Data Analysis for Braking System in Time Domain for Fault Diagnosis

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Abstract - *Brake system in automobiles are the most importance component for the vehicle to avoid from accident occurrence. Therefore brake system needed to be in a good condition in all time. Hence detection of defect from this system must be detected in advance to avoid any failure. The signal for both good and fault conditions of brake has been simulated in MATLAB by using brake transfer function. In order to characterize any fault from the signals, features plays an importance role to describe the signal characteristic. In this paper, the statistical feature like Skewness, Maximum, Minimum, RMS, Standard Deviation, and Variance have been used to compare the percentage accuracy for the system. The results are discussed and the conclusion is presented.*

Key Words: Time Domain, Statistical Feature, ANN, Fault Diagnosis.

1. INTRODUCTION

Brakes system are the essential part for control component in automobile in order to promote the safety for the persons inside and outside the vehicle. In April 2007, BMW recalled over 160,000 SUVs because of a problem that could cause a potential loss of brake fluid or even the brake circuit to fail completely. And in May of the same year, Chrysler recalled 60,000 vehicles due to an issue with potential brake failure (Nick Johnson, n.d.). Every brake system should ensure the stability of the vehicle and should provide a reasonable distance before the vehicle at rest. In accordance with that, every brake should be convenient with the pedal effort. Since there are many moving component involved, the percentage to get fault higher. When such thing like leak, fade, and wearing happen the performance of brake reduce and may lead to accidents. Therefore it is important for the brake component and brake system to be monitor and diagnosed all the time when the fault happen. For common recognition brake system can be identified through some warning light on dashboard. However those light only show when the brake system is fully or 80% fault.

Monitoring the condition of the brake system is not an easy job. However, this can be solve using intelligent techniques which called fault diagnosis through machine learning. There are many method involve in fault diagnosis like vibration analysis (Sakthivel, Sugumaran, & Babudevasenapati, 2010), thermal imaging (Allred & Kelly, n.d.), acoustic emission (Sik & Keun, 2011), and other. Usually the common method used is vibration analysis. The vibration signals are analysed by using methods like spectral analysis, wavelet analysis, waveform analysis, and other (Jegadeeshwaran & Sugumaran, 2015).

In machine learning method for determine the fault of the signal consists three steps, first is feature extraction, second feature selection, and lastly feature classification. There are a lot of feature available like histogram feature (Sakthivel, Indira, Nair, & Sugumaran, 2011; Elangovan, Ramachandran, & Sugumaran, 2010), statistical feature (Elangovan, Ramachandran, & Sugumaran, 2010), and wavelet feature (Kong & Chen, 2004). Statistical feature most commonly used in present day. This statistical feature were used to extract the information from the brake vibration signals under various condition. There may not all statistical feature required for classification, however only for the most importance feature that contain information are required for classification. This will achieved using feature selection. Principle component analysis (PCA) (Zheng, Pan, & Cheng, 2017) and decision tree (DT) (Cui, Qiao, Yin, & Hong, 2016) are the example of available technique for feature selection. However this analysis is not suitable for incomplete data set.

In this paper, the statistical feature parameter is used to find the best classification accuracy for Artificial Neural Network (ANN). The literature review illustrate the conventional and the latest method used for fault diagnosis for bearing fault. The result compared the statistical feature with number of hidden neuron to find the optimum classification accuracy.

2. LITERATURE REVIEW

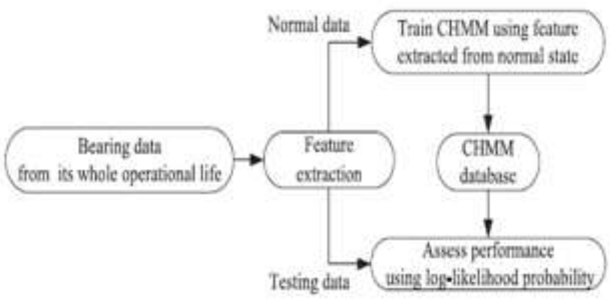
2.1 Bearing fault diagnosis technique.

In recent years, there are many method for fault detection have been proposed and developed. Compare to other traditional method, machine learning method the popular among those.

Based on the study, ratio of neighbouring singular value (NSVRs), singular value (SV), and singular value decomposition (SVD) are used for feature extraction of vibration signal. Based on (Jiang, Chen, Dong, Liu, & Chen, 2015) in their research for bearing fault diagnosis use singular value, singular value decomposition (SVD), and ratios of neighbouring singular value (NSVR) for feature extraction method of the signal. Those method is called SV-NSVR. The combination of continuous hidden Markov model

(CHMM) with SV-NSVR feature for better classification. After that, those methods would be apply to the fault diagnosis.

For training procedure, all data are properly sample and pre-process. After that, feature will be extracted using SV-NSVR and then input into CHMM for training using Baum-Welch algorithm. Lastly the fault can be tested.



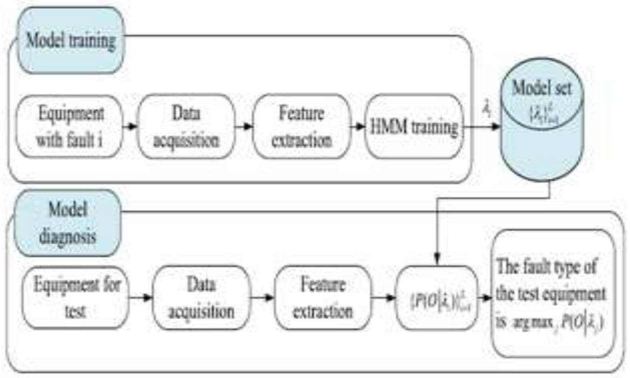


Fig -1: The SV–NSVR and CHMM based fault diagnosis scheme

Fig -2: The scheme of bearing performance assessment

According to (Jiang, Chen, Dong, Liu, & Chen, 2015) state that SVs-CHMM and NSVRs-CHMM based method can easily recognize the bearing fault type. The proposed method is beneficial for the equipment condition monitoring and maintenance (Jiang, Chen, Dong, Liu, & Chen, 2015). Thus the combination of SVs and NSVRs can be more effective to vibration signal for fault diagnosis.

While, based on upon research, fault diagnosis for fault signal not necessarily use SV-NSVR method. However there are some method that can enhance the signal to give better classification result. Based on (Cui, Qiao, Yin, & Hong, 2016) conducted a research on how to detect the rolling bearing fault at early stage. The researcher (Cui, Qiao, Yin, & Hong, 2016) said it is the early detection of fault for rolling bearing are really difficult solve because the sensor produce non-stationary signal and low signal to noise ratio. So the paper (Cui, Qiao, Yin, & Hong, 2016) tries to solve it by comparing the high frequency band power. If a fault occurs, we first de-noise the vibration signals using wavelet de-noising and then extract the fault characteristics in both the time domain and the time frequency domain to avoid the limitations of using only one domain (Cui, Qiao, Yin, & Hong, 2016). In time and frequency domain the feature like variance, root mean square (RMS), and average value are extracted because those value are sensitive to the amplitude. While for the time frequency domain, entropy are used for feature extraction method. Lastly, grey correlation method is use to determine the fault location. Grey relation analysis is a new method to obtain the related of each data because this method exhibit in quantity and quality. Grey relational analysis is calculating the geometric similarity degree of curves to determine the degree of predicament. When two data have similar curve, then their geometric similarity degree is larger.

According to the method application results, the recognition accuracy using the method proposed in this paper is satisfactory, proving that the method has superior performance (Cui, Qiao, Yin, & Hong, 2016). Compare with other traditional method, time domain and time-frequency domain combine with grey relational is simple and feasible.

Table -1: Correct rates of grey relational identification with and without using high-frequency analysis

Number of standard samples	Without high-frequency analysis			After high-frequency analysis		
	1	3	5	1	3	5
Time domain	71%	73%	73%	92%	95%	95%
Time-frequency domain	77%	69%	73%	64%	81%	80%
Combined time and time-frequency domain	91%	89%	84%	96%	96%	96%

The other research from (Zheng, Pan, & Cheng, 2017) conducted a study to find out the accurate location for rolling bearing failure. In this study they propose method based on the composite multiscale fuzzy entropy (CMFE) and ensemble support vector machines (ESVMs). This study, they will compare the result between Sample entropy, Fuzzy entropy, Multi scale fuzzy entropy, and composite multiscale fuzzy entropy (CMFE). They come out with this method to overcome the short-term time series analysis which exist in MSE.

There are many nonlinear dynamic theory that provide method for extracting the defect related feature hidden in measure vibration signal which may not be effective using other method. The recent nonlinear dynamic parameter that have been used for fault diagnosis for rolling bearing are correlation dimension (Yang, Zhang, & Zhu, 2007; Yang, Jin, Du, & Zhu, 2011), Lempel-Ziv complexity (Ibáñez-Molina, Iglesias-Parro, Soriano, & Aznarte, 2015), approximate entropy (ApEn) (Yan & Gao, 2007), sample entropy (SamEn) (Aktaruzzaman & Sassi, 2014), permutation entropy (PE) (Yan, Liu, & Gao, 2012; Zheng, Cheng, & Yang, 2014), and multiscale entropy (MSE) [(Costa, Goldberger, & Peng, 2005; Costa, Goldberger, & Peng, 2002; Zhang, Xiong, Liu, Zou, &

Guo, 2010). MSE was proposed by Costal etal. [(Costa, Goldberger, & Peng, 2005; Costa, Goldberger, & Peng, 2002) is used to calculate the SampEn to represent the complexity of the physiological, biological, and vibration signal for analysing complex time series. MSE still has the weakness that need to be improve (Wu, Wu, Lin, Wang, & Lee, 2013). MSE method have two procedures which are: (1) the dynamics representation of a system on different time scales is derived by conducting a coarse-grained procedure, (2) the regularities of the coarse-grained time series are quantified by applying SampEn with unity delay (Zheng, Pan, & Cheng, 2017).

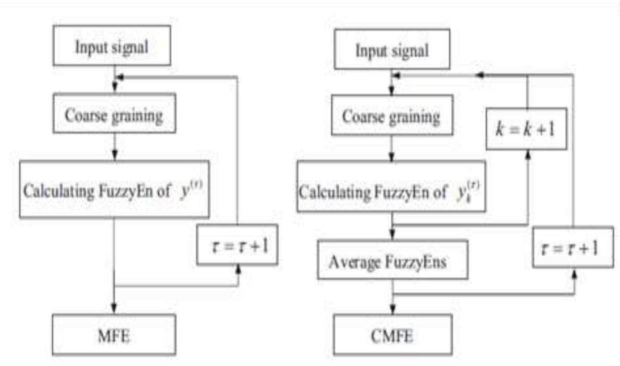


Fig -3: Flowchart comparison of CMFE and MSE

In their study, (Zheng, Pan, & Cheng, 2017) found that proposed method for rolling bearing fault diagnosis has a good performance for experiment data and the recognition rate is up to 100% . From the result CMFE has the following advantages which are anti-noise calculation, data can be short for getting stable and coherent, and overcoming the problem in MFE.

It is appear that, there are many method that can be used fault diagnosis analysis in order to determine the best classification result. It is found that, for the bearing fault diagnosis using vibration signal the combination of continuous hidden Markov model (CHMM) with SV-NSVR feature for better classification. However in the recent study discover that the best classification accuracy can be achieve by comparing the high frequency band power by combine the time domain and time-frequency domain with grey relation method. Other research found that the combination of continuous hidden Markov model (CHMM) with SV-NSVR feature would give better classification result. Caution must be advice, through (Zheng, Pan, & Cheng, 2017; Jiang, Chen, Dong, Liu, & Chen, 2015) those study was conducted in the experiment limited to bearing fault.

3. METHODOLOGY

The data used in this study based on brake system transfer function that derived from quarter brake mathematical modelling [(Oniz, Kayacan, & Kaynak, 2009; F L. & G Y., 2012). The model have been implemented into Matlab for data acquisition. The signal was taken with the following settings:

- The input signal had been sample to 0.01s. (100 Hz)
- The amplitude of disturbance signal is set to 0.2 to represent 20% of fault.
- The seed of the input signal had been adjusted from 1 to 100 for 100 sample.
- The model had been simulated for 10 seconds.
- The total of 400 samples forms the dataset.

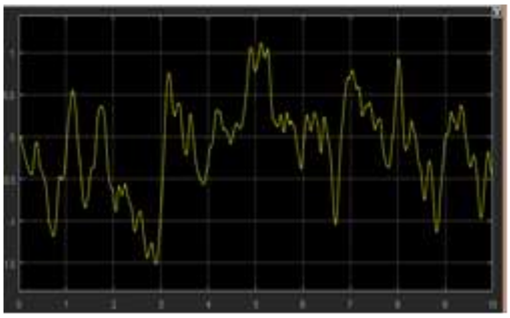


Fig -4: Clean System

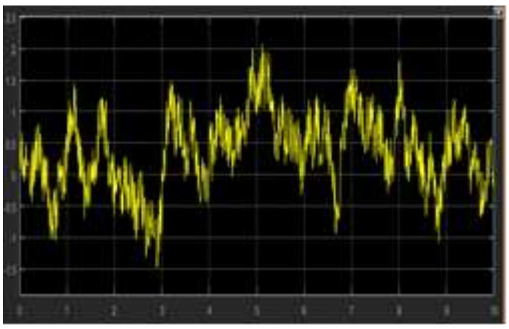


Fig -5: Brake with noise

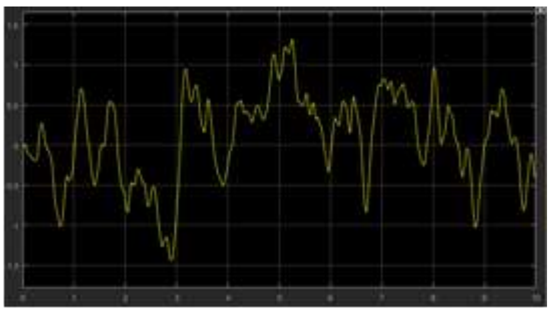


Fig -6: Brake system with disturbance

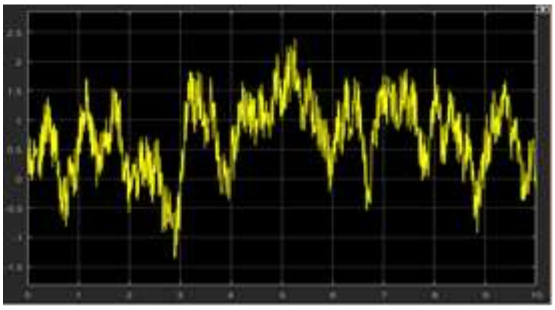


Fig -6: Brake system with noise and disturbance

There are four different brake conditions which are clean system, brake system with noise, brake system with disturbance, and brake system with noise and disturbance. Clean system represent the normal condition of the brake. Brake system with noise indicate the system is in good condition but the sensor recorded the unwanted signal. Therefore random number was introduce to indicate the noise in the system with sample time 0.01s.The fault system represent by brake system with disturbance and brake system with noise and disturbance. The disturbance signal represented by pulse signal. The pulse signal had been set 0.2 to indicate 20% of fault. Brake system with noise and disturbance means that sensor recorded fault signal from the system with additional noise from other system. Noise represent by white noise and disturbance represent by pulse signal.

3.1. Pre-Processing

The primary aim of pre-processing is to enhance the characteristic of the brake signal for proper signal processing and analysis. The simulated signal are not undergo the noise removal process because noise signal is purposely added, so that the system could classify the signal with and without noise. At this stage, the signal only been normalize and de-trend to improve the characteristic of the signal.

3.1.1 Filter Design Band Separation.

The segmented frame signal are filter to remove the frequency below 1 Hz and above 49 Hz. For the frequency band separation are categorized into five different band from 1 – 10 Hz, 10 – 20 Hz, 20 – 30Hz, 30 – 40Hz, and 40 – 49Hz using infinite impulse response digital filter. In this study, Butterworth 10th order bandpass filter has been used among three type of band pass filters which are Butterworth, Chebyshev, and Elliptic filter. The Butterworth band pass filter has several advantages when compare to other filters as maximally flat magnitude response in the pass band, good all-around performance, good rate of attenuation, and pulse response better than Chebyshev.

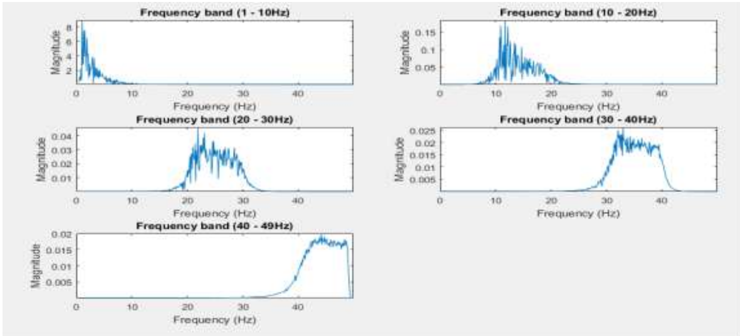


Fig -7: Frequency band separation based on filter design for each data

3.2 Feature extraction

The acquired signal required to undergo several process before it can produce good result. The primary aim here is to study the characteristic of signal and to reduce representation set of feature. The statistical feature parameter like maximum, minimum, skewness, standard deviation, mean, and sample variance. Brief description for statistical feature extraction are given below.

STANDARD DEVIATION = $\sqrt{\dfrac{\sum x^2 - (\sum x)^2}{n(n-1)}}$

MAXIMUM VALUE
It refer to the maximum value form the signal.

VARIANCE = $\dfrac{\sum x^2 - (\sum x)^2}{n(n-1)}$

MINIMUM VALUE
It refer to the minimum value from the signal.

SKEWNESS = $\dfrac{n}{n-1}\sum\left(\dfrac{x_i - \bar{x}}{s}\right)^3$

RMS
Root Means Square of the signal

Fig -8: Statistical Feature

3.3 Feature classification

Artificial Neural Network (ANN) are biologically inspired tools for information processing and it is nonlinear in nature. Classification of signal basically falls on the pattern recognition problem, and because neural network are good at pattern recognition. In recent years there has been a significant work that has established the idea of ANN as a useful tool for brain activity recognition. Unlike other artificial intelligent and expert system method, multilayer feed forward neural network (MLNN) models can be trained to associate input data with respect to the output data, to learn unknown tasks.

The main focus of this work is to generate the neural network so that it can detect the state of the brake system. The supervise network that has been utilized is called feed-forward network trained with back propagation. The training process consist of four stages which are assemble the data that used for training, create the network object, train the network, and provide new input to simulate the response. The feature from signal are store as input matrix and target matrix for training.

The second step is to create the network and train the system between given inputs and target. The network use back-propagation with three layer feed-forward network. For each condition which are brake system without noise and disturbance, brake system with noise, brake system with disturbance, and brake system with noise and disturbance were collected with total sample 400. From 400, 90 samples from each condition were used for training and 10 are saved for testing neural network. Training the ANN done by selecting three layers of neural network which are input layer, hidden layer, and output layer.

The artificial neural network was build based on forward neural network trained with back propagation for network type, used TRAINLM (Levenberg-Marquardt) for training function, sigmoid transfer function in hidden and output layer for transfer function, MSE (mean square error) for performance function, number of hidden layer: 1, and number of hidden neurons : varies.

3.3 Braking Fault Diagnosis in IOT Environment

The setup was done in accordance with figure. The mathematical model of the braking system has been implemented in the raspberry PI 3. The raspberry PI 3 was connected to the ThingSpeak via a Wi-Fi connection. The baud rate for the transmission was. The baud rate could have been higher if a different serial connection using cable was used.

The information is simultaneously uploaded to the Thingspeak channel. The channel reads data from the Thingspeak channel **189402**. The channel is refer as a "Request Channel". This channel was created to enable remote request for specific information from the signal. The application continuously updates the channel fields.

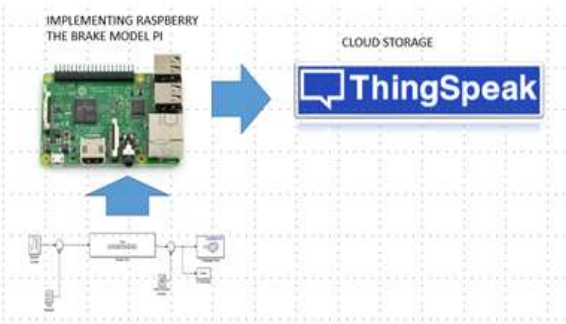


Fig -9: IOT Block Diagram

4. RESULTS & DISCUSSION

In this chapter, various feature extraction and the effect of hidden neuron in the ANN were discussed. The performance of RMS, maximum, minimum, Standard Deviation, Skewness, and Variance are compared based on the percentage accuracy from the ANN based on number of hidden neuron. The results are discussed below.

Table -2: Percentage Accuracy for Training Data

Training Samples = 360; Testing samples = 40		Training Tolerance = 0.01			
Feature Extraction Method	Class Accuracy (%)			Input data = 5x400	Output data = 4x400
	Min	Mean	Max	Hidden neurons	
Variance	98.33	98.38	98.61	8	
Skewness	96.38	96.75	97.22	7	
Minimum	96.94	97.19	97.77	6	
RMS	98.05	99.38	99.72	9	
STD	97.5	97.86	98.33	5	
Maximum	96.94	97.75	98.33	10	

From the table, it can be noted that the performance using variance feature has a minimum classification rate of 97.22% and the maximum classification rate of 99.17%. The performance using skewness feature has a minimum classification rate of 97.22% and the maximum classification rate of 98.33%. The performance using minimum feature has a minimum classification rate of 97.50% and the maximum classification rate of 98.89%. The performance using RMS feature has a minimum classification rate of 97.50% and the maximum classification rate of 99.44%. The performance using standard deviation feature has a minimum classification rate of 97.50% and the maximum classification rate of 98.33%. The performance using maximum feature has a minimum classification rate of 97.78% and the maximum classification rate of 98.61%.

4.1 Braking Fault Diagnosis in IOT Environment

The data from the brake model has been store into the ThinkSpeak cloud as a platform for the IOT environment. The time interval between each successive sample appearing at the channel is approximately 20s which is the delay incorporated in the program. This delay could be affected by the stability of the internet connection and the inherent sampling delay. It also allows for trend analysis to be conducted visually. The date and time of the signal was recorded is plotted against the value of the signal data. This information can be exported into spreadsheet format for further processing.

Fig -9: IOT Result

5. CONCLUSION

It was found that conventional time domain statistic parameter such as RMS, Skewness, Maximum, Minimum, Standard Deviation, and Variance for simulated brake signal with ANN served as good condition indicators. However there are some problem were found to be associated with these parameter. They are sensitive to many different events from different source and often required for further analysis. This drawback can be overcome by using appropriate filter. The overall result shows that the statistical feature method using the root mean square is the best method to classify the braking condition compare to others. RMS has the highest classification rate, which is 98.73% with 9 hidden neurons. Whereas skewness give the lowest classification accuracy compare to others which is 97.62% with 7 hidden neurons.

REFERENCES

[1] Nick Johnson. (n.d.). Brake Failure Accidents. Retrieved from www.articles3k.com/article/144/176520/Brake_Failure_Accidents/.

[2] Sakthivel, N., Sugumaran, V., & Babudevasenapati, S. (2010). Vibration based fault diagnosis of monoblock centrifugal pump using decision tree. *Expert Systems with Applications*, *37*(6), 4040-4049.doi:10.1016/j.eswa.2009.10.002.

[3] Allred, L., & Kelly, G. (n.d.). A system for fault diagnosis in electronic circuits using thermal imaging. *Conference Record AUTOTESTCON '92: The IEEE Systems Readiness Technology Conference*. doi:10.1109/autest.1992.270076.

[4] Sik, D., & Keun, B. (2011). Machinery Faults Detection Using Acoustic Emission Signal. *Acoustic Waves - From Microdevices to Helioseismology*. doi:10.5772/22892.

[5] Jegadeeshwaran, R., & Sugumaran, V. (2015). Brake fault diagnosis using Clonal Selection Classification Algorithm (CSCA) – A statistical learning approach. *Engineering Science and Technology, an International Journal*, *18*(1), 14-23. doi:10.1016/j.jestch.2014.08.001.

[6] Sakthivel, N., Indira, V., Nair, B. B., & Sugumaran, V. (2011). Use of histogram features for decision tree-based fault diagnosis of monoblock centrifugal pump. *International Journal of Granular Computing, Rough Sets and Intelligent Systems*, *2*(1), 23. doi:10.1504/ijgcrsis.2011.041458.

[7] Elangovan, M., Ramachandran, K., & Sugumaran, V. (2010). Studies on Bayes classifier for condition monitoring of single point carbide tipped tool based on statistical and histogram features. *Expert Systems with Applications*, *37*(3), 2059-2065. doi:10.1016/j.eswa.2009.06.103.

[8] Kong, F., & Chen, R. (2004). A combined method for triplex pump fault diagnosis based on wavelet transform, fuzzy logic and neuro-networks. *Mechanical Systems and Signal Processing*, *18*(1), 161-168. doi:10.1016/s0888-3270(03)00049-9.

[9] K.P. Soman, K.I. Ramachandran, Insight into wavelets from theory to practice, Prentice-Hall of India Private Limited, 2005.

[10] Zheng, J., Pan, H., & Cheng, J. (2016). Rolling bearing fault detection and diagnosis based on composite multiscale fuzzy entropy and ensemble support vector machines. *Mechanical Systems and Signal Processing*, *85*, 746-759. doi:10.1016/j.ymssp.2016.09.010.

[11] Cui, H., Qiao, Y., Yin, Y., & Hong, M. (2017). An investigation of rolling bearing early diagnosis based on high-frequency characteristics and self-adaptive wavelet de-noising. *Neurocomputing*, *216*, 649-656. doi:10.1016/j.neucom.2016.08.021.

[12] Jiang, H., Chen, J., Dong, G., Liu, T., & Chen, G. (2015). Study on Hankel matrix-based SVD and its application in rolling element bearing fault diagnosis. *Mechanical Systems and Signal Processing*, *52-53*, 338-359. doi:10.1016/j.ymssp.2014.07.019.

[13] Yan, R., Liu, Y., & Gao, R. X. (2012). Permutation entropy: A nonlinear statistical measure for status characterization of rotary machines. *Mechanical Systems and Signal Processing*, *29*, 474-484. doi:10.1016/j.ymssp.2011.11.022.

[14] Yang, J., Zhang, Y., & Zhu, Y. (2007). Intelligent fault diagnosis of rolling element bearing based on SVMs and fractal dimension. *Mechanical Systems and*

Signal Processing, *21*(5), 2012-2024. doi:10.1016/j.ymssp.2006.10.005.

[15] Yang, X., Jin, X., Du, Z., & Zhu, Y. (2011). A novel model-based fault detection method for temperature sensor using fractal correlation dimension. *Building and Environment*, *46*(4), 970-979. doi:10.1016/j.buildenv.2010.10.030.

[16] Ibáñez-Molina, A. J., Iglesias-Parro, S., Soriano, M. F., & Aznarte, J. I. (2015). Multiscale Lempel–Ziv complexity for EEG measures. *Clinical Neurophysiology*, *126*(3), 541-548. doi:10.1016/j.clinph.2014.07.012.

[17] Yan, R., & Gao, R. X. (2007). Approximate Entropy as a diagnostic tool for machine health monitoring. *Mechanical Systems and Signal Processing*, *21*(2), 824-839. doi:10.1016/j.ymssp.2006.02.009.

[18] Aktaruzzaman, M., & Sassi, R. (2014). Parametric estimation of sample entropy in heart rate variability analysis. *Biomedical Signal Processing and Control*, *14*, 141-147. doi:10.1016/j.bspc.2014.07.011.

[19] Zheng, J., Cheng, J., & Yang, Y. (2014). Multiscale Permutation Entropy Based Rolling Bearing Fault Diagnosis. *Shock and Vibration*, *2014*, 1-8. doi:10.1155/2014/154291.

[20] Costa, M., Goldberger, A. L., & Peng, C. (2005). Multiscale entropy analysis of biological signals. *Physical Review E*, *71*(2). doi:10.113/physreve.71.021906.

[21] Costa, M., Goldberger, A. L., & Peng, C. (2002). Multiscale Entropy Analysis of Complex Physiologic Time Series. *Physical Review Letters*, *89*(6). doi:10.1103/physrevlett.89.068102.

[22] Zhang, L., Xiong, G., Liu, H., Zou, H., & Guo, W. (2010). Bearing fault diagnosis using multi-scale entropy and adaptive neuro-fuzzy inference. *Expert Systems with Applications*, *37*(8), 6077-6085. doi:10.1016/j.eswa.2010.02.118.

[23] Wu, S., Wu, C., Lin, S., Wang, C., & Lee, K. (2013). Time Series Analysis Using Composite Multiscale Entropy. *Entropy*, *15*(3), 1069-1084. doi:10.3390/e15031069.

[24] Oniz, Y., Kayacan, E., & Kaynak, O. (2009). A Dynamic Method to Forecast the Wheel Slip for Antilock Braking System and Its Experimental Evaluation. *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics)*, *39*(2), 551-560. doi:10.1109/tsmcb.2008.2007966.

[25] F L., & G Y. (2012). Optimization of PID Controller Based on Particle Swam Algorithm for Automobile ABS. *International Journal of Advancements in Computing Technology*, *4*(3), 50-58. doi:10.4156/ijact.vol4.issue3.7\.