Proceedings of the 7th JFPS International
Symposium on Fluid Power, TOYAMA 2008
September 15-18, 2008

P2-19

COMPARISON OF VIBRATION AND PRESSURE SIGNALS FOR FAULT DETECTION ON WATER HYDRAULIC PROPORTIONAL VALVE

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ABSTRACT

The goal of this paper is to detect internal leakages created by seal faults and also identify which seal is damaged from water hydraulic proportional valve using vibration and pressure signals which are analyzed using different data analysis methods. In this study water hydraulic spool valve is studied in a test system during extending and retracting strokes of cylinder while vibration and pressure signals from the valve are measured in normal and different fault situations. Feature extraction is performed using descriptive statistics and wavelet analysis to identify the most influential variables from the measured signals which are then used to classify the state of the system using Self-Organizing Maps (SOM).

KEY WORDS

Water hydraulics, proportional valve, vibration, pressure, condition monitoring

NOMENCLATURE

- a : Acceleration [m/s^2]
- I : Current [A]
- m : Mass [kg]
- p : Pressure [bar]
- Q : Flow [l/min]
- t : Time [s]
- T : Temperature [˚C]
- U : Voltage [V]
- v : Velocity [m/s]
- x : Position [m]

INTRODUCTION

Environmental friendliness of hydraulic systems can be increased by using different fluids instead of oil. Despite of its good properties water hydraulics have some challenges which need to be taken into consideration. The component technology is rather undeveloped when compared to oil hydraulics. In water hydraulic systems there are usually difficulties concerning wear and corrosion of components and also sticking of valves and other components. This requires on-line condition monitoring of the components and fluid as well.

Condition monitoring of hydraulic systems is based on measurements from these systems and especially deviations in these measurement variables. Different measurement variables are more sensitive than others to show early changes in state of the system and components. In this study vibration and pressure signals are used as an indicator of systems health state and the sensitivity of these different measurement variables are compared while final classification result is used as a criterion. Pressure signals are more often used in condition monitoring of control valves than vibration signals. Vibration signals are instead often used to monitor rotating components like a pump or a motor [1, 8, 11]. But there have also been research for monitoring other hydraulic components using vibration measurements. For example in [11] the condition of seals of hydraulic cylinders are studied using vibration measurements.

Neural network research has been very active for several years and there has also been interest in neural network applications to fault diagnosis problems [1, 5, 6, 8, 10]. Neural network is one possible method which is suitable for classifying different system states of the water hydraulic components. Usually all the damages are not known before diagnostics, therefore neural network method Self-Organizing Maps with unsupervised learning are used in this study [2, 6]. Since this type of neural network can perform non-linear functional mapping between sets of variables they can be used to classify raw input data directly [6, 10]. But it is important to preprocess any raw and/or dynamic data before classifying them to improve the performance of the classifier. In this study measurement signals are preprocessed using descriptive statistics and wavelet analysis.

STRUCTURE OF THE TEST SYSTEM

In this study a water hydraulic proportional valve is studied in a test system during extending and retracting strokes of cylinder while vibration and pressure signals are measured in normal and different fault situations. The hydraulic circuit of the test system is presented in Fig. 1.

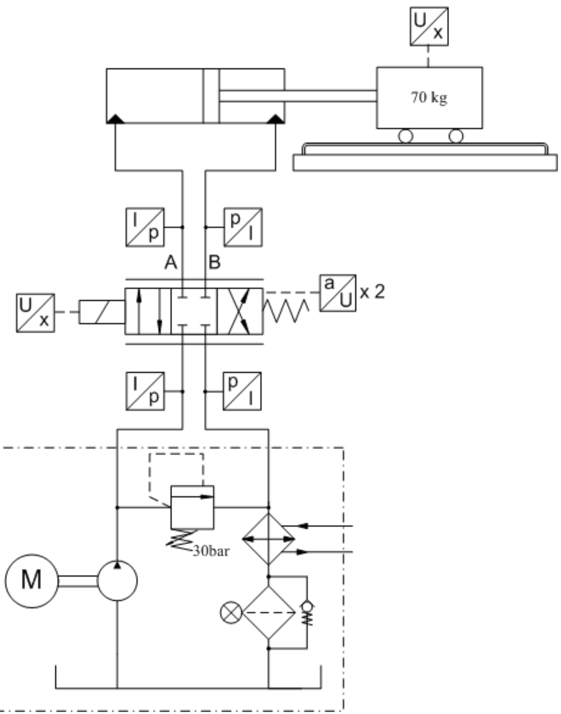

Figure 1 The hydraulic circuit of the test system

The studied water hydraulic proportional valve is 4/3-way spool valve which is modified from a pneumatic on/off valve and it is designed for low-pressure water hydraulics. The position of the spool is measured by a LVDT sensor and the measured signal is used as a feedback signal for a PI-controller. [9]

The dSpace DS1102 controller board was used to control the proportional valve and to measure all variables except the acceleration. It was also used to trigger the acceleration measurements when the control sequence starts. The acceleration signals were measured with IMC Cronos PL measurement device.

An axial displacement pump with maximum delivery of 10 l/min (1500 rpm) is used in the system and the size of the double-acting cylinder is 32/16-500. The supply pressure is 30 bar but also up to 70 bar pressure levels have been tested with this valve. The load used in testing was 70 kg.

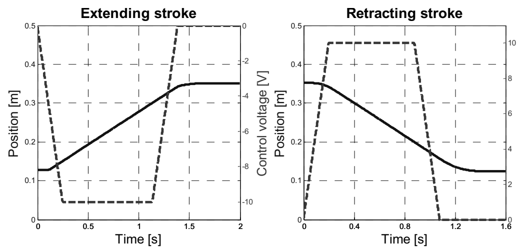

Figure 2 An example of cylinder position and control signal of the control valve from the extending and retracting strokes

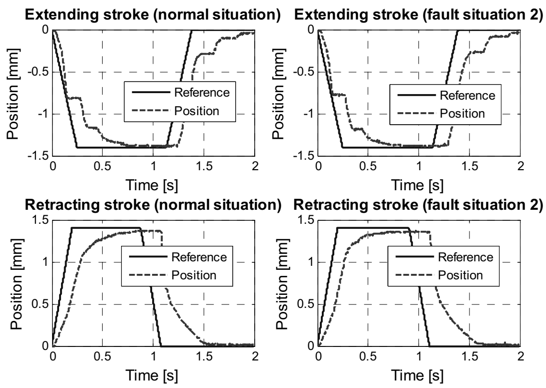

Figure 3 An example of spool position and reference from the extending and retracting strokes

The cylinder is driven in a specified sequence using programmable position limits. After the limit is exceeded the control signal of the control valve is driven to zero using a specified ramp. The upper limit used in the test system is 300mm when the cylinder is extending and the lower limit 200mm when the cylinder is retracting. The starting point of the stroke is where the cylinder has stopped last time. An example of cylinder position and control signal of the control valve in the extending and retracting strokes of the cylinder are shown in Fig. 2 and spool position and reference signal in Fig.3.

Monitored component and fault type

The potential fault type in the studied proportional valve is increased internal leakage. The construction of the valve is such that the spool is inside a sleeve that is mounted in the body of the valve and between the sleeve and the body are o-ring seals [9]. If these o-rings are damaged the result is increased internal leakage between the ports of the valve. This kind of fault type can be caused by deterioration of the seal material or poor assembling of the spool sleeve into the valve. The used spool sleeve with the seals and an example of a faulty seal are shown in Fig. 4. In Fig. 5 is shown a 50x magnification of a seal fault.

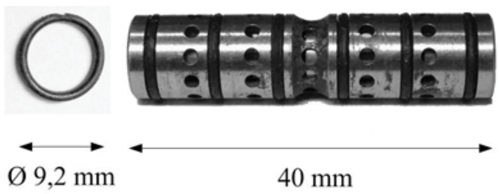

Figure 4 The spool sleeve of the valve and a seal fault

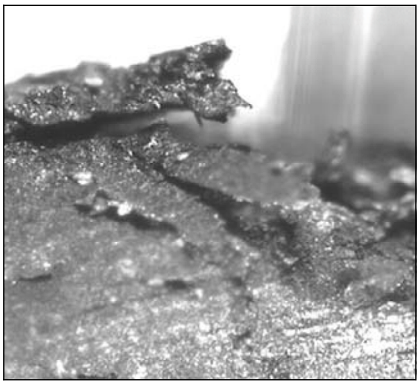

Figure 5 An example of seal fault (50x)

In this study a seal fault in the spool sleeve of the valve has been used as a fault case. The used proportional valve has a spool sleeve with six seals and four of them are of interest in this study. The outermost seals are only for sealing the drain line from the tank line and do not affect the behavior of the system. Therefore, the outermost seals are not used in this study. The effects of the seal faults in these seals are investigated one at a time. The studied seals are numbered 1 to 4 (S1 to S4) starting from the spring end of the valve and the fault situations are 1 to 4 equally. At non-controlled state the cylinder tends to crawl slowly when S2 or S3 is damaged. In the earlier study [4] differences between the velocities of the sequences could be seen between the normal and the fault situations. A same phenomenon is not possible to see in the present system during the sequence because of a low pressure level, small load and the cylinder is driven horizontally. In [4] the cylinder was driven in vertical direction.

Measurement methods

Acceleration sensors were used to measure the vibrations of the proportional valve during the extending and retracting strokes of the cylinder and pressure sensors were used to measure the pressure from the actuator ports A and B. The locations of the sensors can be seen from Fig. 1.

The model of the pressure sensors is Trafag 8891 NA 100.0A. This type uses a thin film strain gauge technology. The pressures of the cylinder chambers were measured with similar sensors.

The accelerometers exploited were IMI Sensors 603C11 and Kistler 8702B50M1. The frequency range of both sensors is 0.5 Hz to 10 kHz and the resonant frequency 25 kHz and 54 kHz respectively. The signal processing of the measurements was conducted by using a 15th order Chebyshev band-pass filter. The lower and upper cut-off frequencies were 2 Hz and 20 kHz respectively.

The final selection of the two ICP sensors was the IMI Sensors industrial grade accelerometer due to the final classification results compared to the other accelerometer, better mechanical structure, low-cost price and robustness, which are essential in every day use in final applications.

Training and testing data

Training and testing data for use in classification are measured from the test system. The test system is run in normal and four fault situations (four different seal faults) in the extending and retracting strokes. The measured variables are pressures A and B from the actuator ports and acceleration which is measured from the other end of the valve in axial-direction of the spool of the valve (see Fig. 1). The measurement time in the extending stroke is 2.0s and 1.6s in the retracting stroke. The same sequence is measured 10 times in each case for both directions so the total amount of sequences is 100. The measurement frequency with the pressure measurements is 1 kHz and with the acceleration measurements 20 kHz. Multiple sequences are driven because this way it is possible to improve the generalization of the network when new data is presented to the network.

In Fig. 6-7 are shown examples from the pressure measurements. From the figures can be seen how some of the normal and faulty measurement points are very close to each other especially in the middle of the sequence. That is why the whole sequence is classified here as a normal or fault state instead of classifying each measurement point like in [3]. Biggest differences can be seen in the beginning and at the end of the sequence.

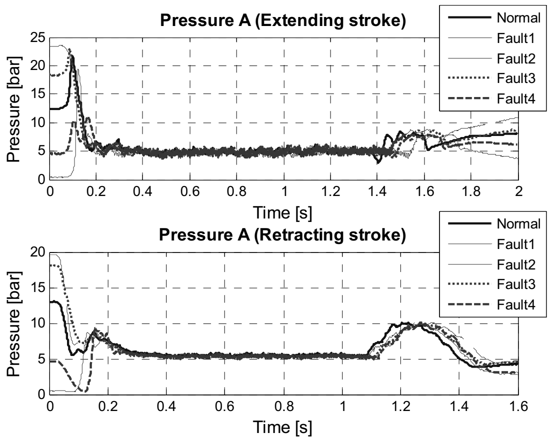

Figure 6 An example of pressure A from the actuator ports from the extending and retracting strokes

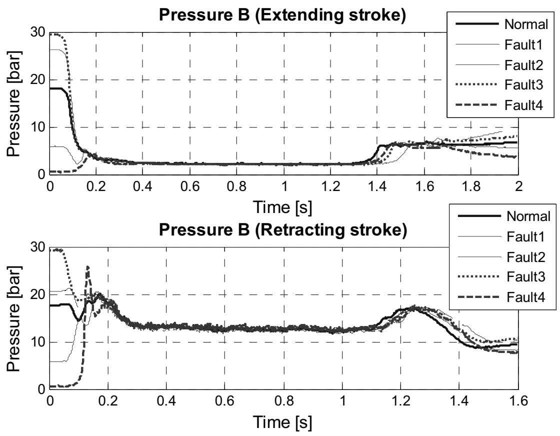

Figure 7 An example of pressure signal B from the actuator ports from the extending and retracting strokes

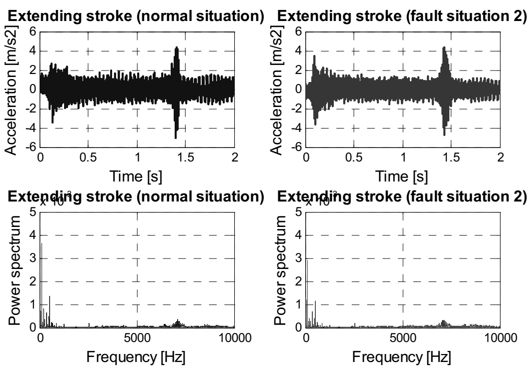

Figure 8 An example of vibration signals from the extending stroke (normal and fault situation 2)

In Fig. 8-9 are shown examples from the vibration measurements in the normal and fault situation 2 in the extending and retracting strokes. In the figures are shown the time and frequency domain of the vibration signal. Deviations from the normal situation are easier to detect from the frequency domain than from the time domain. In this study the entire measured frequency area 2 Hz - 10 kHz is used in the data analysis. Studying the effect of using different frequency areas in data analysis to improve the classification results are left outside the scope of this paper.

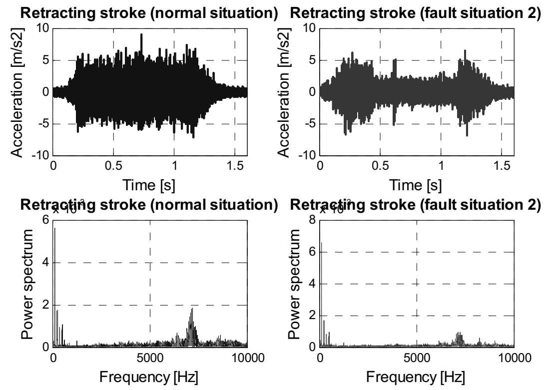

Figure 9 An example of vibration signals from the retracting stroke (normal and fault situation 2)

FEATURE EXTRACTION OF THE MEASUREMENT DATA

Preprocessing of the measurement data usually involves extracting relevant and discriminating information and in so doing reducing data dimensionality. This process is often called feature extraction. [4, 7]

It is important to preprocess any raw and/or dynamic data before classifying them to improve the network performance [4]. Two different type of feature extraction methods are exploited in this study which are descriptive statistics and wavelet analysis.

Descriptive statistics

Descriptive statistics are used to describe the basic statistical features of the data in a study. In this study 11 different statistical values were extracted from both the pressure and the vibration signals to get relevant information for classification. These are: arithmetic mean, median, standard deviation, mean deviation, variance, rms, skewness, kurtosis, maximum, minimum and sum.

Wavelet analysis

The basic idea of wavelet analysis is to adopt a wavelet prototype function, called an analyzing wavelet or mother wavelet. In the wavelet analysis original measured signal is broken up into shifted and scaled versions of the analyzing (or mother) wavelet. In this study analyzing/mother wavelet which was used is Daubenchies (db2). Because the original signal or function can be represented at certain accuracy using only approximation coefficients, data analysis can be performed using just the wavelet coefficients [7].

In the extending stroke 65 coefficients are extracted from both pressure signals and 315 from the vibration signal. In the retracting stroke 52 coefficients points are extracted from both pressure signals and 252 from the vibration signal.

CLASSIFICATION OF THE EXTRACTED FEATURES

Different system states (normal and four fault states) are classified using Self-Organizing Maps. The extracted information from the pressure and vibration signals is used as inputs to the network.

Self-Organizing Maps

The Self-Organizing Maps (SOM) is a neural network method which can represent any functional relationship between inputs and outputs. The SOM uses unsupervised learning where network learns by evaluating the similarity between the input patterns presented to the network and perform some kind of clustering operation where they categorize the input patterns into a finite number of classes [4]. Training algorithm and more details of the Self-Organizing Maps are presented in the earlier publications [3, 4].

In this study the SOM is first trained to detect the state of the system which is either normal or fault and only the data from the normal situation is used in the training. So the analysis is concentrated on finding the properties of the normal data and the appropriate means to identify the deviations from the normal situation [2, 10]. After the fault states of the system have been identified then the network can be used to identify a specific fault from the measurement data. Here also the data from the fault situations are used in the training.

Classification of the system state

The number of map units in this situation is 4 x 3. The size of the map is quite small but it is not necessary to use a bigger one because it does not make the results any better and it also slows down the calculation [4]. Five sequences from the normal situation are used in the training and five sequences from each system state (normal + 4 x fault) are used in the testing.

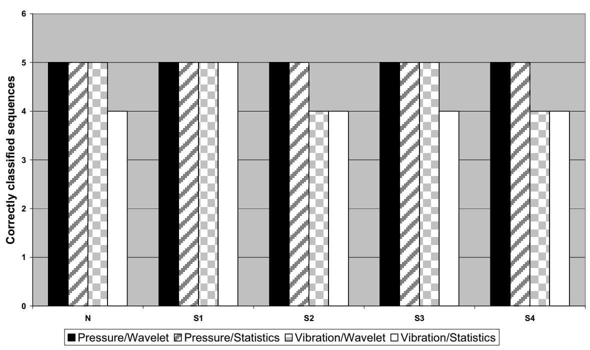

Figure 10 Classification results from extending stroke

In Fig. 10-11 are presented the classification results of the system state. From the results can be seen that almost all the sequences are classified correctly. When the pressure signal is used as an indicator of the system state all the states are correct but when the vibration signal is used there are few wrong classified states in both situations (extending and retracting strokes).

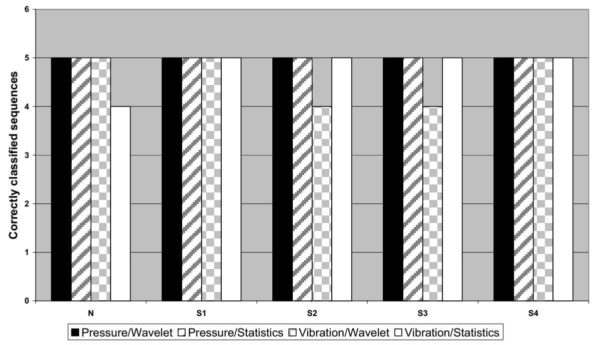

Figure 11 Classification results from retracting stroke

Classification of the fault situations

The number of map units used in this situation is 5 x 2, 4 x 3 or 3 x 3. Five sequences from each system state are used in the training and other five from each system state in the testing. In Fig. 12-13 are presented the classification results of the specific faults situations. Most obvious result is that the pressure signal gives much better classification results than the vibration signal. In extending stroke especially the seal faults S2, S3 and S4 were quite hard to classify regardless of the feature extraction method. For example the classification result for S3 is 0 % when the descriptive statistics were used in feature extraction. The wavelet analysis seems to be a little better feature extraction method in the extending stroke.

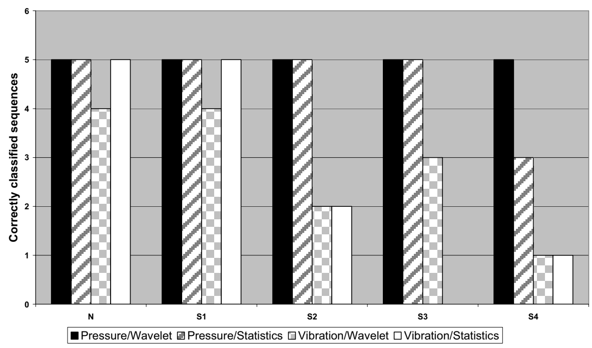

Figure 12 Classification results from extending stroke

In the retracting stroke the difference between the pressure and the vibration is even bigger than in the extending stroke. Only in cases N/statistics and S1/wavelet the vibration signal is as good as the pressure signal. Again S2, S3 and S4 were hard to classify using the vibration signal. In the retracting stroke the descriptive statistics were overall as good as the wavelet analysis in feature extraction.

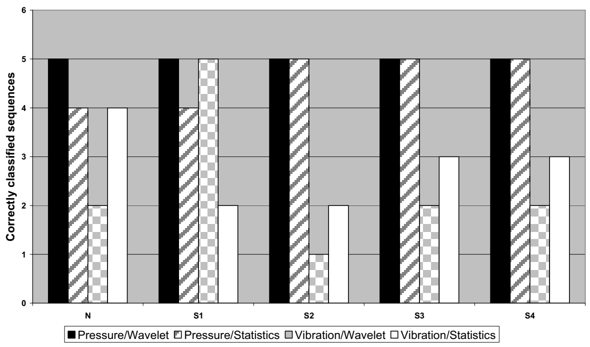

Figure 13 Classification results from retracting stroke

CONCLUSION

The main goal of this research was to detect internal leakages created by seal faults and also to identify which seal is damaged from the water hydraulic proportional valve using the vibration and the pressure signals which were analyzed using different data analysis methods.
Descriptive statistics and wavelet analysis were used to extract information rich features from the pressure and vibration signals which were then used in classification of the system state.
The SOM is first trained to detect the state of the system. When only normal state was used in classification and state was classified either normal or fault almost all the sequences were classified correctly with pressure and vibration with both feature extraction methods.
After the fault states of the system were identified then it was possible to use the network to identify the specific fault from the measurement data that have not been presented to the network before. In this case also data from the fault situation were used in the training of the network. Here the classification results were much better when the pressure signal was used instead of the vibration signal. The differences between the feature extraction methods are not so high than with the measurement variables.
Preprocessing of the measurement data needs more research so that the best statistical values are found and right amount of wavelet coefficients are extracted. In the measurements there were also changes in the vibration signal in different measurement times when the conditions were the same so more measurements needs to be done so that reliable results can be achieved. Also different frequency areas need to be studied more carefully.
In this study the vibration signal was measured only from one direction. Combining this with two other axial-directions can also give better results. Also effect of different load situations needs to be studied

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