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Detection and classification of mechanical faults of an engine alternator based on vibration signals and frequency analysis

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ABSTRACT

In this article, an intelligent system is introduced to the detection and classification of some common mechanical faults of an engine alternator based on the frequency analysis of vibration signals. For this purpose, firstly the vibration signal of an alternator under four conditions, including healthy, bearing corrosion, cracked rotor, and the unbalanced excited shaft was captured by an accelerometer. Time-domain signals were then transformed into frequency-domain with the aid of FFT. At the next step, the power spectral density (PSD) method was used for the second frequency signal processing level. Afterward, in the data mining step, twelve statistical features were extracted from the PSD values of the signals, which were fed as the input data into the ANN classifier to detect and classify the alternator faults. The results indicate that the proposed method has the capability of detecting the different alternator faults with an accuracy higher than 92%.

1) Introduction

Large portions of our world's electricity are produced by induction motors. Nowadays many internal combustion engines are using alternators to produce their electricity needs, so the alternator is one of the most important parts of engines [1].

Reliability, accessibility, and lower failure and service time of the machines are highly important in industrial applications [2].

Fracture and failure of alternator cause fast discharge and damage to the battery. Therefore, fault diagnosis of alternators can increase the reliability and accessibility of the engines and automobiles [3].

In the same regard, condition monitoring is widely considered as an effective and efficient method for increasing factors such as reliability, health, and optimized performance of machinery [4].

Due to the sensitivity and importance of alternators, a wide range of studies have been conducted regarding condition monitoring and fault diagnosis of alternators, and many articles have been published in this field [5].

Moyes et al. (1995) designed an expert system for fault diagnosis of alternators. The inputs of the expert system were engine rotational speed, current of the battery, alternator current, and voltage [6].

Prashad (1996) studied various methods for fault diagnosis of alternator bearing [7].

Scacchioli et al. (2007) investigated a model-based method aim at fault detection of automobile alternators [8].

Hashemi et al. (2011) introduced a knowledge-based method goal to health monitoring of alternators, in which the fault diagnosis was carried out by determining a threshold for functional parameters of alternators [1].

For more information, the readers can refer to [9,13]. Also, some patents have been registered in this regard by King [14], Balan [3], and Edwards (1986) [15] to fault diagnosis of alternators and induction motors.

In the present work, an appropriate method based on vibration analysis, signal processing method, and artificial neural network (ANN) has been introduced to detect some of the most common and important faults of an IC engine's alternator. To this end, the vibration signals were firstly captured by an accelerometer under different conditions of the alternator.

Four common mechanical faults of the alternator were investigated 2in this research, namely, healthy (H), worn bearing (WB), unbalanced drive shaft (UDS), and cracked rotor (CR). The vibration signals were transmitted from time-domain into frequency-domain by fast Fourier transform (FFT) tool.

The power spectral density (PSD) method was used for the secondary processing of the frequency-domain signals. Twelve statistical features were extracted from the processed signals in the data mining step. Afterward, ANN was used as a classifier for fault detection and classification.

Extracted features were used as classifier inputs to determine the accuracy of the designed method for fault diagnosis of the alternator.

The main goal of this paper was to find a simple but at the same time flexible, appropriate, and applied method for fault diagnosis of the alternator. The method combines frequency and time features to find a powerful and simple way for fault diagnosis of the alternator.

2) Experimental Setup

For this work, a test rig comprised of an alternator, electromotor, transmission equipment, and four shock absorbers for canceling out vibrations was designed and built. A 1.5 kW electromotor was used to drive the alternator.

The alternator was coupled to the electromotor which was controlled by an inverter. The operating speed was kept at 3000 rpm. Figure 1 illustrates the schematic and real experimental setup and equipment used in this research. A piezoelectric accelerometer types Global Test AP 98-100 was used for measuring the alternator vibration.

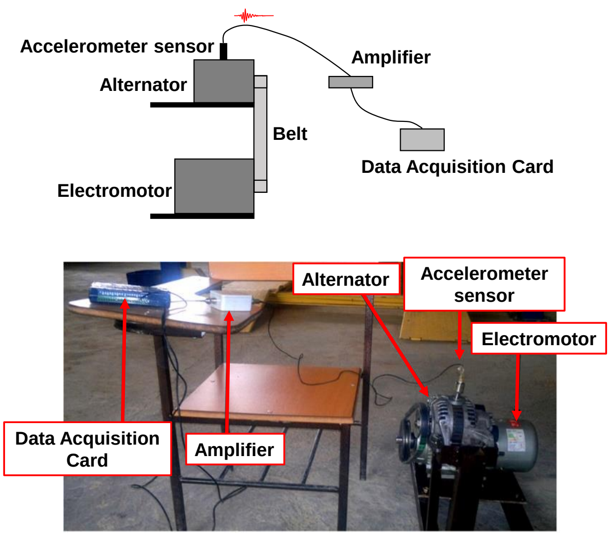

Figure 1: The schematic and real experimental test rig built for this research

The applied accelerometer has a sensitivity of 100mV/g and a resolution of 0.0002 g-rms. The monitored frequency range was 12 kHz in this research. Also, an amplifier and data acquisition was used for amplifying and capturing data.
As mentioned before, four classes were studied in this work, namely, healthy alternator (H), unbalancing in the driven shaft (UDS), the crack in the rotor (CR), and worn bearing (WB). These faults were created manually on the mechanical parts of the alternator. Figure 2 represents the faults studied in this research.
In the vibration measuring step, 140 vibration signals with 1s duration were captured for each alternator condition. Based on the sampling frequency of 2000 Hz and the rotational speed of 3000rpm, the vibration signals with 1s duration are sufficient for further analysis.

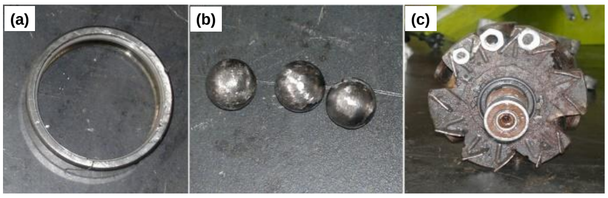

Figure 2: Mechanical faults of the alternator:
(a) Cracked rotor, (b) Worn bearing, (c) Unbalancing

3) Signal Processing

Signal processing is one of the most important parts of a fault detection process. The noises in time-domain signals provide several problems for fault detection. To remove the noises as well as obtain important frequency information, it is necessary to use signal processing methods [16].
It was mentioned that the use of the signal processing method is essential for good feature extraction and noise effect reduction [17].
FFT is one of the commonest signal processing methods which is widely used in condition monitoring. FFT is a special case of the generalized discrete Fourier transform. It converts the vibration signal from time-domain representation to its equivalent frequency-domain representation [18].
In this research, firstly, time-domain signals were transmitted into frequency-domain by FFT method which is suitable for the steady conditions and constant speed.
Fourier transform is defined by the following equation [19]:

$$X(f) = \int_{-\infty}^{+\infty} x(t) e^{-j\omega t} dt \qquad (1)$$

where t and f are time and frequency parameters, respectively. Also, $X(f)$ is the Fourier transform of $x(t)$ and $\omega = 2\pi f$.
Power spectral density (PSD) is one of the signal processing methods which shows the strength of frequency-domain signals' peaks as a function of frequency. PSD method shows, at which frequencies, variations are strong and at which frequencies, variations are weak [20]. PSD can be determined by the following equation [21]:

$$PSD(f) = \frac{[x(f)]^2}{f} \qquad (2)$$

where the PSD method was used for amplifying the main frequency characteristics of the vibration signals.

4) Data Mining and Feature Extraction

It was mentioned in various researches that the effect of noise can be decreased by using feature extraction and then the accuracy of fault diagnosis increases [22].
Therefore, in this work with the aim to extraction of more information from the signals, twelve statistical features were extracted from each signal and afterward statistical features were used instead of the raw data for feeding the classifier.
This strategy allows us to deal with less data, and so the complexity and computation time of the system will be decreased, also statistical methods can provide the physical characteristics of time frequency-domain data [23].
Table 1 shows the statistical features and their formulas that were used for data mining in this research.

Table 1: Features name and formula extracted from vibration signals

Feature description	Formula
Mean	$T_1 = \frac{\sum_{n=1}^{N} x(n)}{N}$
Standard Deviation	$T_2 = \sqrt{\frac{\sum_{n=1}^{N} [x(n) - T_1]^2}{N-1}}$
Root Mean Square	$T_3 = \sqrt{\frac{\sum_{n=1}^{N} [x(n)]^2}{N}}$
Peak Amplitude	$T_4 = \max(\lvert x(n) \rvert)$

Third Central Moment	$T_5 = \frac{\sum_{n=1}^{N}[x(n) - T_1]^3}{N - 1}$
Fourth Central Moment	$T_6 = \frac{\sum_{n=1}^{N}[x(n) - T_1]^4}{N - 1}$
Kurtosis	$T_7 = \frac{\sum_{n=1}^{N}[x(n) - T_1]^4}{(N - 1)T_2^4}$
Skewness	$T_8 = \frac{\sum_{n=1}^{N}[x(n) - T_1]^3}{(N - 1)T_2^3}$
Geometric Mean	$T_9 = N\sqrt{\prod_{n=1}^{N} x(n)}$
Variance	$T_{10} = \frac{\sum_{n=1}^{N}[x(n) - T_1]^2}{N - 1}$
Harmonic Mean	$T_{11} = N \Big/ \sum_{n=1}^{N} \frac{1}{x(n)}$
Coefficient of variation	$T_{12} = \frac{T_2}{T_1} \times 100$

5) Classification Method

ANN is one of the most commonly used methods of artificial intelligence. Today, everybody knows its efficiency and many applications. One of the major applications of this method is the detection and classification of faults. This method has widely been employed for monitoring and diagnosing mechanical systems [24].

In this study, a feed-forward back-propagation neural network was adopted for fault diagnosis of the alternator. ANN was trained using the Levenberg–Marquardt method and hyperbolic tangent sigmoid (tansig) transfer function was used as the activation function in the hidden layer and output layer. The selected network configuration had three layers. Extracted feature vectors were used as inputs for the ANN.

To create a network structure, one neuron was defined for each feature in the input layer of the network. Also, one neuron was defined for each node in the output. The number of hidden layer neurons has a considerable effect on network performance.

After several trials and errors, the maximum accuracy of the network was obtained with 6 neurons in the hidden layer. After that, the network accuracy did not change by increasing neurons. Therefore, the network's optimal structure in this study was determined as 12×6×4.

6) Results and Discussion

Figure 3 shows the time signals of the four alternator conditions at 1sec duration. As it can be seen, finding the differences between these conditions is very difficult from the time-domain plot.

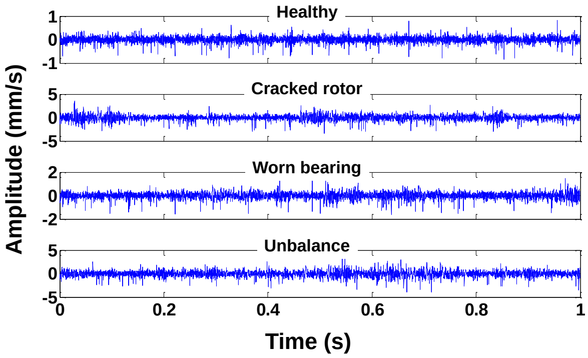

Figure 3: Time-domain vibration signals of the different alternator conditions

However, as a preliminary analysis, the vibration amplitude of the faulty conditions is more than the healthy condition. By using this plot, it is not possible to obtain some detailed and precise information to distinguish the different conditions. Therefore, it is needed to employ a signal processing method.

In this paper, as a signal processing method, the vibration signals were transferred into the frequency-domain due to reveal useful diagnostic information. To this end, the well-known FFT method was used. Figure 4 shows the frequency-domain signals for the four conditions.

It is observed that the differences between these conditions are more obvious in this plot. For example, at the frequency of about 600 Hz, the vibration amplitude for the cracked rotor condition is more than for others.

But at the frequencies of about 200 Hz, 2.8 kHz, and 3 kHz, the vibration amplitude of the unbalance condition is the most. To reveal more the differences in the conditions, the power spectral density (PSD) technique was employed. The PSD plot of the vibration signals of the four alternator conditions is given in Fig. 5. This technique causes noise to remove and significant frequency contents to remain.

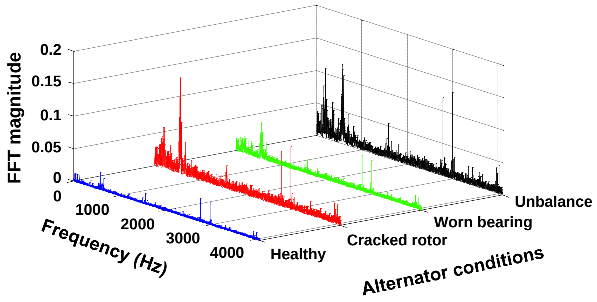

Figure 4: Spectrum of the vibration signals (FFT output)

As mentioned before, according to Figure 5 the differences between the alternator conditions are clearer using the PSD technique, so it is possible to discriminate them easier. Therefore, it is concluded that applying statistical features on the PSD values of the signals can generate proper results.

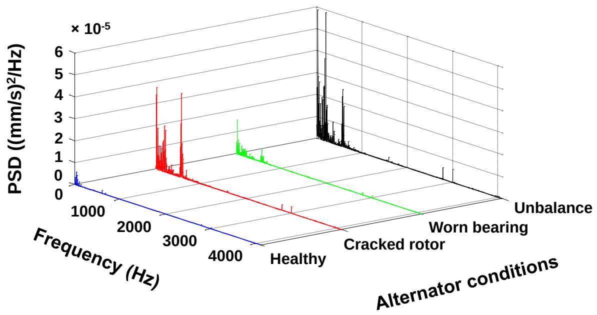

Figure 5: PSD plot of the vibration signals

In the feature extraction stage, twelve features which are given in Table 1 were extracted from the PSD values of the signals. Note that the selection of proper and relevant features can help to increase the classification accuracy.

On the other side, the use of unsuitable features decreases the classification accuracy, because they cannot provide useful diagnostic information. As an example, Figure 6 shows the influence of the three features, namely, mean, maximum, and standard deviation on discrimination of the classes.

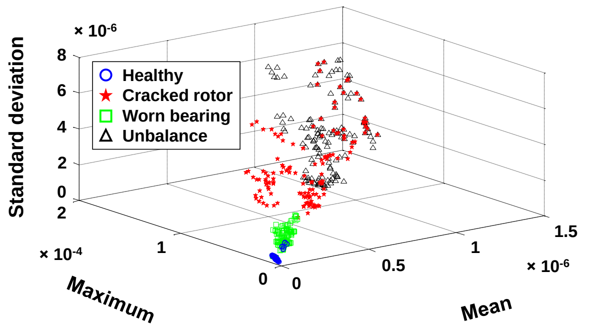

Figure 6: Class discrimination based on three proper features

It can be seen that these features have separated the classes so they are proper for this case study. Of course, there is a slight overlap between some classes.

For example, the cracked bearing and unbalance classes have overlap. This is due to the relatively same vibration behavior of these two conditions in the alternator.

For such cases, applying a powerful classifier can substantially help to detect and classify the conditions. Figure 7 shows the effect of the shape factor, coefficient of variation, and kurtosis on the class separation.

It can be observed that the classes have not been distinguished well based on these features. In this case, the classifier will face problems in the classification stage so the classification accuracy will reduce. It is concluded that these features are not proper for this case study and should not be used. It is emphasized that the features used in this paper are among the proper features for this case study.

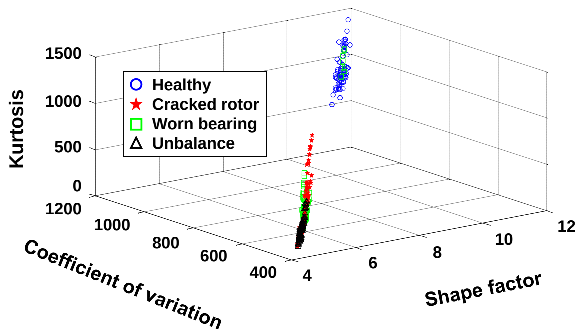

Figure 7: Class discrimination based on three improper features

As mentioned in the Experimental Setup section, each class contained 140 samples. Therefore, in the feature extraction stage, a feature vector that included 560 rows (4×140) and 12 columns (12 features) were constructed.

The feature vector was used as input to the ANN classifier. ANN had 12 and 4 neurons in the input and output layers, respectively. After several trials and errors, it was found that ANN with 6 neurons in the hidden layer gave the maximum accuracy.

Table 2 represents the confusion matrix of the ANN classifier in fault detection and classification of the different conditions of the alternator. It is observed that the classification accuracy of 92.9% was gained.

This accuracy is good enough for practical applications. According to the results, the ANN classifier has detected 129 healthy samples as the healthy condition and 11 healthy samples as the worn bearing condition.

From 140 cracked rotor samples, 125 samples have correctly detected, but the remaining has been detected as the unbalance condition. For the worn bearing condition, 130 samples have correctly recognized but 10 samples have wrongly detected. For the unbalance condition, 136 samples have correctly identified but 4 samples have been detected as the cracked rotor condition. Referring to the obtained results, it can be mentioned that the proposed method is capable of detecting the alternator faults so it can be used in practical applications. Moreover, this method is suggested for detecting such faults in similar alternators.

Table 2: Confusion matrix of ANN for alternator fault classification

Alternator condition	Output class of ANN				Accuracy (%)	Average accuracy (%)
	H	CR	WB	UDS		
H	129	0	11	0	92.14	92.9
CR	0	125	0	15	89.29	
WB	9	0	130	1	92.86	
UDS	0	4	0	136	97.14	

7) Conclusions

In this study, an appropriate approach was proposed with the purpose of detection and classification of some common mechanical faults in an automobile alternator. To this end, FFT and PSD methods were employed in the signal processing stage.

Data mining was performed to construct a better input vector for the classifier. Finally, ANN was used as a classifier due to detecting the mechanical faults of the alternator. The results showed that the proposed approach could detect four conditions of the healthy alternator (H), crack in the rotor (CR), worn bearing (WB), and unbalancing in the driven shaft (UDS) with the accuracy of 92.14, 89.29, 92.86, and 97.14%, respectively.

The total accuracy of this method in the alternator fault detection was 92.9 %. The results confirmed the effectiveness of the proposed intelligent approach for fault diagnosis of the alternator.

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تشخیص و طبقه‌بندی عیوب مکانیکی مولد برق موتور بر پایهٔ علامت‌های ارتعاش و تحلیل بسامد

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چکیده

در این مقاله، یک سامانهٔ هوشمند به منظور تشخیص و طبقه‌بندی عیوب مکانیکی رایج مولد برق موتور بر پایهٔ تحلیل بسامد علامت‌های ارتعاش توسعه داده شد. بدین منظور، در ابتدا علامت‌های ارتعاش یک مولد برق تحت چهار وضعیت سالم، خوردگی یاتاقان، محور دوار ترک خورده و نامتعادل در محور توسط یک شتاب‌سنج دریافت شد. سپس علامت‌های حوزهٔ زمان با روش تبدیل سریع فوریه به حوزهٔ بسامد منتقل شدند. در گام بعد، روش چگالی طیف توان برای دومین مرحلهٔ تحلیل بسامد استفاده شد. پس از آن در مرحلهٔ داده کاوی، دوازده ویژگی آماری از مقادیر چگالی طیف توان علامت‌ها استخراج و به منظور تشخیص و طبقه‌بندی عیوب مولد برق، به‌عنوان ورودی به طبقه‌بند شبکهٔ عصبی مصنوعی داده شدند. نتایج نشان داد که روش ارائه شده، قادر به تشخیص عیوب مختلف مولد برق با دقت بیش از ۹۲٪ است.

اطلاعات مقاله

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کلیدواژه‌ها:
تشخیص عیب
مولد برق
تحلیل ارتعاش
موتور درون‌سوز
شبکه عصبی مصنوعی