International Journal of Fluid Power 11 (2010) No. 2 pp. 5-13

PARTICLE COUNTER AND NEURAL NETWORK USED TO DETECT SLIDING WEAR AND PITTING IN A RADIAL HYDRAULIC MOTOR

Ove Isaksson

Division of Computer Aided Design, Luleå University of Technology, Luleå, Sweden
ove.isaksson@ltu.se

Abstract

A particle counter was used to detect sliding wear and pitting in a low-speed hydraulic motor. The features used by a neural network were accumulated mass, number of particles and time above threshold. The diagnostic tool was experimentally evaluated by collecting data from a test rig running under heavy-duty conditions in a laboratory.

Accumulated time above a threshold value seems to be an adequate feature to detect severe damage to a low speed motor at constant operating conditions. Using a neural network to combine the three features gives earlier and more reliable detection of which wear mode is prevailing than when only using the features singly.

Keywords: diagnostics, particle counter, hydraulic motor, neural network, pitting, wear

1 Introduction

When component or system suppliers are going into a new business, access to knowledge concerning a product's performance in use is an asset to improving reliability and thereby reducing the business risk. Lacking information about how components operate in service reduces the ability to improve the component and increases the risk of future warranty claims. In order to develop high-quality components that meet customers' requirements, it is necessary to monitor the performance and use the data to improve component quality. For products operating continuously and located in remote rural areas, a diagnostic system is a further guarantee of speed, reliability and economy in monitoring and maintenance. Suppliers need to be confident that monitoring will benefit their products.

Access to a suitable indication of the deterioration of the product in use is also valuable in order to rectify the defect or shut down the plant before major breakdown. The demand on the diagnostic system is that it needs to provide real-time performance monitoring with reliable indicators, so that the number of false alarms is minimized; otherwise, the loss of profit due to unnecessary plant stops increases. Even in applications using advance monitoring technology such as aircraft, the number of false warnings results in major losses. According to Stewart and Ephraim (1997) the average number of false warnings is 1 per 100 flight hours.

This manuscript was received on 11 September 2008 and was accepted after revision for publication on 23 May 2010

It is also of great interest in some applications to obtain an early indication to be able to act adaptively and change operating conditions so that the plant can be run safely for a short period of time but at reduced capacity. Therefore, establishing objective methods for diagnostic analysis that detect the gradually changing status of the product is of great interest. Trend analysis is able to provide the required background to find out the true system condition, and give a definitive go/stop measure of condition. Furthermore, the real-time measures and analysis can also be used as a design tool in the development of new hydraulic components and systems.

To monitor the condition of a hydraulic system, different technologies, capable of predicting impending system failure, are suggested in the literature. Some of the methods can be connected to system and measurements done on-line or even in-line. The monitoring system provides important information on the condition of the system.

Vibration analysis is widely used in research for detecting faults, such as bearing damage, Dempsey and Afjeh (2002) and Dempsey et al. (2004), cavitation, volumetric losses and bearing faults, Oppermann et al. (2005), and assembly faults by Ramden et al. (1995). Vibration is a single parameter that contains a good deal of information about the status of a machine. Vibration monitoring utilizes techniques of varying degrees of complexity, where the simple model for frequency analysis involves vibration signature including a root cause analysis. Filters are used to distinguish, for instance, bearing damage from other machine vibrations. Even though specially designed filters give damage detection at a very early stage, the damage has already occurred. Furthermore, the fault detection rate of condition monitoring by analysis of vibration data is about 70 % according to Larder (1999).

An essential component in hydraulic transmission, the hydraulic fluid, needs to be clean to ensure long system life. Contamination levels within the hydraulic system also give an indication of the status of the components in the system. According to Roylance and Hunt (1999), solid particulate matter in hydraulic systems is the most likely cause of failure.

Normally, hydraulic component suppliers recommend that the oil should be analyzed regularly to determine properties such as viscosity, oxidation, water content, additives and contamination level. Elemental analysis can determine which part in the system is worn. Off-line contamination analysis is carried out by analyzing the content taken from the filter, oil samples or magnetic plugs.

Other factors of interest in analysis of contaminants are quantity, size, composition and morphology (Park et al., 2003). The morphology analyses of wear debris are recognized by computer image analysis. Debris shape is used to classify the wearing mechanism (Howard et al., 1998).

Inductance-type sensors were used on-line to measure debris size and to count debris particles (Hunt, 1993). By monitoring the size and generation rate online, wear trend analysis can predict accelerated wear conditions before significant or catastrophic damage occurs. Aircraft engine and gearbox oils are monitored by using on-line chip detectors that warn the pilot of excessive wear conditions. On-line sensors are used to measure the number of particles and their approximate size, and then calculate accumulated mass (Dempsey, 2004). They used a technology where change in a magnetic field caused by the passage of a metal particle is measured. Ahn et al. (1996) used blockage principle as monitoring device and based on the Weibull distribution function, the skewness and mean particle size distribution were used for the explanation of trends in wear debris generation. The shape of the particle also holds information about the wear mechanism that generated it (Edmonds et al., 2000).

In the work by Lukas and Anderson (1998), a high-intensity laser light source and a photo sensor are used to count the number and size of particles. An alternative method uses acoustics for detecting forerunner wear debris particles (Edmonds, 2000). It works by insonifying the oil with a high-frequency acoustic impulse and analyzing the reflected signals.

Integrating the sensor in the system can potentially improve detection capabilities. A built-in capacitive sensor that measures on-line oil film breakthrough in bearings was used in Tuomas and Isaksson (2008). Krallmann et al. (2005) studied hydraulic oil ageing and combined several sensor readings to improve the statement on the oil conditions. In their work, resonant frequency was measured to estimate change in viscosity, change in resistance to estimate temperature change, and a capacitor to estimate electric permittivity.

To improve the capability to detect the condition of the system, Stewart and Ephraim (1997) and Dempsey et al. (2004) used fuzzy logic techniques. Neural networks have been applied in many different fields, such as neural aided landing control (Pashilkar et al., 2006), image analysis (Park, 2003), wear debris identification (Sugimura and Yamamoto, 1995), oil condition (Krallman et al., 2005), fault detection (Ramden et al., 1995 and Paya et al., 1997), medical diagnosis (Mohamed et al., 2003).

Using these techniques on the oil debris data, threshold limits are defined that discriminate between different stages and types of wear, such as pitting wear (Dempsey et al., 2002).

The objective of this research was to improve detection capability of combined detection features such as wear debris quantity, size and time during which the contamination level exceeds a set threshold value, by applying neural network analysis techniques to hydraulic motor failure data collected at the Hägglunds Drives test rig. The failures that are addressed are sliding wear on piston, cylinder and roller, and pitting on cam ring.

The paper is organized as follows: After the introduction in section 1, the detection features' accumulated number, time and mass are presented in section 2 and neural network approach in section 3, where the output target levels that distinguish between levels of wear are also defined. In section 4, the hydraulic motor in the test rig used for failure data collection is briefly described. In section 5, the results from measurements, neural network modelling and simulations are presented, followed by a discussion in section 6. Section 7 of the paper rounds off with overall conclusions.

2 Detection Features

The aim of this study is the on-line early detection of damage in hydraulic motors by counting the number of particles in the hydraulic fluid. Although preventive maintenance is known to be effective, unnecessary stops are not avoided and operators have less access to classify the apparent failure of elements if it occurs between service periods. It is clear that the quantity of particles, their size and the time the particles are within the system influence the degree of degradation of the system. The presence of particles also indicates that hydraulic components generate wear particles, or they result from fluid or additive decomposition, or enter from the surroundings, and are carried through the system (Hanawa, 1998).

Two failure modes that are of interest are cam ring and roller pitting, and sliding wear on roller, piston and cylinder. Four different features that use the information about particle distribution are suggested, and then it is determined whether a correlation exists between the various prediction techniques and the observed failure modes.

According to the declaration by the manufacturer of the hydraulic motor, the target cleanliness level for heavy-duty industrial applications should not exceed ISO 4406 16-13. Having established the minimum fluid cleanliness level required for acceptable component life for the system, the next step is to monitor the actual cleanliness of the fluid to ensure that the target cleanliness level is maintained on a continuous basis. It is important to keep the surfaces smooth during the whole operation of the system and not allow them to be destroyed by particulate contamination. The quantity measure gives information about severity and rate of wear, while the size distribution also suggests the wear mode, according to Roylance (1997). Laitinen and Pietola (2005) found that erosive wear gave more crucial damage on a valve spool than abrasive wear with high contamination concentration. Therefore, the first feature is to monitor the accumulated number n_{acc} of particles greater than x µm

$$n_{\text{acc}} = \sum_{i=1}^{i=j} n_{\text{x,i}} \tag{1}$$

The algorithm computes a statistical history of the number of particles and is used to determine the wear status of the motor. In the second feature the prediction of early motor failure is based on trend monitoring of the accumulated time when the particle concentrations are above a given threshold value. This is illustrated in Fig. 1.

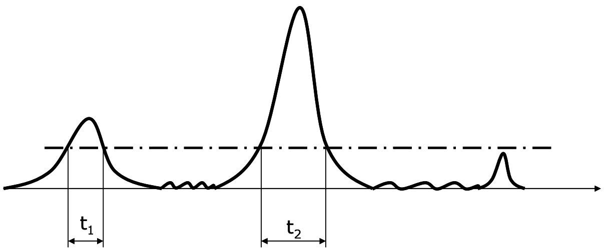

Fig. 1: *Accumulated time above;* —·—, *threshold*

The accumulated time is expressed as

$$t_{\text{acc}} = \sum_{i=1}^{i=n} t_{\text{i}} \tag{2}$$

where t_{i} is i:th time interval when the reading is above the threshold value. It should be observed that a single reading will not contribute to the accumulated time. Two threshold values are defined in this paper and ISO 4406 is used to set the two levels. The accumulated time, t_{acc1} and t_{acc2} are calculated when the number of 4 µm particles > 65500, and 14 µm particles > 8200, respectively. The contamination level corresponds to the company declaration on hydraulic motor cleanliness target for heavy-duty applications.

For the explanation of trends in wear debris generation, several indicators have been used. Roylance (1983) found that mean and variance are important. Ahn et al. (1996) stated that if there is severe wear, both mean size and skewness are expected to rapidly increase. The accumulated mass has been found to be a good predictor of pitting damage on spur gears, Dempsey (2001). The size of the debris changes when the wear mode is changed. In abnormal wear the size will be higher according to Hudnik and Vizintin (1991) and the larger the particles the more severe wear (Edmonds et al., 2000). When a machine element is suspected to be in an abnormal wear mode the latest reading should be significantly greater than the previous one.

According to Frith and Scott (1994, 1996), the pump flow degradation is related to the mass of wear debris generated and that certain pumps show no evidence of wear until a larger contaminant size range was added. They concluded that only contaminants greater than a certain critical size related to the gap size cause wear.

Therefore, the fourth feature considers the accumulated mass of debris which is expressed as

$$m_{\text{acc}} = \frac{4}{3}\pi \cdot \rho \cdot \sum_{i=1}^{i=j} (n_{\text{x1,i}} \cdot r_{\text{x1,i}}^3 + \ldots + n_{\text{xn,i}} \cdot r_{\text{xn,i}}^3) \tag{3}$$

If the density of the particles is assumed constant, then the accumulated volume of particles can be used instead.

Wear and contamination caused by damaged surfaces mainly occurs in regions of close contact. In high-torque hydraulic motor, different lubrication regimes exist (Isaksson and Larker, 2000). Elastohydrodynamic contact between cam ring and roller with high contact pressures and thin lubricating film are comparable to conditions prevailing in a gearbox.

3 Neural Network Analysis

Three important objectives of analysis are: catch faults early, identify the precise source of a fault, and define the remaining operating life. It is of major concern to be able to predict a threshold value when it is critical to continuously running the motor. The purpose of performing neural network analysis is to achieve a more reliable signal at the decision level than the features alone can give. The advantage of neural network analysis is that new features from multiple sensors can be added to the system without changing the entire analysis. A neural network was selected as it is known to be robust to input and system noises, it has learning capabilities, and can perform in real time. These are important demands on a future diagnostic system for the high-torque motor in a critical application.

The neural network analysis needs data from the system when the component is known to be in good health, as well as indications of gradually increasing damage from early detection wear to a stage when the system should be shut down. Supervised training or learning of the neural network utilizes the inputs and the corresponding output value, called target or desired output, and modifies the weights and biases until there is sufficient agreement in the network's output. The output of the model shows the health of the hydraulic motor.

The neuron has k inputs, z_{i}, and the corresponding connection weights are w_{i}, then

$$y = f(\sum_{i=1}^{k} w_{\text{i}} \cdot z_{\text{i}} + b) \tag{4}$$

where f is the transfer function. Both weighted input w

and scalar bias b are adjustable of the neuron.

The inputs are the damage detection features given by

accumulated number of particles, n_{acc}
accumulated time, t_{acc1};4 µm particles > 65500
accumulated time, t_{acc2};14 µm particles > 8200
accumulated mass, m_{acc}

The output is the state of the motor. Four different threshold limits were defined that discriminate between levels of sliding wear and pitting, respectively. These are shown in Table 1. The pitting mode should not produce so many particles compared to sliding wear and is expected to be low. However, the accumulated mass during pitting mode should increase when large particles are released from the surfaces.

Table 1: Condition of the motor given by the level and the different feature status, L=Low, H=High

Level		0.5	1.5	2.5	3.5
Sliding wear	n_{acc}	L	L	L	H
	t_{acc1}	L	L	L	H
	t_{acc2}	L	H	H	H
	m_{acc}	L	L	H	H
Pitting	n_{acc}	L	L	L	L
	t_{acc1}	L	L	H	H
	t_{acc2}	L	H	H	H
	m_{acc}	L	L	L	H

4 Test Rig

Endurance tests were conducted using a hydraulic motor testing facility located at Hägglunds Drives. The rig was capable of running a motor at high load and a speed corresponding to heavy-duty industrial application until the motor received critical damage. The hydraulic motor was a radial-piston type motor with rotating cylinder block/hollow and a stationary housing having a displacement of 35,200 cm3/rev, see Fig. 2.

High-torque hydraulic motors are developed toward more compact units delivering higher specific torque and power output (> 1 kW/kg of motor weight). As a crucial part of this, roller element bearings are replaced by slider bearings in the transferring parts. This has been one of the reasons for choosing to look at the high-torque motor when studying sliding wear and pitting.

The pistons are located in bores inside the cylinder block, and two valve plates direct the incoming and outgoing oil to and from the working pistons. Each piston works against a cam roller. When the hydraulic pressure is acting on the pistons, the cam rollers are pushed against the slope on the cam ring that is rigidly connected to the housing, thereby producing torque. The cam rollers transfer the reaction force to the pistons, which are guided in the rotating cylinder block. Rotation therefore occurs, and the torque available is proportional to the pressure in the system, 560 Nm/bar.

The endurance tests were carried out at a higher system pressure than under normal duty to create accelerated test conditions. The surface structure is changed by the run-in process, where material is removed, deformed plastically or moved in the contact until a steady-state condition can be maintained (Tuomas and Isaksson, 2008). The aim is to reach the right load-carry capacity as smoothly and quickly as possible. Therefore, the test started with a run-in period when the system pressure was reduced to 60 %. The shaft speed was at a constant level during the whole test period.

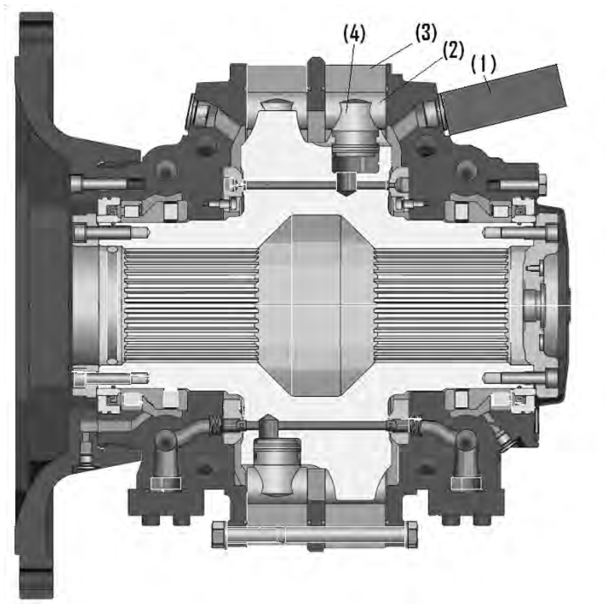

Fig. 2: *Hydraulic motor with particle counter (1) attached at drainage line; (2), roller; (3), cam ring; (4), piston*

Particulate counts were monitored by means of a particle counter placed in the drain line of the motor. The commercially available monitoring device for quantitative measurement of solid contaminants uses a high-intensity laser light source and a photo sensor to count the number and size of particles in the fluid. The particles produce a measurable interference in the transmission of light through the sample in the light-scattering cell. The increase in energy due to scattering effect produced by the particle when interrupting the focused laser light across the sampling area was measured. Three particle size channels were used to measure contaminants greater than 4, 6 and 14 micrometers.

5 Results

Three experiments were carried out. During the tests; data from the particle counter was collected once per 10 minutes. Tests always started with run-in at lower pressure after an inspection. Indicators that are normally used to terminate a test are increased leakage flow, high temperature in motor housing or chips on the magnetic plug that is regularly checked.

5.1 Test 1

After 1120 hours of run time with data collection the hydraulic motor was disassembled. 20 micometers radial wear on cylinder bore in the position of the piston ring was observed. The testing continued with new seals and wear rings, without replacement of any other components. The test was terminated after total testing time of 1,549 hours. First, some chips were observed on the magnetic plug (about 24 running hours before bringing the test to a halt), then increased leakage in the drain line, chips in the filter and increased temperature in the motor housing. The failure mode was sliding wear on cylinder and the radial wear on the bore was 200 micrometers.

5.2 Test 2

A new cylinder block and pistons were installed and the other components within the motor were the same as during test 1. After 1,145 hours the test was ended, as chips were found on the magnetic plug. The failure mode pitting damage was found on one of flanks of the cam ring.

5.3 Test 3

The test proceeded with a new cam ring and one new piston unit. The test was stopped after 4,885 hours. In subsequent inspection the motor was found to be in good condition.

5.4 Run-in Condition

During a run-in period the contamination level is normally high, due to entrance of particles from the surroundings and run-in of surfaces such as bearings and cam rings, which gradually reduce until the system settles in. In Fig. 3 the accumulated number of particles is plotted for the three tests. Due to the large variation in the contamination level during run-in, the first readings are not included in the accumulated features.

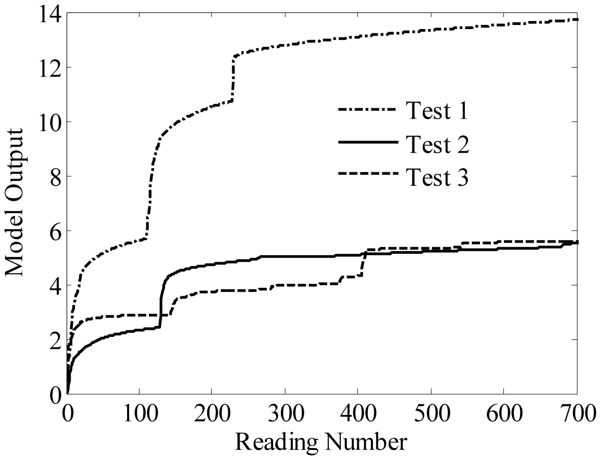

Fig. 3: *Accumulated number of particles, n_{acc} /1 x 10^8 during the start-up*

The readings used in the accumulated features start after 500 samples (or approximately 83 hours). When the system is stable and in a normal operation mode, the particle counting can be used for trend analysis.

In Fig 4 the accumulated number of particles is plotted when excluding the first 500 samples. It is clear that the contamination level of test 1 still increases faster than test 2 and 3. A high single reading was also observed during experiment 3 at reading 2500. The high reading was due to problems with the cooler system and the test was halted and restarted.

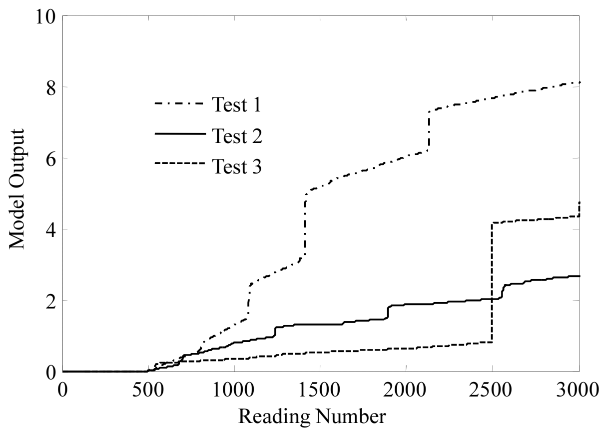

Fig. 4: *Accumulated number of particles, n_{acc}/1 x 10^8 after 500 samples*

5.5 Accumulated Number of Particles

In Fig. 5 the accumulated number of particles is shown for the three tests. It was not possible to set a threshold value for test 1 and 2 so that test 3 could run without giving an alarm at the end of the test. If setting a higher threshold so that test 3 returns a good result, then also test 2 passes without alarm. It is notable that test 1 (24 hours) and test 2 (122 hours) do have a high increase in contamination level just before the test was terminated.

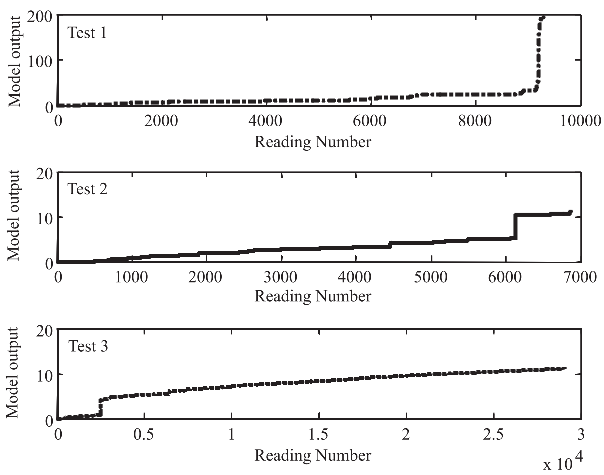

Fig. 5: *Accumulated number of particles, n_{acc}/1 x 10^8*

During test 1 there is a clear increase which starts 24 hours before final stop. When studying the measurements of test 2 more carefully, 122 hours before the test was terminated, there is an increase in accumulated number of particles during a time period of half an hour and thereafter more or less a steady-state level.

5.6 Accumulated Mass

The feature accumulated mass gives similar results as accumulated number of particles. The problem with an excessively high level in test 3 is even more pronounced in this case, Fig. 6. The rapid increase in accumulated mass at the end of test 1 and 2 is also observed.

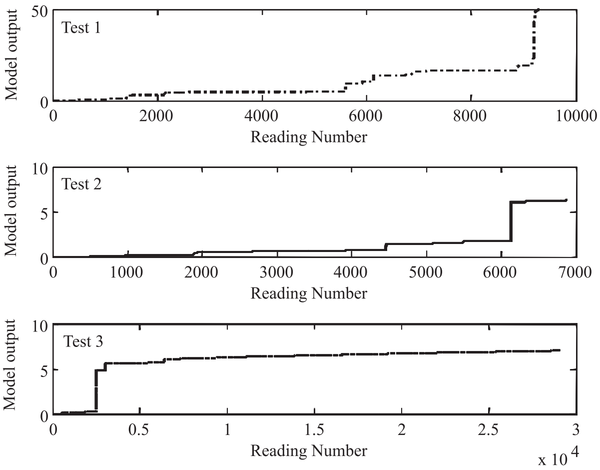

Fig. 6: *Accumulated mass, $m_{acc}/(1 \times 10^{-7}\ \rho)$*

5.7 Accumulated Time

Accumulated time above the threshold 1 is shown in Fig. 7 and above threshold 2 in Fig. 8. The output from the model is zero during the complete test 3, while test 1 gives a clear reading just before the test was ended.

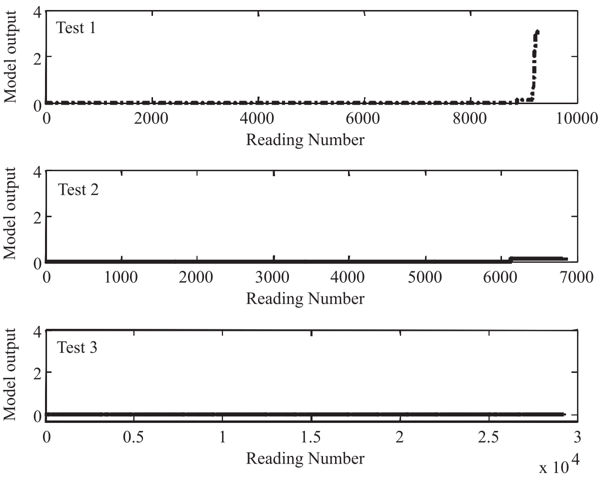

Fig. 7: *Accumulated time, $t_{acc,1}/1 \times 10^4$, when number of particles is greater than 4 μm*

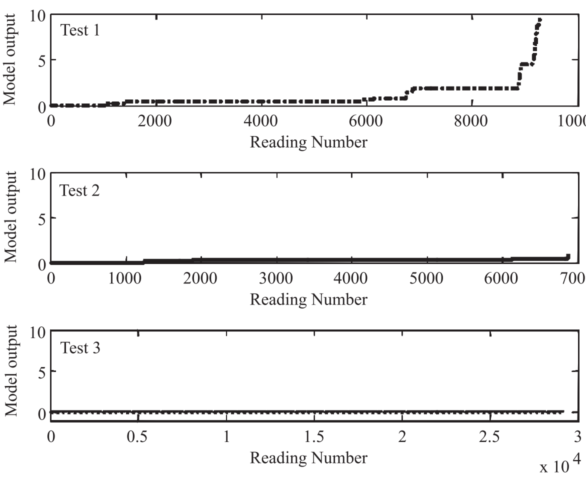

Fig. 8: *Accumulated time, $t_{acc,2}/1 \times 10^4$, when number of particles is greater than 14 μm*

Accumulated time for the large particles, $t_{acc,2}$, gives a clear indication about 70 hours before test 1 was terminated. Test 2 gives a first level indication at the end of the test, when the failure mode is pitting.

5.8 Neural Network

The sigmoid function was used as the non-linear activation function for all neurons, and the network was trained using the back-propagation algorithm.

Neural network training for pitting and sliding wear was carried out by randomly using 60 % of data in test 1 to 3. The condition of each feature, when changing from low to high level is given in Table 2. Fig. 9 shows the results from that training pitting and shows clear target levels for test 1 and 2. At the end the level of test 1 decreases while test 2 increases, indicating that pitting damage should be expected.

Training of the neural network seems to also give an appropriate output signal for test 3. The output value is close to 0.5, which it should be as no damage occurred during this test.

Table 2: Feature conditions

Feature change to high when
$n_{acc}/1 \times 10^8 > 25$
$m_{acc}/(1 \times 10^{-7}\ \rho) \geq 10$
$t_{acc,1}/1 \times 10^4 \geq 0.1$
$t_{acc,2}/1 \times 10^4 \geq 0.1$

In Fig. 10 the results of the tests are shown when data from all three tests are used in the training of the network model for sliding wear. Both test 1 and 2 give increase warning level during the test. The highest level is for test 1, which gives a value of 3.5 at the end, while test 2 reaches a level of 2.5.

The final step in increase in test 1 comes about 70 hours before end of test, compared to 24 hours using only accumulated number of particles or accumulated mass.

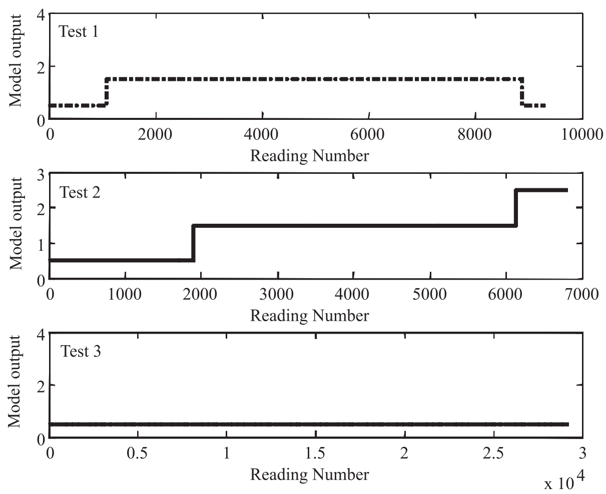

Fig. 9: *Simulation output for pitting*

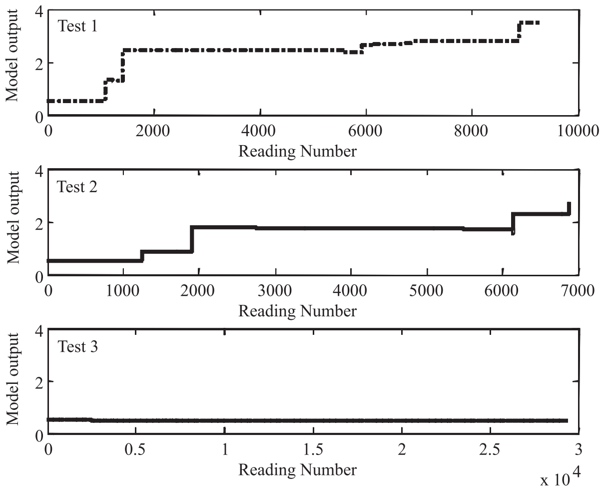

Fig. 10: *Simulation output for sliding wear*

6 Discussion

During the common run-in of lubricated surfaces the surfaces become smoother. Therefore, when starting up the motor it is important that the motor output power is limited. However, the run-in period when contamination level is high needs to be investigated more carefully, as contaminants entering high-loaded contacts such as cam/roller cause indentation of the surfaces that might drastically decrease the life of the components permanently. Sayles and MacPherson (1982) showed that 10 % of the rolling contact surfaces became covered with indentations when roller bearings were run 30 minutes in a lubricant contaminated with wear debris from a gearbox. This unfavourable situation consumed 90 % of the expected life of the bearing. The reduction in life was permanent, even if the bearing was run in clean oil for the remainder of the test. A particle induces plastic deformations of the surfaces, deformations which remain even if the lubricant is filtered later on. Thus, the smooth surfaces are destroyed, making them rough, and the rough surface then has high contact stresses and a short life, even with a low load.

During test 1 the increase in accumulated number of particles is much higher than for tests 2 and 3. The sliding wear produces more particles at an early stage. In test 1 we have intense wear to piston and cylinder, and a large number of particles are generated compared to test 2, where final shutdown was done due to pitting on the cam ring which is supposed to produce a much smaller number of particles. This is a way of improving prediction of which type of failure is prevailing. Instead of using neural network analysis it might be possible to use clustering analysis instead.

The back-propagation rules were used to adjust the weight and biases of network so as to minimise the error. The neural network may be trained with different algorithms, but this would exceed the scope of this paper. Remaining to examine is how reliable a statement is. It would be useful to prove the statement with additional testing with several others but same motor type.

In order to obtain stated service life it is important, according to the manufacturer of the hydraulic motor, to follow the recommendation concerning contamination. There seems to be a good correlation between the cleanliness level recommended and the health of the motor.

In lubricated contacts, the coefficient of friction and lubricating film thickness depends on the speed, viscosity and pressure, commonly illustrated by a Stribeck curve. Hence, changing the operating conditions influences the wear and it will be necessary to add more information to the neural network, such temperature, speed and pressure.

Impact of oil type might be considered by training the neural network, as additives influence lubricating film and wear, Toumas and Isaksson (2007).

7 Conclusions

A particle contamination diagnostics tool for detecting wear type in a hydraulic motor was evaluated. Three features; accumulated number of particles, accumulated mass and accumulated time above threshold value, were used as particle-counting algorithms to detect sliding wear and pitting damage in a hydraulic motor.

Accumulated time of service above a certain threshold seems to be an adequate feature to detect the damage to the hydraulic motor. One observation is that a technique for setting accurate threshold limits for particle-counting algorithms' fluid cleanliness levels defined according to ISO 4406 could be used.

Using a neural network to combine the three features gives more reliable detection earlier and thereby improves the decision-making capabilities, compared with only using the features singly.

The generation of particles appears to depend strongly on the wear mode. Sliding wear produces many more particles at an early stage of service compared to pitting.

The use of an automatic particle counter in determining which wear mode is applicable gives promising results. More tests need to be carried out and an additional feature for run-in period after each stop should be introduced.

Nomenclature

b	Scalar bias	
f	Transfer function	
m_{acc}	Accumulated mass	[kg]
n_{acc}	Accumulated number of particles	
$n_{x,i}$	Number of particles greater than x, for sample number i	[m²]
$r_{x,i}$	Particle radii	[m]
t_{acc}	Accumulated time as number of particles above threshold	[s]
t_i	Time the number of particles are above threshold	[s]
y	State of the motor	
w_i	Neural network weight factors	
Z_i	Input to neural network	
ρ	Density	[kg/m³]

Acknowledgements

This work was conducted at the Faste Laboratory, Centre for Functional Product Innovation, a VINNOVA (Swedish Governmental Agency for Innovation Systems) Excellence Centre located at Luleå University of Technology, Sweden.

References

Ahn, H. S., **Yoon, E. S.**, **Sohn, D. G.**, **Kwon, O. K.**, **Shin, K. S.** and **Nam, C. H.** 1996. Practical contaminant analysis of lubricating oil in a steam turbine-generator. *Tribology International,Vol. 29, No. 2*, pp. 161-168.

Dempsey, P. J. 2001. *Gear Damage Detection Using Oil Debris Analysis*. NASA TM-210936.

Dempsey, P. and **Afjeh, A. A.** 2002. *Integration Oil Debris and Vibration Gear Damage Detection Technologies Using Fuzzy Logic*. NASA/TM-2002-211126.

Dempsey, P. J., Morales W, and **Afjeh, A**. 2002. Investigation of Spur Gear Fatigue Damage Using Wear Debris. *Tribology & Lubrication Technology*, *58*, pp. 18-22.

Dempsey, P. J., **Lewicki, D. G.** and **Decker, H. J.** 2004. *Transmission Bearing Damage Detection Using Decision Fusion Analysis*. NASA/TM – 2004-213382.

Edmonds, J., **Resner, M. S.** and **Shkarlet, K.** 2000. Detection of precursor wear debris in lubrication systems. *IEEE Aerospace Conference Proceedings*, Vol. 6, pp. 73-78.

Frith, R. H. and **Scott W.** 1994. Wear in external gear pumps – A simplified model. *Wear*, 172, pp. 121-126.

Frith, R. H. and **Scott W.** 1996. Comparison of an external gear pump wear model with test data. *Wear*, 196, pp. 64-71.

Grahl-Madsen, M. 2003. An automated approach to the analysis of particulate contamination in multi-branch hydraulic circuits. *The Eighth Scandinavian International Conference on Fluid Power, SICFP'03,* Tampere, Finland.

Hanawa, S. 1998. Filtration focus fixes faults. *Hydraulics and Pneumatics*, June.

Howard, P. L., **Roylance, B.**, **Reintjes, J.** and **Schultz, A.** 1998. *New Dimensions in Oil Debris Analysis – The Automated, Real Time, On Line Analysis of Debris Particle Shape*. Naval Research Lab. Washington, DC.

Hudnik, V. and **Vizintin, J.** 1991. Key parameters for the reliable prediction of machine failure using wear particle analysis. *Tribology International,* Vol. 24, No. 2.

Hunt, T. M. 1993. *Handbook of Wear Debris Analysis and Particle Detection in Liquids*. Elsevier Applied Science, London.

Isaksson, O. and **Larker, R.** 2000. Performance Improvement Under Boundary Lubrication Conditions Using Slider Bearings with Silicon Nitride/Steel in High Torque Hydraulic Motors. *Transactions of the ASME*, Vol. 122, pp. 348-353.

Krallmann, J., **Lang, T.** and **Harms, H.-H.** 2005. Multi-Sensor for Condition Monitoring of Hydraulic Oils. *The Ninth Scandinavian Conference on Fluid Power, SICFP'05*, Linköping, Sweden.

Kwon, O. K., **Ahn, H. S.**, **Yoon, E. S.** and **Han, H. G.** 1990. *Establishment of quantitative techniques in machine health monitoring based on the rotary particle depositor*. Government Contract Report, N603(1)-3925-2.

Laitinen, L. and **Pietola, M.** 2005. Effect of contamination on wear of proportional control valves. *The Ninth Scandinavian International Conference on Fluid Power, SICFP'05*, Linköping, Sweden.

Larder, B. D. 1999. Helicopter HUM/FDR: Benefits and Developments, in *Proc. Of the 55th AHS Int. Annual Forum, American Helicopter Society*, Alexandria, VA

Lukas, M. and **Anderson, D. P.** 1998. Laboratory used oil analysis methods, *Lubrication Engineering,* Vol. 54, No. 1*1*, pp. 19-23.

Mohamed, E. I., **Maiolo, C.**, **Linder, R.**, **Pöppl, S. J.** and **De Lorenzo, A.** 2003, Artificial neural network analysis: a novel application for predicting site-specific bone mineral density, *Acta Diabetologica,* Vol. 40, October.

Oppermann, M. and **Ivantysynova, M.** 2005. In-Field Tests of a Modular Condition Monitoring System using an Experimental Off-Road Vehicle, *The Ninth Scandinavian International Conference on Fluid Power, SICFP'05*, June, Linköping, Sweden.

Ramden, T., **Krus, P.** and **Palmberg, J.-O.** 1995. Fault Diagnosis of Complex Fluid Power Systems Using Neural Networks, presentation at the *Fourth Scandinavian International Conference on Fluid Power*, Tampere, Finland.

Ramden, T., **Krus, P.** and **Palmberg, J.-O.** 1995. Condition Monitoring of Fluid Power Pumps Using Vibration Measurement and Neural Network Trained with Complex Optimisation, Presented at *Noise and Vibration '95*, Venice, Italy.

Park, H.-S., **Kim Y.-H.**, **Kim D.-H.**, **Cho Y.-S.** and **Park J.-S.** 2003. A Study on Recognition of Operating Condition for Hydraulic Driving Members, *International Journal of the Korean Society of Precision Engineering,* Vol. 4, No. 6.

Pashilkar, A. A., **Sundararajan, N.** and **Saratchandran, P.** 2006. A fault-tolerant neural aided controller for aircraft auto-landing, *Aerospace Science and Technology*, 10, pp. 49-61.

Paya, B. A., **Esat, I. I.** and **Badi, M. N. M.** (1997). Artificial neural network based fault diagnostics of rotating machinery using wavelet transforms as a preprocessor, *Mechanical Systems and Signal Processing*, 11(5), pp. 751-765.

Roylance, B. J. and **Pocock, G.** 1983. Wear studies through particle size distribution – I. Application of the Weibull distribution to ferrography, *Wear*, 90, pp. 113-136.

Roylance, B. J. 1997. Some current developments for monitoring the health of military aircraft using wear debris analysis techniques, *TRIB, v 7, Emerging Technologies for Machinery Health Monitoring and Prognosis*, pp. 55-60.

Roylance, B. J. and **Hunt, T. M.** 1999. *The Wear Debris Analysis Handbook*. Coxmoor Publishing Company, Oxford, UK.

Sayles, R. S. and **Macpherson, P. B.** 1982. Influence of Wear Debris on Rolling Contact Fatigue, *Rolling Contact Fatigue*, ASTM STP 771, ASTM 1982, pp. 255-274.

Stewart, R. M. and **Ephraim, P.** 1997. Advanced HUMS and Vehicle Management Systems Implemented Through an IMA Architecture, *Proc. Annual Forum of the American Helicopter Society,* 53/V2, pp. 1257-1266**.**

Sugimura, J. and **Yamamoto, Y.** 1995. Wear Debris Identification with Neural Network, *JSME(C*), Vol. 61, No. 509, pp. 4055-4060.

Tuomas, R. and **Isaksson, O.** 2007. The effect of phosphate additives on lubrication in a refrigerant environment, *International Journal of Refrigeration*, 30, pp. 28-36.

Tuomas, R. and **Isaksson, O.** 2008. Measurement of Lubrication Conditions in Rolling Element Bearing in a Refrigerant Environment, *Industrial Lubrication and Tribology*, Accepted for publication.

Ove Isaksson
Assistant professor at Division of Computer Aided Design, Luleå University of Technology. His research interests are in the area Fluid Power Systems and Condition monitoring – modelling and simulation.