Application of multi-fuzzy system for condition monitoring of liquid filling machines

Article · March 2012

DOI: 10.1109/ICIT.2012.6210054

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Application of Multi-Fuzzy System for Condition Monitoring of Liquid Filling Machines

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Abstract: In this paper a novel approach is implemented for investigation of failures in Stork bottle filling machines. Fuzzy based system is used to detect the abnormalities present in machine by using time and frequency domain statistical features. Statistical analysis of vibration data determined the gearbox failure which correlated with engineer's findings. The method used has shown promising results to predict the failure in this case of low speed rotary machines. It has been concluded that statistical based analysis of vibration signal is a suitable for predicting machine faults with low rotating speeds. This paper presents a system, implemented on the industrial process machine, which has successfully predicted the faults in the gearbox before the catastrophic failure.

Keywords: Fuzzy Inference System (FIS), Cleaning in Place (CIP), Graphical User Interface (GUI), Fast Fourier Transform (FFT), MATLAB, Condition Monitoring System

1. INTRODUCTION

This paper presents the condition monitoring of liquid filling machines. Stork Rotary fillers are normally used in the dairy and juice industries to fill liquid into different size of bottles. The machine can be customised for different size and volume of bottles. The main filling station of these machines rotates around 7 revolutions per minute. Speed fluctuations in the typical filler operation are shown in figure 1. This variation in speed is caused by various problems in capping or printing sections or in-feed bottle stoppage on conveyor. At each speed, different vibration signatures are observed. Inference system learns these states of the machine to predict any faults present in the machine. Fuzzy system has been modelled in four machine states based upon speed as shown in table 1.

TABLE 1 FILLER SPEED

Speed	Machine status
0 RPM	Filler is stop
2 RPM	Cleaning in Place (CIP)
3.5RPM	Filler half Speed
7 RPM	Filler Full Speed

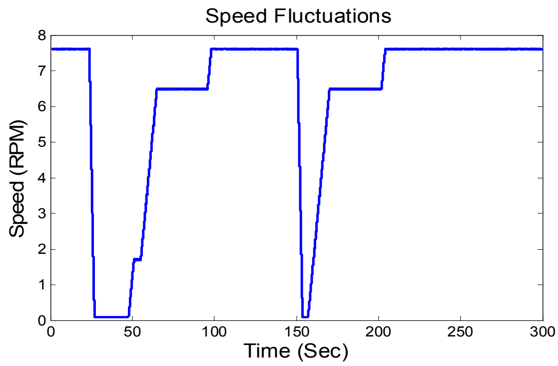

Figure 1 Typical machine speed variation

Due to the growing demands for the reliability, availability and productivity, condition monitoring system for these machines is increasing importance. Early prediction provides engineers information scheduling the maintenance. The cost of repair in case of catastrophic failure of these fillers is estimated at £10-20K and loss of production up to £20K per day. To prevent this loss, monitoring of critical parts especially filling station main bearing and driving gearbox (Figure 2) is an important part of this research.

In condition monitoring applications, different approaches are used for fault detection and prediction [15]. These techniques include model-based parameter estimation [10], statistical based system [7], [14], knowledge based expert system [3], [5], genetic algorithms and neural network [5], Fuzzy inference system [16], [22]. Artificial Intelligence techniques have numerous advantages over conventional fault diagnostic approaches. These techniques can be made adaptive by incorporating new data and information. But their performance is reduced when enough knowledge of abnormal behaviours is not present. An advantage of Fuzzy logic is that it matches closely the human decisions making system. Fuzzy logic gives the clear rule base approximation of functions of the machine [15]. This is first time fuzzy system has been used in the field of bottle filling machines. Experiments have been taken to check its feasibility in machine failure detection scenarios.

In this paper fuzzy based system has been used to map the normal and expected abnormal behaviours of the machine. Different authors used the different techniques in classification of machines faults data. In [14], Ramachandaran used the fuzzy classifier system to detect faults present in the bearings. Statistical features are extracted and selected by the decision tree and passed to fuzzy inference system. In [20], hybrid technique is used in which time domain, frequency domain and time-frequency domain features are extracted for gearbox and passed to the neural network classifiers for fault analysis. Since neural network is like a black box and does not provide additional explanations of relationships of defect symptoms and causes. Therefore rule base approach is used to predict the abnormalities present in the machine components. Fuzzy system is developed based on the process of the machine and implemented on the machine to predict any deviation from the normal behaviour.

2. CONDITION MONITORING OF FILLING MACHINE

Condition monitoring of Stork filler is based on vibration signal analysis and development of a standalone application for automatic diagnostics of critical machine components. The system is composed of three sub-systems; sensing system, acquisition system, statistical features analysis & fuzzy inference.

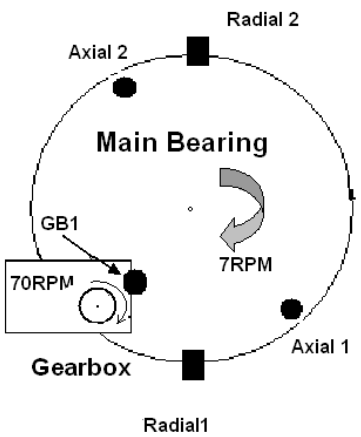

Figure 2 Accelerometers location on the filler

2.1. Sensing System

Accelerometers are used to measure vibration signature from critical components of the machine. Industrial standard accelerometer with sensitivity 100mV/g is used in this research. Four accelerometers are placed on the main bearing because it is the most critical part of the filler, one on the main gearbox, and one on each shaft bearing. The location of vibration sensors is an important part of designing condition monitoring system. Optimal locations for sensors are determined by looking at the design of the machine. The placement of accelerometers is a challenging task because access to machine components like main bearing is limited which is a constraint for installation. Figure 2 shows the location of two accelerometers on the main bearing bolted in axial/load direction and two sensors glued in radial direction

2.2. Data Acquisition System

National Instrument USB 6210 is used to capture the vibration data from the accelerometers. Algorithms are written in MATLAB to acquire data from hardware and stream it to the SQL server database for storage.

2.3. Statistical Data Analysis

The stored data is analysed in MATLAB by using time and frequency domain features. Fuzzy systems are developed for both time and frequency domain features separately. This will produce two parallel outputs for each machine component health status as indicated in figure 14. Two outputs of the fuzzy system provide confidence on analysis.

3. TIME DOMAIN DATA ANALYSIS

Vibration signature changes with varying speeds of machine. Algorithms are written to classify the data on the basis of the speeds of the filler. Different statistical features are extracted from the raw vibration data. Table 2 shows the features extracted from time domain vibration signal and their mathematical equations.

TABLE 2. TIME DOMAIN FEATURES DESCRIPTION

Time Domain Features	Mathematical Expressions
Root Mean Square: It shows the effective energy or the power content of vibration signal [23]. xi=vibration data, N= Total samples	$rms = \sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i^2}$

Variance: It is variance of values around the mean value.	$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^2}$
Kurtosis: It indicates the flatness or spikiness of the signal [23]. It is a good indicator of outliers. Fourth power gives considerable weight to large amplitudes and good indicator of spikiness from whole signal.	$Kurt = \frac{\sum_{i=1}^{N}(x_i - \mu))^4}{N\,\sigma^4}$
Crest Factor: Ratio of peak value to root mean square value. It tells information of repetitive Impacts.	$cf = \frac{\max(x)}{rms(x)}$
Skewness: Degree of asymmetry of the signal around its mean [27].	$Skew = \frac{\sum_{i=1}^{N}(x_i - \mu))^3}{N\,\sigma^3}$
Shape Factor: Ratio of the RMS value to mean absolute value [23].	$sf = \frac{rms(x)}{mean[abs(x)]}$

3.1 Feature Selection by Correlation Coefficients

Correlation coefficients are calculated for time domain statistical features dataset. From correlation matrix, eigen values are created. The features that have eigen values within +/-10% error are grouped together. Figure 3 indicates the different features in three dimensional co-ordinates. RMS and variance have strong correlation because they have similar values if the mean value is zero. Skewness and kurtosis carrying different information about data have considerable variance. Figure 3 shows kurtosis and shape factor have strong correlation and having less variance. So either kurtosis or shape factor can be selected for fuzzy system input.

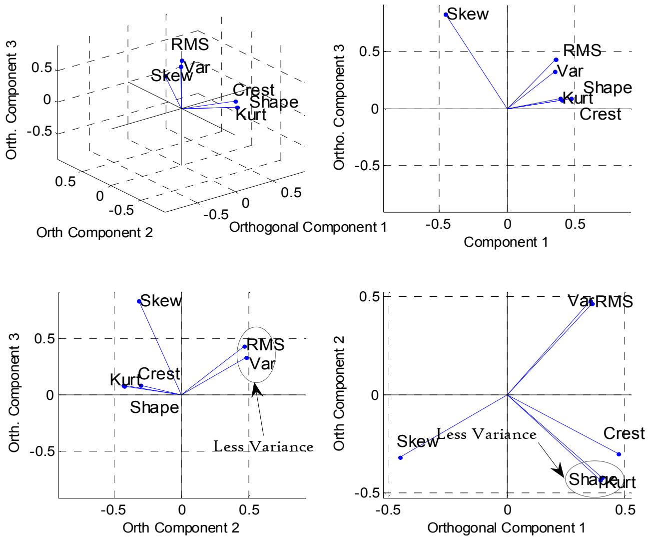

Figure 3. Plots for features selection

4. FUZZY BASED INFERENCE SYSTEM

Fuzzy systems are capable of handling complex, non-linear and dynamic systems using simple solutions [16]. In fuzzy systems, the numerical input values should be first converted into the corresponding fuzzy representations by using fuzzifiers [26]. Fuzzy outputs are then provided by a fuzzy model, which could be a set of fuzzy logic rules, fuzzy relations or even a simple fuzzy table. Finally, the fuzzy output can be converted back to their relevant numerical crisp outputs through defuzzifiers [16]. Basic configuration of fuzzy systems is shown in Figure 4.

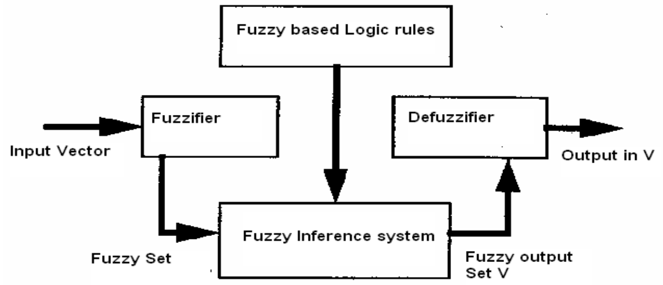

Figure 4. Fuzzy Inference Systems

Matlab provides a Fuzzy Logic Toolbox to help design and test a fuzzy logic control system. The toolbox includes Fuzzy Inference System (FIS) Editor that helps the users to define the input and output membership functions and to create rules [11]. Matlab fuzzy toolbox provides Mamdani and Sageno type of FIS. Mamdani has easy formalization and interpretability, reasonable results with relatively simple structure, used for multi-input multi-output and multi-input single-output system. Sugeno is more robust and good for noisy data but only provide one output [17]. In this paper, Mamdani inference system has been deployed to analyse the features of the vibration data. Selected features are used as fuzzy input to the FIS.

4.1 Inputs for FIS

Trapezoidal membership functions are used in Matlab FIS [18]. Their values are chosen by looking at the data distribution. The percentile ranks approach is used and two times standard deviation (95%) are used for selecting membership functions. Three membership functions are selected by mapping each of four inputs features of the vibration data. 95% of feature values from full running speed of machine are mapped in the normal membership function while 95% of the CIP vibration data features values are mapped in the medium membership function because these features have significantly different distribution compared to full running speed features. Membership functions for time domain features are shown in figure 5-7.

4.2 Output Membership Function

The output of the Mamdani based system is defuzzified by the use of centroid method. The output shows the indication of the machine status shown in figure 8. Green indicates the normal behaviour of the machine, amber indicates the start of wear or CIP process and red indicates severity of fault. The output of the filler is shown along with filler speed shown in figure 14.

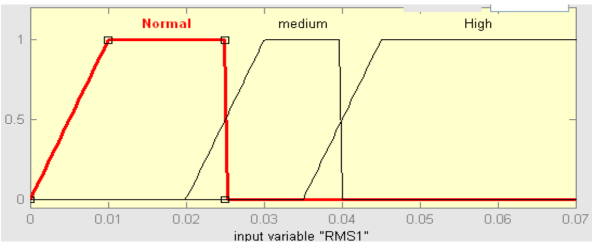

Figure 5 RMS Input with Three Membership Functions

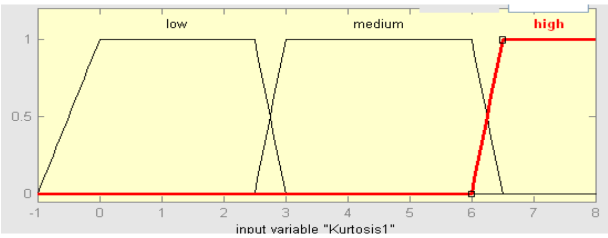

Figure 6 Kurtosis Input with Three Membership Functions

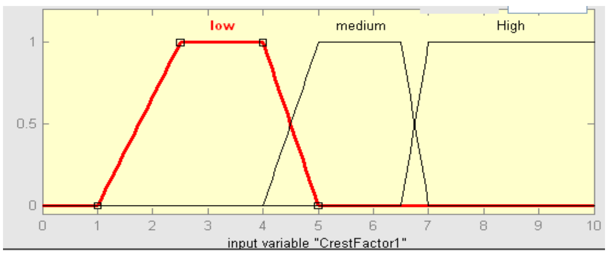

Figure 7. Crest Factor with Trapezoidal Membership Functions

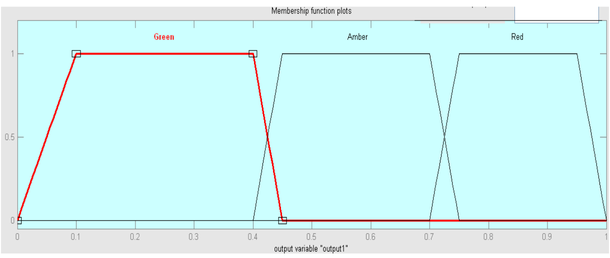

Figure 8. Output Membership Functions

5. FREQUENCY DOMAIN ANALYSIS

Frequency based statistical analysis is done to increase the confidence on time domain analysis. Frequency domain statistical features are extracted from the vibration spectrum and input to the fuzzy system. The MATLAB fast Fourier transform function is used to compute the spectrum of the data. Table 3 shows the frequency domain features extracted from FFT of vibration signal.

Table 3. FREQUENCY DOMAIN FEATURES DESCRIPTION

Frequency Domain Features	Mathematical Expression
Mean frequency: The average value of the spectrum is useful feature. xi=FFT lines, N=Length of series	$Mean = \frac{1}{N}\sum_{i=1}^{N} x_i$
Maxima: It is dominant frequency component in spectrum [19].	$Maxima = \max(x_i)$
Entropy: It is the overall energy carried by the spectrum [19].	$Ent = -\sum_{i=1}^{N} x_i.\log_{10} x_i$
Spectral Centroid It is central frequency of the spectrum and indicates the relative location of centre of gravity [7].	$Centroid = \frac{\sum_{i=1}^{N} x_i \cdot f(x_i)}{\sum_{i=1}^{N} f(x_i)}$

5.1 Inputs for FIS

Mamdani based system has been used for the frequency domain features mapping. These features are mapped by calculating feature distribution. Trapezoidal membership functions are used as shown in figure 9-12.

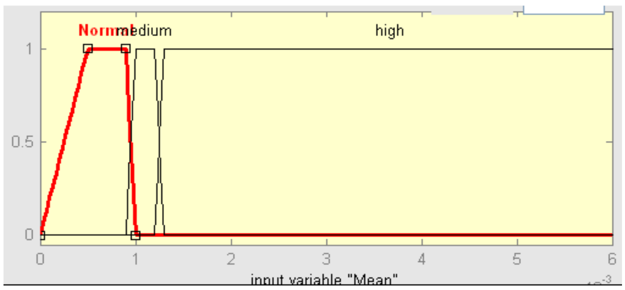

Figure 9. Mean value Membership Functions

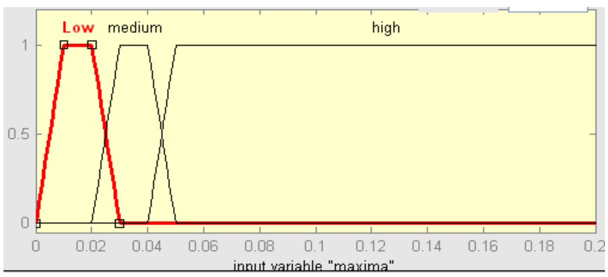

Figure 10. Maxima Membership Function

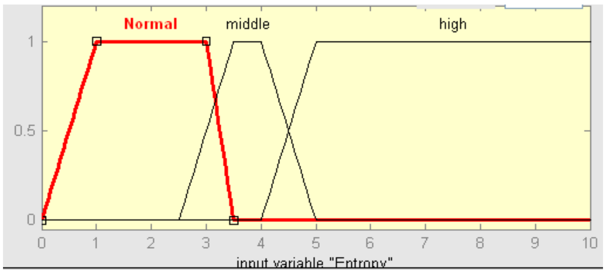

Figure 11. Entropy Membership Function

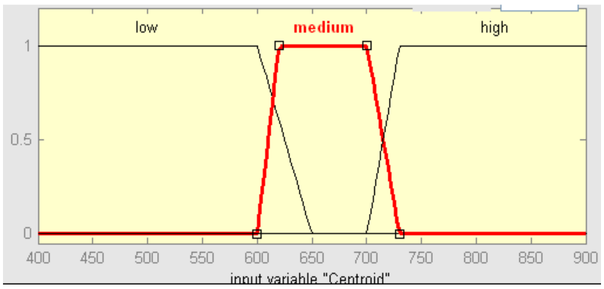

Figure 12. Spectral Centroid Membership Functions

5.2 Output Membership Function

The output of the fuzzy system is used to decide the machine condition. The data from the membership function (MF) is mapped in the output membership function to detect the machine scenarios. Red MF corresponds to the presence of fault in the bearing or gearbox. MATLAB GUI shows two fuzzy outputs for time and frequency domain analysis.

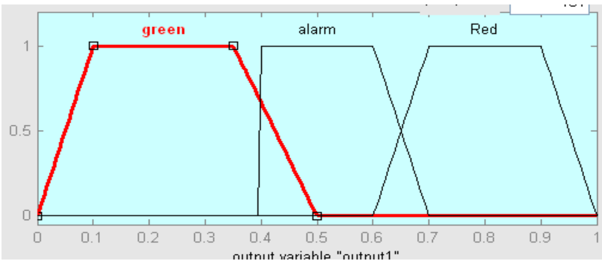

Figure 13. Output Fuzzy Membership Function

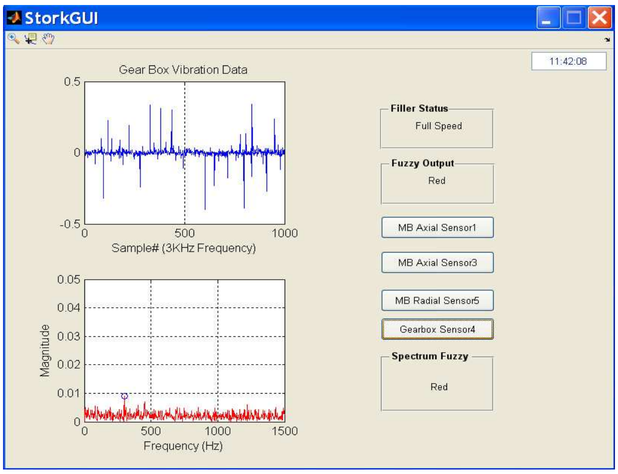

Figure 14. GUI for Monitoring System indicating Fault

6. ANALYSIS & RESULTS

The vibration data taken from normal machine operations have been mapped in fuzzy based system. System has been attached the filler to predict any abnormalities in different components. The system continuously monitored the filler vibration signature and stored the data in SQL server database. The system output is checked at different intervals of time. After two months of installing the system, the fuzzy based system indicated red output in main gearbox sensor output as shown in figure 13. Data have been carefully analysed to check the accuracy of fuzzy algorithm. The main gearbox attached to the filler is generating the spiky signal and both time and fuzzy domain fuzzy algorithm shows the red output.

6.1 Engineer Findings

Fuzzy based system predicted the fault present in the gearbox. To justify that, an engineer was sent to the machine to manually look on the gearbox. It has been found out that gearbox output shaft is loose and rubbing with the outer wall of the gearbox which indicated that gearbox inner shaft bearing is damaged. Since Management of the company decided to run the machine until new gear box arrived. High vibration in the machine may affect the other parts of the machine but company does not want to stop the machine.

6.2. Statistical Features

Time domain statistical features are analysed based upon faulty data. The mean value of the both signal is almost the same but kurtosis, crest factor and skewness is changed significantly as shown in figure 15. Kurtosis is sensitive to spikiness in the signal and a very helpful tool for finding faults in the initial stage. Figure 16 shows the kurtosis factor distribution at different time of vibration data. But as the degradation increases, the RMS value of the signal increases result in decrease kurtosis factor but increase in crest factor gives the good indication of the fault. That is why both kurtosis and crest factor are used in the feature dataset. Figure 15 indicates the developing gearbox fault in the machine.

In frequency domain, entropy and centroid gives good indication of faults. Figure 17 indicate the normal vibration features and faulty vibration features in one graph. During the shaft rubbing and looseness, the signal energy increases and entropy is good indicator of this change.

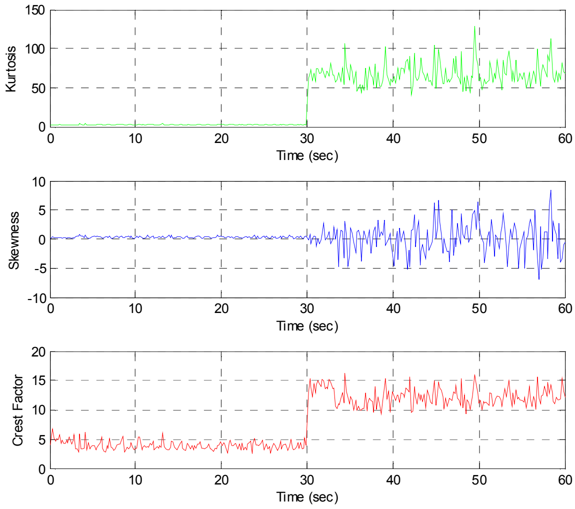

Figure 15. Normal& Faulty statistical features for gearbox

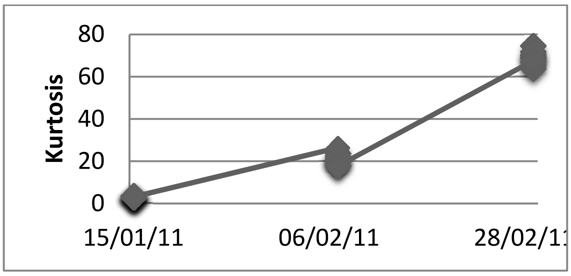

Figure 16. Kurtosis factor increase over time

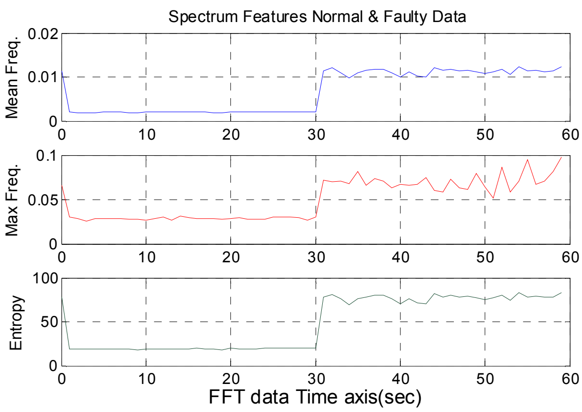

Figure 17 Normal & Faulty statistical features for gearbox

CONCLUSION

Condition monitoring system is implemented on the machine and has successfully detected gearbox defect. The eminent time and frequency domain statistical features provide the intelligent way of predicting the condition of the low rotating machines. At this low speed, frequency components present in vibration spectrum are buried in the noise floor and difficult to distinguish. But statistical features provide the systematic way of modelling the process machines and fault findings based upon vibration data. The proposed methodology has several advantages. The fuzzy based approach is simple and industrial engineers can understand the algorithms and tune the system based upon data. Another big advantage of using fuzzy system is that it can be customised to other Stork fillers. Fuzzy membership function values are determined from data distribution and rules for data remain the same. The rules used for fuzzy system are interpretation of expert knowledge and experience. In this system, simple traffic light based system Red, Amber, Green has been used which make the visualisation easier and simple.

REFERENCES

[1] M. M. Gupta, "Fuzzy Logic and Fuzzy Systems: Recent Developments and Future Directions," *Intelligent Systems Research Laboratory*, 1996.

[2] H. R. Martin, F. Honarvar, "Application of statistical moment for diagnosis of rolling element bearing," 1997

[3] J. B. Kneale, "Application of expert system techniques to fault tree diagnostic data," *IEEE Autotestcon Proceedings,* 1997

[4] M. P. Norton, D. Karczub, "Fundamentals of noise and vibration analysis for engineers," Cambridge University Press, 2003

[5] M. T. Jones, "Artificial Intelligent Application Programming, 1st Edition," New Delhi, 2003, p235-255

[6] S. Ahmed, S. Al-Kazzaz , G.K. Singh, "Experimental investigations on induction` machine condition monitoring and fault diagnosis using digital signal processing techniques," *Electric Power System Research,* 2003

[7] Z. Kiral, H. Karagulle, "Simulation and analysis of vibration signal generated by rolling element bearing with defects," *Tribology International,* 2003

[8] X. Lou, K. A. Loparo, "Bearing fault diagnosis based on wavelet transform and fuzzy inference," 2004

[9] A. Malhi, "PCA based features selection scheme for machine defect classification," *IEEE Transaction in Instrumentation and Measurement,* Vol. 53, No. 6, 2004.

[10] R. Isermann, "Model based fault detection and diagnosis - Status and application," 2004

[11] W. D. Harbour, T. W. Martin, "Development of a Fuzzy Logic Control System in Matlab for an Air Impingement Oven," *IEEE Conference on Industrial Electronics,* 2006

[12] H. Qian, Y. Liu, P. Lv, “Kernel principal component analysis for early identification of gear tooth crack,” *Congress on Intelligent Control & Automation,* 2006

[13] B. D. Hahn, D. T. Valentine, “Essential Matlab for Engineers and Scientists,” 3rd Edition, 2007

[14] N. Saravanan, K. Ramachandran, “Automatic rule learning using decision tree for fuzzy classifier in fault diagnostic of roller bearing,” *Mechanical Systems & Signal Processing* 21,2007, pp. 2237-2247

[15] F. Filippetti, A. Bellini, Advancements in diagnostic techniques for induction machines, 2008

[16] B. S. Nordin , O. Wahyunggor, “Development of Fuzzy-Logic-Based Self Tuning PI Controller for Servomotor,” *International Conference on Control, Automation, Robotics & Vision* 2008

[17] A. Hamam, N. D. Georganas, “A Comparison of Mamdani and Sugeno Fuzzy Inference Systems for Evaluating the Quality of Experience of Hapto-Audio-Visual Applications” *IEEE Workshop on Haptic Audio Visual Environments and their Application,* 2008

[18] K. Mollazade, H. Ahmadi, M. Omid, R. Alimardani, “An intelligent combined method based on the Power spectral density, decision trees and fuzzy logic for hydraulic pumps fault diagnostic,” *International Journal of Electrical and Computer Engineering,”* 2008.

[19] W. Dargie, “Analysis of time and frequency domain features of accelerometer measurements,” 2009

[20] Y. Lei, M. J. Zuo, Y. Zi, Z. He, “A multidimensional hybrid intelligent method for gear fault diagnostic,” 2009

[21] C. Ching, S. Shieh, Intelligent Vibration signal diagnostic system using artificial neural network, *Second International Conference on Computational Technology & Automation,* 2009

[22] L. Jin, W. Shufen, “Applications of Information Fusion Based on Fuzzy Neural Network to Rotating Machinery Fault Diagnosis,” *Intelligent Information Technology Workshop* 2009

[23] Z. Luo, Q. Chen, P. Chen, X. Zhou, “Multi-fault Diagnosis of Gear based on Sequential Fuzzy Inference,” 2010

[24] L. Navarro, M. Delgado, J. Urresty, J. Cusidó, L. Romeral, “Condition monitoring system for characterization of electric motor ball bearings with distributed fault using fuzzy inference tools,” *IEEE Instrumentation and Measurement Technology Conference,* 2010

[25] W. Dargie, M. K. Denko, “Analysis of Error-Agnostic Time and Frequency domain features of extracted from measurement of 3-D Accelerometer Sensors,” *IEEE Systems Journal*, Vol. 4 No.1, March 2010

[26] H. Wang, P. Chen, “Fuzzy Diagnosis Method for rotating machinery in variable rotating speed,” *IEEE Sensors Journal,* Vol. 11 No.1, Jan 2011

[27] Matlab Data acquisition, Database Toolbox, Fuzzy and Statistical toolbox, www.mathworks.co.uk

[28] Stork Food and Dairy System, Stork Bottling & Blow Moulding www.sfds.eu

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