Proceedings of the 6th JFPS International
Symposium on Fluid Power, TSUKUBA 2005
November 7-10, 2005

WAVELET APPROACH FOR PERFORMANCE MONITORING AND DIAGNOSIS OF A HYDRAULIC PUMP

Yingjie GAO*, Xiangdong KONG*, Qin ZHANG**

* Department of Mechatronic Engineering, ,
Yanshan University
Qinhuangdao, Hebei, 066004 China
(E-mail: yjgao@ysu.edu.cn)
** Department of Agricultural and Biological Engineering
University of Illinois at Urbana-Champaign
Urbana, IL 61801, USA

ABSTRACT

Hydraulic pump performance monitoring methods that can detect failures by using the outlet pressure signals of the pump are investigated. Two faults diagnosis methods, namely conventional spectral analysis method based on FFT and wavelet based multi-resolution analysis method, are introduced and their efficiency and reliability are discussed. The performance of both diagnoses methods were evaluated based on simulation results and experimental results. Validation results obtained from using both methods in analyzing the same sets of data indicated that the wavelet transform based fault diagnosis method showed a more sensitive and robust detecting results for all three tested pump faults than that obtained from a spectrum analyses approach.

KEY WORDS

Wavelet based MRA, FFT spectrum analysis, fault diagnosis, hydraulic pump

INTRODUCTION

The purpose of performance monitoring and fault diagnostics are to detect and distinguish faults occurring in machinery, in order to provide a significant improvement in plant economy, reduce operational and maintenance costs, and improve the level of operation safety. Hydraulic systems have been used in a wide variety of applications ranging from precision control on machine tools to task implementation on construction equipment and aircraft because of its advantages, i.e., the high force to weight ratio, forces can be rapidly generated and transmitted over considerable distances with very little loss, etc. A hydraulic pump is a key component in a hydraulic system, and its performance will affect the reliability of any hydraulic systems. Therefore, a sensitive and accurate faults detection and identification method for hydraulic pump performance monitoring and diagnosis has great interest to the industry.

For hydraulic pump/motor performance monitoring, potential signals which can be employed include oil chemical properties, temperature signal, vibration of the shell, flow rate and pressure signals. Efforts have been made to implement on-line monitoring and fault detection techniques using easily monitored operating parameters. Jardine *et al*. [1] used a proportional hazards modeling statistical approach to optimize a mine haul truck wheel motor condition monitoring program by analyzing oil test results. Although oil analysis has proven a good tool for timing oil changes and even fault detections, it has two drawbacks: 1) the difficulty of obtaining a representative of oil sample and 2) the temporal requirements for sampling, testing, and evaluating results. Flow data is a hydraulic pump operation parameter that is a good indicator of pump failure; however, flow data is not cheaply and reliably obtained during typical operation and is not applicable to variable displacement pump either in real applications. As temperature signals are associated with the working environment, they are not fit to detect the malfunction of pump. Therefore, reliable means of analyzing more readily sensed signals is more desirable. Because of high noise levels in the pump pulsation pressure signal, many existing health diagnosis methods, such as limit checking, spectrum analysis, and logic reasoning, cannot effectively perform a reliable on–line health diagnosis for hydraulic pumps [2].

Many different diagnostic tools have been used for health diagnosis purposes and system performance monitoring. An and Sepehri [3] demonstrated a scheme in which an extended Kalman Filter is used to estimate the state of a hydraulic actuator system. By comparing with the corresponding measured states, the residuals between the actual state of system and the estimator could be used to determine if there any defects occur. Wolfman, *et al*. [4] proposed a multi-model approach for fault detection and diagnosis of a centrifugal pump. The whole process was decomposed into three sub-models pump, pipes, and mechanical subsystem. Individual neural-fuzzy sub-model was associated with each component to generate relative normal state. Evaluation residuals then were designed to implement the fault detection process. The superior of this method is the capability of supervision of nonlinear system and consequently the accuracy of the diagnosis may be improved.

Parametric models have been developed and tested for on-line diagnostics of hydraulic pumps [5][6]. Although sound and proven theoretical approaches to on-line hydraulic pump health diagnosis, these methods are dependent on the accuracy of the parametric model chosen [7]. Since many factors can influence pump performance, parametric models are difficult to perfect. The complexities of interrelating pump operating parameters are not easily modeled. Using methods that are not sensitive to slight changes of pump operating features would allow more applicable and reliable pump health diagnostics.

Fourier transforms decompose a signal into its frequency content. From this decomposition, a power spectrum can be calculated to determine which frequencies are most prevalent in the signal. Similarly, wavelet analysis, a waveform signal analysis method performed by breaking up an evaluating signal into shifted and scaled versions of a standard wavelet, can identify feature signals in multiple decomposed band window of the original signal [8]. Where the FFT decomposes a signal into scaled versions of a sine wave, wavelet analysis can decompose a signal into both scaled and shifted versions of almost any waveform preserving the time parameter of the signal. Both methods are sensitive to changing of the evaluating signals in interested frequency bands. Therefore, these two methods are promising hydraulic pump fault detection techniques as each method allows for each system to create a characteristic pattern for the pump being monitored on a specific machine. This flexibility will eliminate errors often encountered by model-based techniques.

In this paper, outlet pressure data of the pump is selected as the signal to evaluate because most hydraulic systems already have pressure gauges incorporated into the system for monitoring during operation. The presence of this signal in most hydraulic systems makes it a prime candidate to use in an on-line hydraulic pump health monitoring system. The pressure signals were analyzed using two methods, Fourier transforms and wavelet packet analysis, in order to achieve high accuracy and reliability for pump performance monitoring.

FUNDAMENTAL OF METHODOLOGY

FOURIER TRANSFORMS – Fourier transforms decompose a signal into its frequency content by comparing various scales of a sine wave to the signal. The result is a frequency versus amplitude relationship. Here, the discrete Fourier transform in Eq. (1) is calculated using the Fast Fourier transform (FFT) algorithm.

$$F_n = \sum_{k=0}^{N-1} f_k e^{-(2\pi i)nk/N} \qquad (1)$$

From the Fourier transform of the pressure signal, the power spectra was calculated and used to determine which frequencies are most prevalent in the signal.

WAVELET AND WAVELET PACKET ANALYSIS - Wavelet analysis is a waveform signal analysis method performed by breaking up an evaluating signal into shifted and scaled versions of a standard wavelet. However, there are two important differences between wavelet analysis and Fourier transforms. Where the FFT decomposes a signal into scaled versions of a sine wave, wavelet analysis can decompose a signal into scaled and shifted versions of almost any waveform. Waveforms can be selected to closely match the shape of the signal being analyzed. Selecting a waveform to be similar to a normal signal provides more sensitivity to detecting changes [8]. Secondly, wavelet analysis retains the time dimension of the data. The chosen wavelet is compared to local sections of the signal through translation of the wavelet along the signal at different dilations or scales of the mother wavelet. Wavelet coefficients are preserving the time parameter of the signal. This distinguishing feature of wavelet analysis allows the time of a specific event to be identified. For this research, the discrete wavelet transformation (DWT) is used. The DWT uses the power-of-two logarithmic scaling of both the dilation and translation steps, known as a dyadic grid arrangement. The discrete wavelet transform of a signal using a mother wavelet $\psi_{m,n}(t)$ using the dyadic grid is shown in Eq. (2).

$$W_{m,n}(f) = 2^{-m/2}\int dt f(t)\psi(2^{-m}t-n) \qquad (2)$$

Where, m,n range over Z (integer space). For a special choice of $\psi(t)$, the discrete wavelets can constitute an orthonormal basis, and a signal $f(t)$ can be represented by the sum of its smooth approximation (low-pass) and its detail description (band-pass), which is given by

$$\begin{aligned} f(t) &= \sum_{n=-\infty}^{\infty} < f, \varphi_{m_0,n}(t) > \varphi_{m_0,n}(t) \\ &\quad + \sum_{m=-\infty}^{m_0}\sum_{n=-\infty}^{\infty} < f, \psi_{m,n}(t) > \psi_{m,n}(t) \qquad (3) \\ &= P_{m_0} f(t) + \sum_{m=-\infty}^{m_0} D_m f(t) \end{aligned}$$

Where, the first term $P_{m_0} f(t)$ is the coarser approximation of $f(t)$ in scale m_0, and the second term $D_m f(t)$ leads to the differences among each dilation. $\varphi(t)$ is the so called 'scaling function' [9]. Consequently, there is $P_{m_0-1} f(t) = P_{m_0} f(t) + D_{m_0} f(t)$. Which implies that: if a signal is fine-scale approximated at $P_{m_0} f(t) = f_0$, then it can be decomposed into $f_0 = P_{m_0+1} f(t) + D_{m_0+1} f(t) = f_1 + d_1$, where f_1 is the next coarser approximation of f_0, and d_1 is what is lost in the transition from scale m_0 to m_1. Using the same approach, the ith level decomposition of the original signal f_i can be further decomposed into $f_i = f_{i+1} + d_{i+1}$, i = 1, 2, ..., . The approximation of f_0 in the ith level can be represented with the approximation coefficient vector with the scaling function, whilst the detail of f_0 is represented with the detail coefficient vector and the scaled mother wavelet as shown in Eq. (4).

$$\begin{aligned} f_0 &= \sum_{n=-\infty}^{\infty} < f, \varphi_{0,n}(t) > \varphi_{0,n}(t) = \sum_{n=-\infty}^{\infty} a_{0,n}\varphi_{0,n}(t) \\ f_i &= \sum_{n=-\infty}^{\infty} < f, \varphi_{i,n}(t) > \varphi_{i,n}(t) = \sum_{n=-\infty}^{\infty} a_{i,n}\varphi_{i,n}(t) \qquad (4) \\ d_i &= \sum_{n=-\infty}^{\infty} < f, \psi_{i,n}(t) > \psi_{i,n}(t) = \sum_{n=-\infty}^{\infty} da_{i,n}\psi_{i,n}(t) \end{aligned}$$

In harmonic analysis, such a decomposition procedure is referred to as a 'two-channel' sub-band filtering scheme. The incoming sequence is convolved with two different filters, one low-pass and one high-pass. The two resulting sequences are then sub-sampled. Based on this scheme, a set of examining signals is decomposed using a low–pass filter and a high–pass filter, which results in two sets of sub–band signals. The sub–bands signals are then reassembled to perform wavelet analysis. Schematically, the scheme of a three–level decomposition wavelet analysis to reassemble the original signal and the sub-band by each sub-sampled signal can be represented as shown in Figure 1.

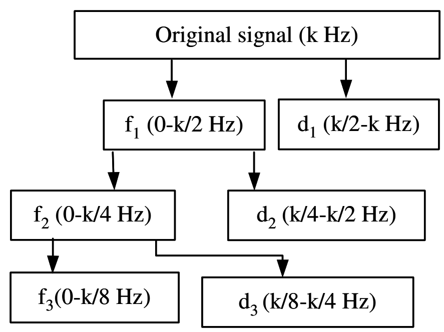


Figure 1 A three level wavelets decomposition scheme

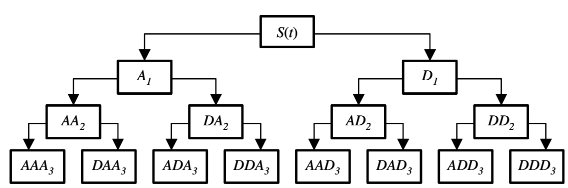


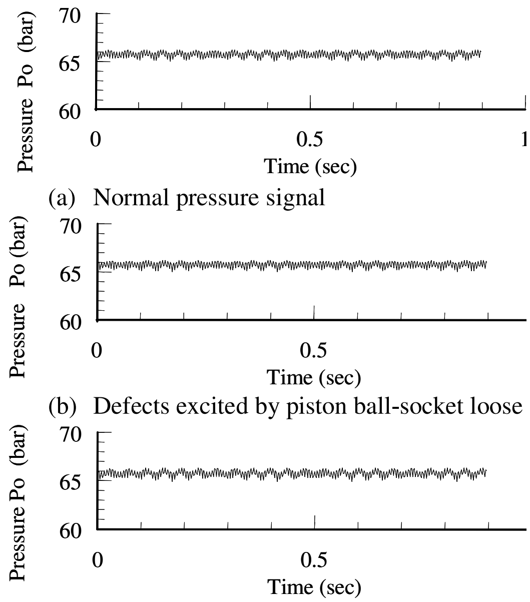
Figure 2 Wavelet packet decomposition

Unlike wavelet analysis, in which only the

approximation of the signal is further decomposed and the number of details depends on the level of decomposition, wavelet packet analysis decomposes both approximations and details of a signal. Hence, wavelet packet analysis is capable of identifying feature signals in multiple decomposed band windows of the original signal. Figure 2 illustrates the decomposition of a signal using wavelet packet analysis with three level decomposition.
From wavelet analysis of the pressure signal, the wavelet coefficients corresponding to interested sub-band are calculated and used to determine if defects of the monitored pump occur.

FAULT DETECTION AND DIAGNOSIS RESULTS

SIGNAL SELECTING - The common faults of an axial piston pump include swash plate wear, control (or valve) plate wear, loose of the ball-socket joints, bearing failure, and fatigue failure of the central return spring. Those faults will be reflected in the pump discharge pressure and are normally buried in the pressure pulsating signals. Furthermore, other fault scenarios, such as cavitation, hydraulic blocking, pipe resonance and leakage, will also be reflected in the discharge pressure signals. Thus, the pressure signal covers sufficient information and takes little effectives of the background noise signals because of its property of ‘inner measurement’. When compared with the vibration signal, the pressure signal is considered more suitable for the analysis and detection of faults of the axial pump. This paper considers two kinds of common faults of the axial piston pump, namely control plate wear and loose ball-socket joints. For validating the proposed method, simulations and analysis based on a theoretical model are carried out prior to completing the experiment itself.
SIMULATION ANALYSIS – A simulation model of piston pump was developed for this investigation in previous work [10]. For a pump with seven pistons, where the rotational speed is n (rpm), then the rational flow pulsation frequency is $\omega_1 = 14\pi n/60$ (rad/s), the disturbance frequency due to piston ball-socket excitation is $\omega_2 = 2\pi n/60$ (rad/s), and the disturbance frequency due to swash plate excitation (ω_3) depends on the worn condition of the swash plate. Under normal operating conditions, the pump speed (n) was set at 1470 rpm, and the swash plate was worn within the high-pressure area. This resulted in the following parameters for the model: $\omega_1 = 1077.57$ (rad/s) = 171.5 (Hz), and $\omega_2 = \omega_3 = 153.94$ (rad/s) = 24.5 (Hz).
In this case, ω_1 is the highest frequency, and ω_2, ω_3 are each $\omega_1/7$. Therefore, the proper critical frequency should be around ω_2. the simulation signals of the normal condition and two malfunction scenarios are shown in Figure 3.



(a) Normal pressure signal

(b) Defects excited by piston ball-socket loose

(c) Defects excited by swash plate worn

Figure 3 Simulation results based on the pump pulsation model

Figure 4 shows the Fourier transform result for the simulation results. From these plots, the feature frequencies are identified to be 25 Hz, 158 Hz, and 185 Hz. Where frequencies of 158 and 185 Hz figure out the normal pulsation frequencies of outlet pressure of the pump, the frequency 25 Hz features malfunction of pump. The power spectrum changes most between pumps at the 25 Hz regions. Therefore, the power of the signal was summed for a 30 Hz window around this key frequency in order to create a feature parameter to judging the performance of the monitored pump.
By applying Fourier transform, the summation of the spectra power of each fault signal from 10 Hz to 40 Hz is compared with the one of the normal signal to form a relative residual. Similarly, applying a three level wavelet packet transform to the original pressure signals, eight wavelet coefficients can be obtained for each signal. The square root of the summation of square coefficient vector to each wavelet coefficient is calculated to construct a wavelet feature parameter. Then the fault wavelet feature parameters are compared with the normal feature parameters to determine the residuals of wavelet analysis. This process can be described as the following equation:

$$FR = \left| \frac{\sum fP - \sum nP}{\sum nP} \right|$$
$$WR_i = \left| \frac{\sqrt{\sum fc_{3,i}^2} - \sqrt{\sum nc_{3,i}^2}}{\sqrt{\sum nc_{3,i}^2}} \right| \qquad (5)$$

where, *FR* is the Fourier residual, *fP*, *nP* the fault and normal power of signal. *WR* is the residual of the wavelet analysis, *fc*, *nc* the fault and normal wavelet coefficients. The results are shown in Table 1.

When looking round the simulation results shown in Table 1, it can be seen that the Fourier residuals and the wavelet residuals within 23 to 46 Hz are sensitive to the change of pump performance. If the obtained residual value exceed relative threshold value for a health pump, it can conclude that the corresponding pump is faulty. This result can be used to design an on-line pump performance monitoring and diagnosis algorithm.

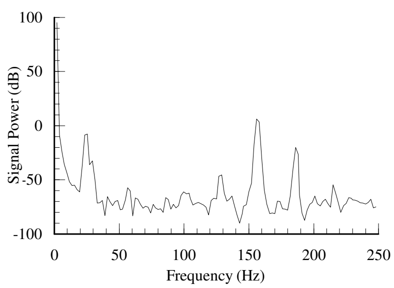
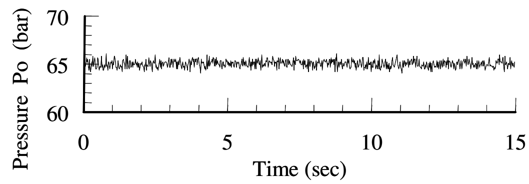


Figure 4 Spectra analysis of the pressure signal

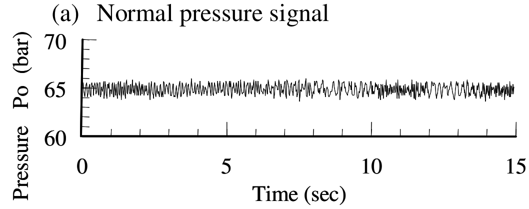
EXPERIMENTAL VALIDATION - The validation test of the proposed fault diagnosis methods are conducted on a laboratory scale hydraulic system test-rig. The test-rig consists of an electro-hydraulic servo valve, two testing pumps (a normal pump and a defected pump), and other auxiliary devices and sensors. The pumps used in this test are 10 ml/rev fixed displacement axial piston pumps. Both pumps were operated at 1,470 rpm. The system pressure was $6.5\text{x}10^6$ Pa set by a relief valve. The pressure sensors are installed on the discharge port of the pumps for collecting the pressure signals. When one pump was being tested, the otherpump was shut off to avoid any possible inference to the discharge pressure of the testing pump. The obtained pressure signal was analyzed on–line using a MATLAB program developed for this research based on the method discussed earlier in this article.

Figure 5 shows the pump discharge pressure obtained from the normal pump, a defective pump with loose ball-socket, and a defective pump with a worn swash plate. The residuals obtained are shown in Table 2.

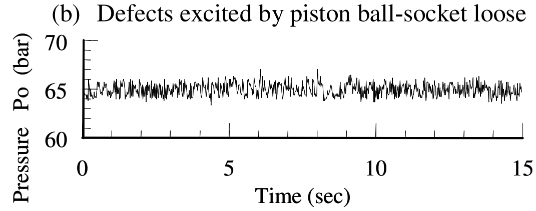
Comparing the results showed in Figure 5, the raw signals, the discharge pressures, showed little difference between the normal pump and the defected pumps. This indicates that the surface data (for the pump outlet pressure), was not able to provide sufficient information to support pump health diagnosis. After applying wavelet decomposition on the raw pressure signals from three pumps, wavelet residuals from both defected pumps (within 23 to 46 Hz and 69 to 93 Hz) resulted in wilder variations than that of the normal pump. Both the theoretical analysis and experimental tests showed that the 3rd level wavelet decomposition could extract the feature signals from pump discharge pressure signal for diagnosing the piston pump health conditions. More importantly, the patterns of the coefficient changes were different for different types of pump defects. This fact verified that the wavelet analysis method can improve the capability of diagnosing the health conditions of the piston pumps by decomposing the original pulsation



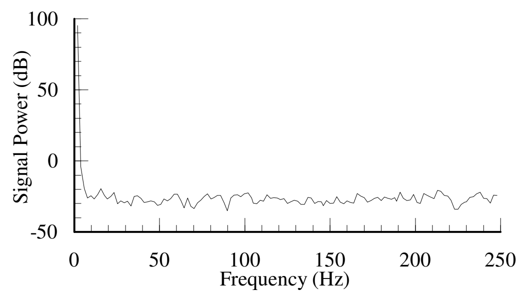
(a) Normal pressure signal



(b) Defects excited by piston ball-socket loose



(c) Defects excited by swash plate worn



(d) Spectra power of the pressure signal

Figure 5 Test pressure signals

Table 1 Simulation results: Fourier residuals and wavelet residuals

	Spectra analysis *FR*	Wavelet packet analysis WR								
		Sub-band (Hz)	0-23	23-46	46-69	69-93	93-116	116-139	139-162	162-185
f_{normal}	0	f_{normal}	0	0	0	0	0	0	0	0
f_{fault1}	3.6	f_{fault1}	0	0.263	0.004	0.021	0.085	0.036	0.003	0.0027
f_{fault2}	15.07	f_{fault2}	0	0.938	0.004	0.039	0.079	0.043	0.003	0.0017

Table 2 Test results: Fourier residuals and wavelet residuals

	Spectra analysis *FR*	Wavelet packet analysis WR								
		Sub-band (Hz)	0-23	23-46	46-69	69-93	93-116	116-139	139-162	162-185
f_{normal}	0	f_{normal}	0	0	0	0	0	0	0	0
f_{fault1}	0.089	f_{fault1}	0.003	0.668	0.707	0.883	0.201	0.178	0.470	0.368
f_{fault2}	2.738	f_{fault2}	0.002	0.949	0.309	0.553	0.871	0.439	0.212	0.322

pressure signals, and that the patterns and the amplitudes of wavelet coefficients obtained from different decomposed signal windows are relevant to the types of pump defects.

CONCLUSIONS

The use of discharge pressure provided the direct information for the diagnosis of the health of system signals. This can improve the diagnostic accuracy by overcoming the limitations caused by noise and disturbances acting on the indirectly measured signals. The following concluding remarks follow from the results obtained from theoretical analysis and experimental testing.

- The decomposition of the original pressure signals resulted in sub–band informative signals. Reassembling these sub–bands signals and comparing them with a standard wavelet resulted in distinguishable changes between wavelet coefficients from normal and defective pumps.
- The differences in the patterns and amplitudes of the resulting wavelet coefficients within different band windows provided distinguishable features to identify the types of pump defects.
- The validation tests proved that the wavelet analysis could be implemented on–line to support real–time health diagnosis without affecting the normal operation of the pump.

REFERENCES

1. Jardine, A. K. S., Banjevic, D., Wiseman, M., Buck, S., and Joseph, T., Optimizing a Mine Haul Truck Wheel Motors' Condition Monitoring Program: Use of Proportional Hazards Modeling, Journal of Quality Maintenance Engineering, 2001, **7**-4, pp.286-301.
2. Gerlter, J., Costin, M., Fang, X., Kowalczuk, Z., Kunwer, M., and Monajemy, R., Model-based Diagnosis for Automotive Engines –Algorithm Development and Testing on a Production Vehicle, IEEE Transactions on Control System Technology, 1995, **3**-1, pp.61-68.
3. An, L. and Sepehri, N., Hydraulic Actuator Circuit Fault Detection Using Extended Kalman Filter, Proceedings of the American Control Conference Denver, Colorado, 2003, June 4-6, pp.4261-4266.
4. Wolfram, A., Fussel, D., Brune, T., and Isermann, R., Component-Based Multi-Model Approach For Fault Detection And Diagnosis Of A Centrifugal Pump, Proceedings of The American Control Conference, Arlington, 2001, June 25-27, pp. 4443-4448.
5. Skormin, V. A., and Apone, J., On-line Diagnostics of a Variable Displacement Pump of a Flight Actuation System, Proceedings of the IEEE 1995 National Aerospace and Electronics Conference, Dayton, NY, 1995, V1, pp.503–510.
6. Liu, S., and Hung J.C., "On-line Diagnostics of a Variable Displacement Pump of a Flight Actuation System," Proceedings of I ECON 91, Institute of Electrical and Electronics Engineers, 1991, pp.2145-2150.
7. Hancock, K. M. and Zhang, Q., Maintenance and Fault Diagnosis Tools For Hydraulic Pumps, Proceedings of the 50th National Conference on Fluid Power, Las Vegas, Nevada, 2005, March 16-18, pp.361-369.
8. Addison, P.S., Discrete Wavelet Transform, Illustrated Wavelet Transform Handbook: Introductory Theory and Applications in Science, Engineering, Medicine, and Finance, Institute of Physics, London, 2002, pp.65–143.
9. Daubechies I., Ten Lectures on Wavelets, Capital City Press, Montpelier, Vermont, USA, 1992.
10. Gao, Y., Zhang, Q. and Kong, X., Waveletbased Pressure Analysis for Hydraulic Pump Diagnosis, Transactions of the American Society of Agricultural Engineers, ASAE, 2003, **46**-4, pp.969–976.