 267-272.
[3] Chen Y, Meng JT. Study on BSS Algorithm used on Fault Diagnosis of Gearbox. *TELKOMNIKA Indonesian Journal of Electrical Engineering*. 2013; 11(6): 2942-2947.
[4] Lei YG, Zuo MJ. Gear crack level identification based on weighted K nearest neighbor classification algorithm. *Mechanical Systems and Signal Processing*. 2009; 23(5): 1535-1547.
[5] Kang JS, Zhang XH. Application of Hidden Markov Models in machine fault diagnosis. *Information-An International Interdispilinary Journal*. 2012; 15(12B): 5829-5838.
[6] Hassiotis S. Identification of damage using natural frequencies and Markov parameters. *Computers and Structures*. 2000; 74(3): 365-373.
[7] Baccarini LMR, Silva VVR, Menezes BRD, Caminhas WM. SVM practical industrial application for mechanical faults diagnostic. *Expert Systems with Applications*. 2011; 38(6): 6980-6984.
[8] Tang XL, Zhuang L, Cai J, Li CB. Multi-fault classification based on support vector machine trained by chaos particle swarm optimization. *Knowledge-Based Systems*. 2010; 23(5): 486-490.
[9] Yen GG, Leong WF. Fault classification on vibration data with wavelet based feature selection scheme. *Instrumentation, Systems, and Automation Society*. 2006; 45(2): 141-151.
[10] Kumar K. Knowledge Extraction From Trained Neural Network. *TELKOMNIKA Indonesian Journal of Electrical Engineering*. 2012; 1(4) :282-293.
[11] Fan XF, Zuo MJ. Gearbox fault detection using Hilbert and wavelet packet transform. *Mechanical Systems and Signal Processing*. 2006; 20(4): 966-982.
[12] Wu JD, Hsu CC, Wu GZ. Fault gear identification and classification using discrete wavelet transform and adaptive neuro-fuzzy inference. *Expert Systems with Applications*. 2009; 36: 6255.
[13] Baccarini LMR, Silva VVR, Menezes BRD, Caminhas WM. SVM practical industrial application for mechanical faults diagnostic. *Expert Systems with Applications*. 2011; 38(6): 6980-6984.
[14] Liu ZL, Qu J, Zuo MJ, Xu HB. Fault level diagnosis for planetary gearboxes using hybrid kernel feature selection and kernel Fisher discriminant analysis. *Advanced Manufacturing Technology*. 2013; 67(5): 1217-1230.
[15] Li HP, Zhao JM, Zhang XH, Teng HZ, Yang RF. Bearing Fault Diagnosis Method Using Envelope Analysis and Euclidean Distance. *TELKOMNIKA Indonesian Journal of Electrical Engineering*. 2014; 3(12): 1887-1894.