Condition Monitoring of an Axial Piston Pump based on Graybox Modelling

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In this paper, a Condition Monitoring systems for axial piston pumps is discussed. As modern drivetrains have already a certain set of sensors included, it is natural to investigate if based on the readings of those standard sensors a condition monitoring system can be derived. The method is a performance-based approach for which the system performance is predicted by a gray box model serving as a reference for comparison with the real system performance gray box models seem to represent a promising compromise between expensive theoretical modelling on one hand and the need for huge data sets for creation of pure black box models on the other hand. The method proposed was tested with multiple measured data sets. It can be concluded that it has a promising potential to detect failures of axial piston units prior to the loss of function of the units.

Keywords: Condition monitoring, axial piston unit, vibration, accelerometer, gray box modelling
Target audience: Mobile Hydraulics, Digital Machine Services, Design Process

Introduction

Condition Monitoring as part of the digitalization mega trend becomes an integral part when we aim for Maintenance 4.0 and advanced fleet management. For condition monitoring of machine parts, as gearboxes and bearings, well-established methodologies have been existing for many years. The advantage in these fields is that the failures create clear vibrations which are also often audible. Thus, the detection and analysis via vibration sensors (accelerometers) is the next logical step. But the topic becomes more complex when it comes to condition monitoring of hydraulic pumps and motors, especially hydrostatic axial piston units. Due to the significant different physics of the propagation of noise and vibrations in hydraulic units, the detection of the state of internal parts is challenging, see **Figure 1** showing the inner parts of the Danfoss H1 Pump, a swashplate type axial piston unit.

Nonetheless, developments to advanced fleet management and full interconnected processes in typical branches like construction, farming, forestry etc. require a more detailed status reporting of the machines and their components. The classical maintenance methods *corrective* and *predictive (timebased) maintenance*, like shown in **Figure 2**, are here not sufficient and efficient anymore, as they are either only reactive after a defect or inefficient from a TCO point of view. Especially for the here investigated hydrostatic components, which have by themselves a very high robustness, this approach leads to unnecessary costs. For a more cost-sensitive solution, a detection of the condition of the to be observed component (healthy → failure) is necessary, leading to *condition-based maintenance*. With that, the reliability of hydrostatic systems can be maximized and the full potential of a fleet management system leveraged.

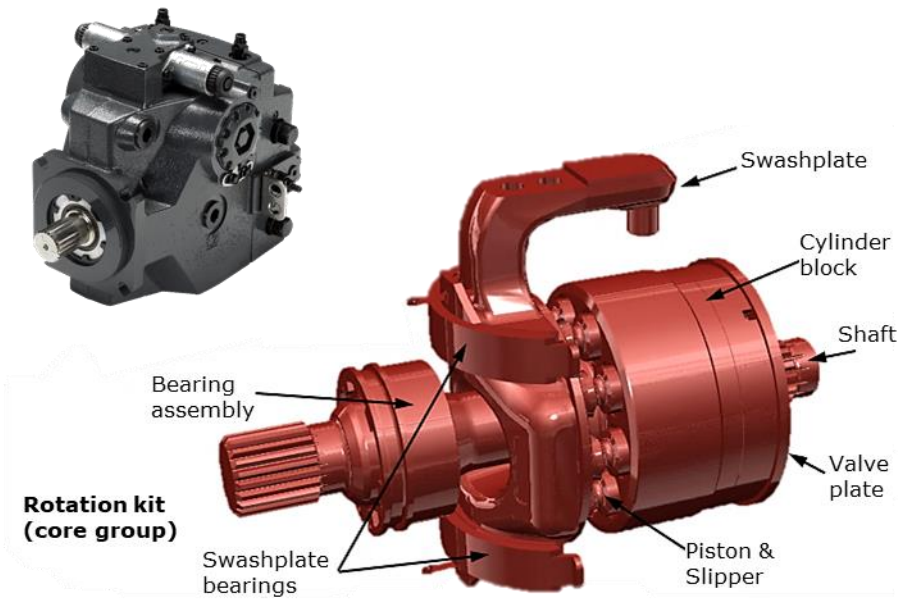

Figure 1: Internal core components of the H1 Pump, a swashplate-type axial piston unit

This includes typically a baseline detection at the beginning of the product life, often already in the factory. Depending on the used monitoring methods, warning thresholds will be implemented which will trigger maintenance activities when these thresholds will be exceeded during the monitoring period, see Figure 2.

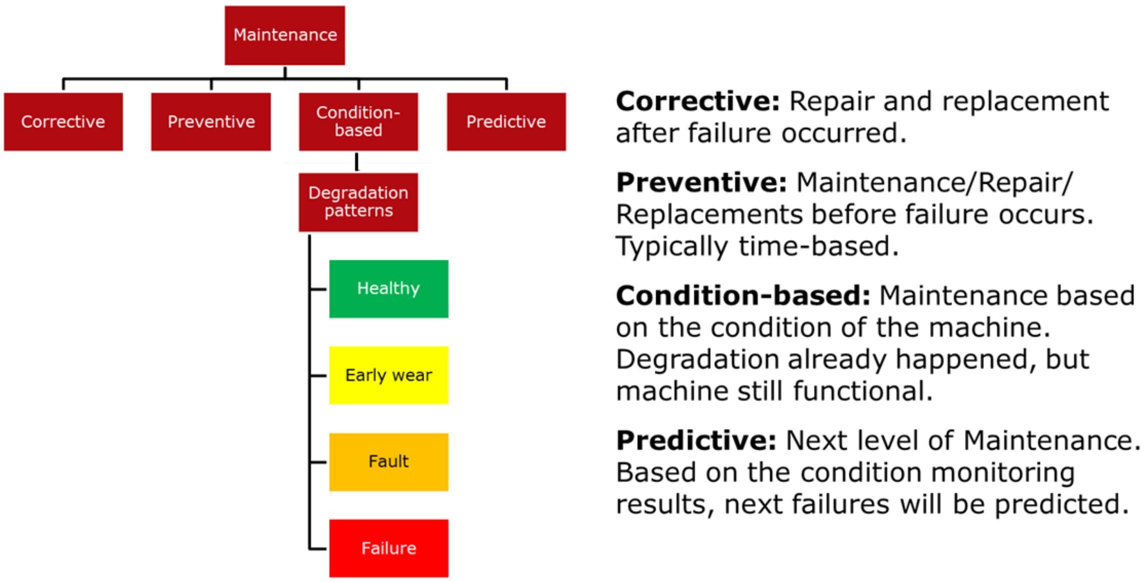

Figure 2: Condition-based Maintenance in the context of other maintenance strategies

An essential technical property of condition-based monitoring is, that a degradation of the component needs to happen to make the change measurable, but compared to corrective maintenance, the defect is detected early and thus the machine is still functioning. In predictive maintenance, the degrading of the machine will be predicted and failure likelihoods will be created. The theoretical background for axial piston units has been derived in [1] and [2]. A possible further extension of this is presented in [3] and [4], where also an assistance system was developed which supports the operation of the machine – here a wheel loader – to minimize the damaging impact during operation.

Both last maintenance strategies, condition-based and predictive, require a technical methodology to monitor the conditions of the observed component and derive the maintenance activities out of it. Appropriate methodologies could be exemplarily classified in two categories, based on the detection principle. The first category is the sensor-based condition monitoring system. Here, sensors are applied to a component, typically special sensors just for that purpose which deliver the component data and an algorithm derives a condition statement. Second category is a performance-based condition monitoring, where the condition is not directly measured but derived from second-level information, like the performance of a component or a system. Benefit of this principle is that the component or system performance is simpler to measure with often already available sensors and without need of additional, specialized sensor technology like in the sensor-based condition monitoring system. Due to this attractiveness, this paper will discuss a performance-based condition monitoring system, focus on the algorithm development for making precise predictions and close with simulation and test stand validations.

Project goal and development context – Bauen 4.0/Construction 4.0

This work was conducted in the context of the Bauen 4.0 (Construction 4.0) project [5]. Bauen 4.0 is a multilateral research project driven by a German industry and university consortium, which develops construction methodologies and scenarios for a more integrated and streamlined construction process. One of the focus points are Digital Machine Services, whereof Condition Monitoring is a part. In the context of Bauen 4.0, the Condition Monitoring project goal is to monitor the condition of the main hydraulic pump of the demonstrator machine, an excavator, and partly also of the connected hydraulic system, like the cylinders. The collected information will be submitted via telematics unit to a local construction cloud so that the machine status can be taken into account in local construction site or remote company fleet administration activities. So, a holistic machine availability and effectivity strategy can be developed for the machine owner and executed over the machine usage. More information is available also in [5].

Although the Bauen 4.0 demonstration system is an open circuit, valve controlled hydraulic cylinder drive, the development activities in this paper will be pursued with a close-circuit hydrostatic drive. The reason behind is the high availability of prototype tests and data of hydrostatic systems in the development location. When the functionality of the approach is proven, it is just a small modification from a closed-circuit to an open-circuit system.

Sensor-based Condition Monitoring System

Condition Monitoring via sensors is the natural way of conducting a Condition Monitoring system. The idea behind this approach is to attach an appropriate sensor to the unit and derive the internal condition from the sensor readings. The change of the readings over time delivers an indication of a condition change, like increased wear. Typically, these sensors are not applied directly where the suspected condition change happens. That might be due to the internal structure and packaging of the specimen, like insufficient space to mount the sensor or rotating parts complicate the sensor application. Besides, those Condition Monitoring systems can be retrofitted/retrofittable and thus must be capable of outside mounting. Therefore, the conditions to be detected must transmit a significant signal so that an outside mounted sensor can measure it.

The state of the art in this field are acceleration sensors/accelerometers or temperature sensors [6]. A mixture out of a thermodynamic and acoustic approach was presented in [7]. Many examples are found that accelerometers measure the vibrations which are caused by the degrading components well – but these examples are mainly found when monitoring the conditions of gears, bearings, and similar machine parts like discussed exemplarily in [8], [9]. In [10] the application of accelerometers has been discussed for hydraulic pumps. It was found and corelated to earlier work [11], that accelerometers are capable to measure the frequency response of an axial piston unit in different operation conditions, especially in combination with typical sensors for pressure, speed, displacement and temperature.

This short state of the art shows on the one side, that a condition monitoring system with accelerometers is realistic and has been successfully implemented. These attempts should be complemented by a new kind of condition monitoring systems without the need of additional sensors like the accelerometers. Such system delivers also acceptable results and represent an attractive solution in the share of the mobile machinery market where it is necessary to implement condition monitoring merely with the sensors already available on the machine.

System-performance-based Condition Monitoring System

The technical concept of this approach is, that the machine performance will be measured and compared against a prediction of a model in real-time. Deviations indicate a deterioration of the system component's conditions, often impacting the volumetric efficiency. Thus, the machine performance declines with increased wear and a leading indicator for the machine performance can be tailored to the monitored system. For a propel drive, a good performance indicator is the vehicle speed. This is simple to measure and gives a good correlation to the wear state of the propel system. The approach is then, that for the given conditions of the propel system, an expected motor speed can be predicted and this will be compared to the measured, real vehicle speed. In good conditions of the components, this will show ideally no difference. With degrading conditions, the measured vehicle speed will drop below the predicted speed and thus demonstrate, that wear happened over time and led to a measurable impact.

The approach seems to be very simple, but it causes some difficulties, which are discussed now. The most prominent one is the calculation or prediction of the performance indicator, here the motor speed.

- One approach is a theoretical approach. The propel system output (motor shaft speed) will be calculated or simulated based on models describing the physical behaviours of the different components for the different operation conditions. This is called a **white box** approach/model. So, the model delivers the comparation value to the measured motor speed.
- The contrasting approach is a pure data driven one where a model or an algorithm will be trained on data and thus does the prediction of the output (motor shaft speed) in relation to the operation conditions. This approach is called **black box** model and became more popular in the past years with the increased use of data analytics.

White, Gray and Black box model for Condition Monitoring

Mathematical models have been successfully applied to simulating various phenomena of highly complex, dynamic, non-linear and multi-variable macroscopic phenomena that even contain chaotic elements. Essential contributions have been made to the detailed understanding of the physics of processes [12]. In the content of this work, models will be used to predict the performance of an exemplary propel system. As mentioned above, several model types could be used and will be discussed here.

White box models

White box models are pure theory-based approaches which derive process models from the fundamental physical mechanisms. Measurements are primarily employed for model fine-tuning and validation. Theoretical models provide the following advantages:

- Flexibility with regard to changes of geometry, material, boundary conditions etc
- Possibility of taking qualitative changes into account
- Information for all unknowns at any location and possibility of simulating on small/large space scale and short/long-time scale
- Isolation of particular phenomena, e.g. influence of gravity.

In combination of a hydraulic propel system speed prediction, the simplest white model is formulated by:

$$n_M = \frac{n_P V_P}{V_M} \cdot \eta_{vol,P} \cdot \eta_{vol,M} \tag{1}$$

where the indices M and P denote motor and pump.

This model could already be sufficient, but it would require an accurate information about the actual displacements V_P and V_M and the volumetric efficiencies $\eta_{vol,P}$ and $\eta_{vol,M}$ of both units. As indicated earlier, the displacement for the pump is simpler to obtain, but displacement sensors for bent-axis motors for usage in mobile applications (vehicles) are not available. In this case, displacement-controlled motors should be used which brings an uncertainty into the system.

The other to be known parameters are the efficiencies which are dependent on the operation conditions speed, displacement, pressure and temperature. This would either require a very accurate implementation of the unit efficiencies which is for mobile controllers a challenge, or this includes inaccuracies. If each of the volumetric efficiencies come with a deviation of only 5 % points, exemplary 90 % instead of 95 %, the vehicle speed will differ by little more than 10 %. For typical maximum vehicle speeds of 40 $^{km}/_{h}$, this would allow a drop of 4 $^{km}/_{h}$ without being detected by the system – but that reduction is already be noticeable for the operator. Thus, it is obvious that this simple model is insufficient. It could be enhanced by including are more detailed loss model, but it has been found in the past, that white box models are not delivering the needed accuracy when representing the loss behaviour of hydrostatic units [13], especially if the computational power of a mobile controller is considered.

Black box models

A different approach is empirical modelling, which is not connected to any theory. The model is being built on data obtained from an observation of a unit. The correlation between input and output is searched. Popular data driven techniques are regression analysis, multivariate splines and artificial neural networks. They are preferred solutions for control applications and especially interesting in situations where physical background knowledge is rare, time for model creation is limited or execution speed is an issue. Such models are robust, real-time capable and relatively easy to apply. These models are typically applied in two steps. Firstly, the model will be trained with a training dataset, consisting of the training input X and the correlating target output Y as shown in **Figure 3**. After training, the model predicts an output y as a function of input x. In the considered case, the theoretical motor speed $y = n_M$ is predicted. It will be used for comparison with the measured motor speed in the vehicle.

However, empirical models are unqualified to fully substitute theory based approaches due to:

- Limitations in filtering inaccurate process data due to lack of physical background
- Difficulties to differentiate between significant and insignificant input
- Reduced ability to extrapolate outside original observation range

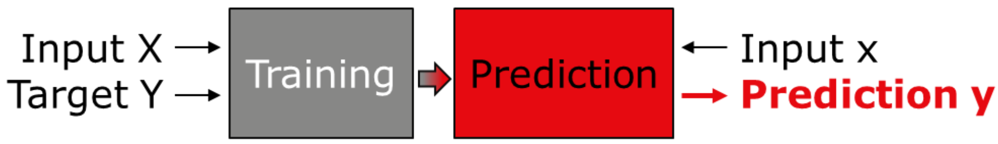

Figure 3: Principle of data usage in a black box model and the two main steps using a black box model.

Another limiting factor for the usage of pure black box models, especially in this content with high demand of accuracy, is the amount of necessary training data. The potential of quantitatively acceptable result reproduction is very limited if the model training is not performed with a substantial number of experiments. Taking efficiency measurements of a hydrostatic unit into comparison, around 1000 datasets are necessary to create an efficiency model with acceptable accuracy. In case of a simple hydraulic propel system with a pump and a motor, the training target is a function of 6 inputs n_P, V_P, ϑ_P, dp, n_M, V_M, ϑ_M. The data points recorded during vehicle operation are repeatedly measured and averaged resulting in immense data set sizes. This causes long, machine-individual training phases in which the Condition Monitoring system cannot deliver results. Especially the very limited data storage of mobile control units makes this approach also very challenging, so that a combination of both approaches in form of a gray box model is proposed.

Gray box models

Gray box models combine theoretical with empirical submodels. Tuning of theoretical models is almost always necessary in order to compensate lack of modelling or of understanding of process details, incompleteness of material properties or inaccuracies of numerical methods. Here, as shown in the discussion above, the theoretical model as represented in Equation 1 is lacking an appropriate modelling of the hydrostatic losses. As further discussed, the modelling of those losses is presumably futile, so the theoretical sub-model (white box) can benefit from a combination with an empirical (black box) sub-model.

The simplest form of combining data with theoretical models is model regression analysis, leading to a kind of light gray box model. Starting from this, the share of the theoretical model in a gray box model can be reduced by combining it with empirical models of different complexity [14]. Definition and their typical characteristics are summarized in **Table 1**.

Model type	Characteristics
White	Theoretical model (purely deterministic)
Light gray	Theoretical model fine-tuned by means of regression
Medium gray	Theoretical submodel gets arbitrary tuning input from empirical submodel
Dark gray	Theoretical submodel output is corrected with output of empirical submodel
Black	Data-driven model (purely stochastic)

Table 1: Characterisation of the different model types

Gray box models have the potential to reduce the total costs of modelling by combining the advantages of their white and black box sub-models. In **Figure 4**, the costs or modelling effort are plotted versus the degree of model transparency (grayness) as a measure of the split in the share of the black box relative to the white one. Pure black boxes require big data sets. The resource need for a white box can rise dramatically if it should be exclusively based on first principles. The economic optimum is often a hybrid solution.

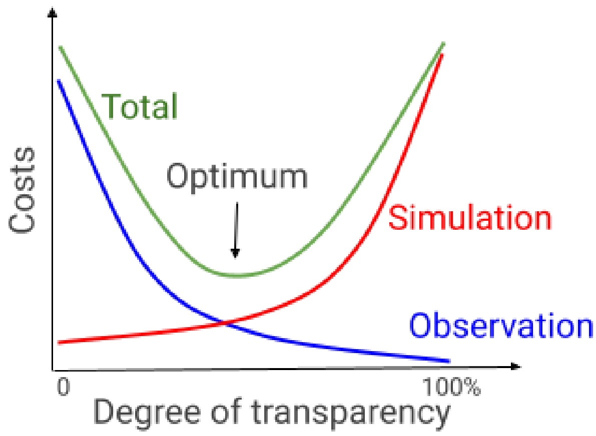

Figure 4: Total effort of gray box model creation as a function of the degree of model transparency

Applied Gray box model

The selection of the Gray box model is based on the accuracy demands. As discussed, for a reliable condition monitoring system, a high prediction accuracy is necessary. Due to the constraints of the theoretical approach, the limitations of the white box model should be compensated by combination with a neural network approach, leading to a dark gray box model. The principle is demonstrated with **Figure 5**.

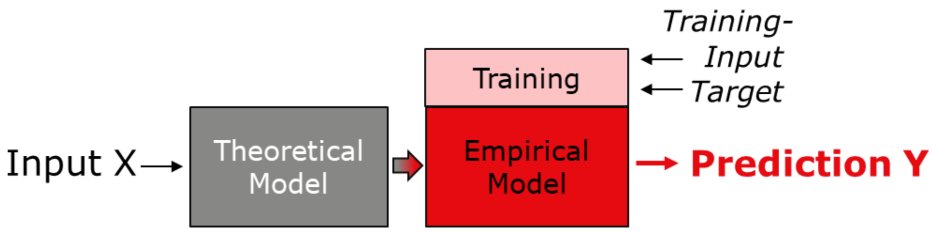

Figure 5: Dark gray box principle used in this approach.

To test the modelling approach, data sets are given out of a high-fidelity simulation model, from selected observations:

$$Y = F(X(t)) \text{ of a healthy system} \quad \text{for } t \text{ in } [0, t_{obs}] \tag{2}$$

$$Y = G(X(t)) \text{ of a degraded system} \quad \text{for } t \text{ in } [0, t_{obs}] \tag{3}$$

X is the input, Y is the output, t is the temporal variable and t_{obs} the end of the observation period.

The responses Y of the healthy system $F(X)$ and of the degraded system $G(X)$ are different for an identical input set X. Thus, the output of a model trained with a $\{X, F(X)\}$ data set will also show a significant difference to the actual observation $\{X, G(X)\}$ of the degraded system and can serve as a degradation indicator.

Input and output of the data set read as:

$$X = \{ n_P, V_P \} \tag{4}$$

$$Y = \{ n_{mot} \} \tag{5}$$

n_P is the rotational speed of the pump, V_P the pump displacement, n_{mot} the rotational speed of the hydraulic motor and p the system delta pressure. In view of the future application in an open circuit system with cylinders, the motor is modelled as motor with fixed displacement as cylinders can't change the piston area – which would be the appropriate complement to a variable displacement in a hydro-motor. Thus, X is not a function of V_M. These variables are connected by a theoretical model k:

$$k = k(n_P, V_P, n_{mot}, p) \tag{6}$$

The output of function k serves as the target for the training of a monitor model $\beta(x, w)$. The input of that model contains the potentially degraded $n_{mot}(t)$ for all times t. w is a set of weights for fitting the model to the data. The optimal w is found by:

$$w = \arg\min \left[\beta\,(X, w) - k\,(F(X)) \right]^2 \tag{7}$$

$\beta(x, w)$ is trained with a subset of a first data set from the healthy system$\{ X(t), F(X(t)) \}$ for t in $[0, t_{trns}]$, where the end of the training period at t_{trn} is a fraction of the end of observation period t_{obs}.

$$D_{trn} = \{X, F(X)\} \text{ for } t \text{ in } [0, t_{trn}] \tag{8}$$

A model test is performed by predicting $k(F(X(t))$ for a subset of data in healthy condition which was not used for the model training

$$D_{tst} = \{X, F(X)\} \text{ for } t \text{ in } [t_{trn}, t_{tst}] \tag{9}$$

This test evaluates the extrapolation capability of the model for times outside of the teaching period. In contrast to that, the validation of the model is conducted with a second data set unknown to the model:

$$D_{val} = \begin{cases} \{X, F(X)\} & : \text{if } t \leq t_{dam} \\ \{X, G(X)\} & : \text{otherwise} \end{cases} \tag{10}$$

For t in $[0, t_{dam}]$ the set D_{val} contains output $\{ X, F(X) \}$ of the system in healthy condition. For times greater than the begin of damage t_{dam}, the validation set contains simulated damages $\{ X, G(X) \}$. The validation should proof the ability to extrapolate to other parameter sets in healthy state as well as the capability to detect anomalies occurring in the degraded state.

In **Figure 6**, the difference between the predicted and the actual flow rate of the system is plotted versus time. Training input was data between zero and the dotted red line. The model is capable to reproduce the training data (blue curve left of red dotted line) as well as the test data outside of the teaching period (blue curve right of red dotted line). As a first attempt in validation, the model was used to predict the volume flow difference in healthy state (orange curve right of red dotted line) and in degraded state (orange curve right of green dotted line). For the degraded state, an artificial leakage has been implemented in the simulation model delivering the data for these tests. The difference in model response is significant and allow to identify the point in time where the degradation starts.

In

Figure 7, the validation of the difference between the flow rates is conducted for another data set. Training input in healthy state was taken from observed data different from validation data – shown in Figure 6. That simulates, that a vehicle is trained with a certain data set in the beginning of the life and then monitoring all other conditions based on the initial training data. The reproduction and extrapolation of the training data is sufficient. The blue and orange curve show a certain deviation in the healthy period (till the dotted green line) which is irrelevant for the intended anomaly detection. For the test of the identification of the degraded state, again an artificial leakage was implemented, here of approx. 5 $^{l}/_{min}$. The model response for the degraded state (orange curve right of green dotted line) shows the expected difference to the response in healthy state (blue curve right of green dotted line).

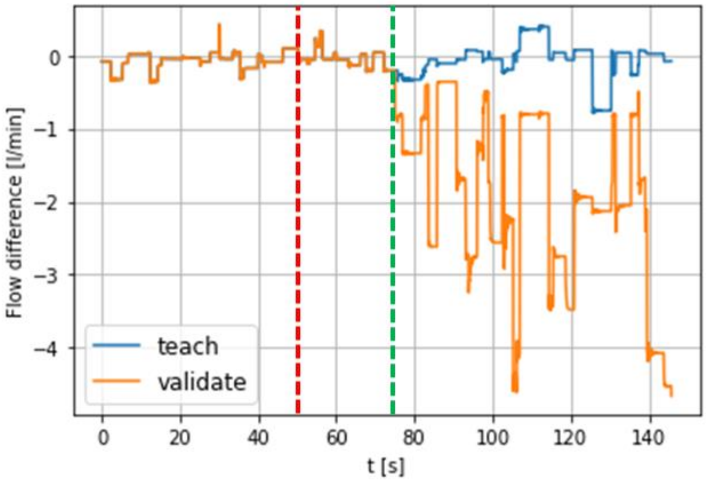

Figure 6: Test and validation on single set: degraded state (orange) and healthy state (blue)

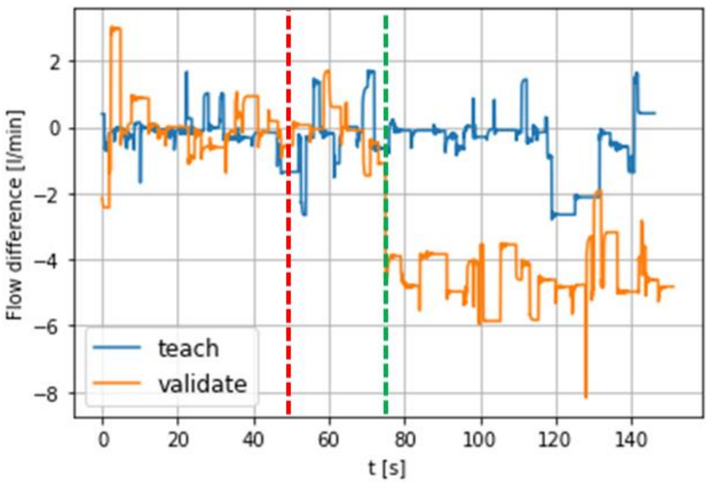

Figure 7: Test and validation on two sets: degraded state (orange) and healthy state (blue)

The prediction of the model and its comparison to the actual flow rate difference occurs to be a safe measure for the detection of the start of severe degradation of the hydraulic system. Thus, a real-life test in the test lab is the next step in validating the approach.

Test results of the Performance-based Condition Monitoring system

The approach of the system is represented in **Figure 8**. The tested hydrostatic circuit, consisting of a standard pump-motor combination, driven by an electric prime mover (PM), is equipped with sensors for the shown quantities pump speed, displacement, pressure and temperature as well as similar for the motor. In the test, the pump was an H1P with 78 $^{ccm}/_{rev}$ and the motor was an H1B with 110 $^{ccm}/_{rev}$ to represent a typical mid-size drivetrain.

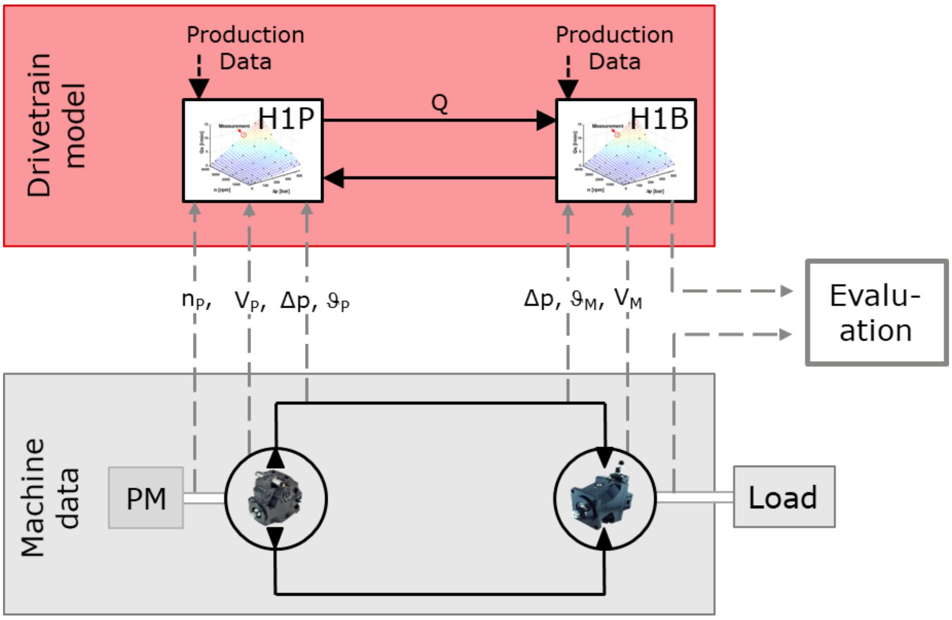

Figure 8: Test setup of the performance-based Condition Monitoring System

The pump was driven by an electric prime mover and the motor was loaded to establish the system pressure Δp. To generate unit failures in a reasonable time, a very high pressure of Δp = 480 *bar* was set. The corresponding empirical model was enriched by production data to increase the accuracy. In contrast to the analyses in chapter 3.1.4, the output is in this case not the absolute difference in flows between pump or motor as here the defect (meaning the flow difference) is not known. So, instead a CM ratio is introduced, as the ratio between the measured motor speed and the predicted motor speed. Thus, when the wear of the units increases, the CM ratio drops below 100 % as the measured speed will get smaller than the prediction.

In the test, the pump ran at 3000 $^{1}/_{min}$ and full displacement, the motor was operated at ~ 40% displacement, leading to a speed of 5100 $^{1}/_{min}$. The setup was chosen in a way to lead to motor and pump failures taking a little shy of 550h runtime. The test results are shown in **Figure 9**, demonstrating the introduced CM indicator as the system output over the test duration.

Some fluctuations of the CM ratio are visible, indicating room for improvement of the accuracy of the Condition Monitoring model. In this example a detection limit of 2 % has been defined to have a very early detection of the failure, representing a drop in vehicle speed of 1 $^{km}/_{h}$ in typical applications. Thus, a warning would be displayed when the indicator drops below 98 %. This is a good compromise between the requirement of warning prior to being noticed by the operator and a tolerance to variations due to measurement effects and model inaccuracy.

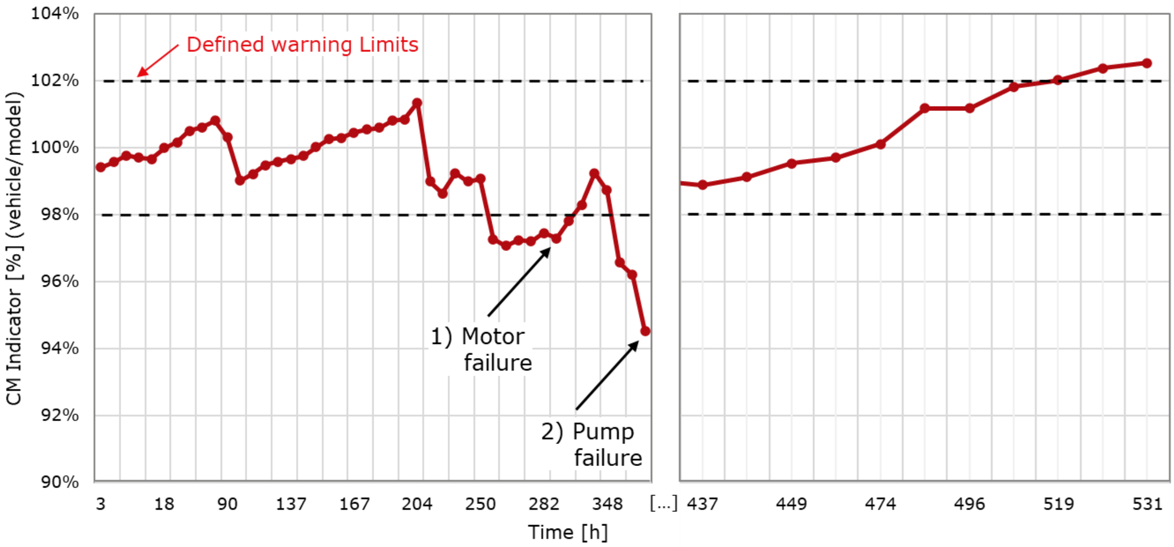

Figure 9: Condition Monitoring System results for the test run.

What becomes obvious out of this test is, that shortly after 250h runtime, the indicator crossed the warning limit and ca. 40h later, the motor lost function – Point 1 in the figure. At this point, the motor was replaced and the test continued – the CM indicator gets back to normal levels. But at 350h of total runtime (Point 2), the indicator fell again below the warning limit and approx. 15h after the crossing, the pump lost its function. The last incident shown here, after the pump was replaced, staring to cross the warning limit at 515h and finally failing 20h later is a good example, that the system might not only detect wear, but also a misposition in the hydrostatic unit and thus also a failure in the control system and its excitation. The failure leading to an exceed of the upper limit was a failure in the control excitation of the motor and thus the motor was on a different position than commanded.

The warning time in these tests is the period of time between passing the warning threshold and the occurrence of the failure. A value of 15 – 40 *h* is indeed promising considering the harsh operation conditions with pressure in the order of Δp = 480 *bar*. Such extreme conditions do not occur often during real machine operation. Therefore, the real unit life times are significantly longer as in the presented test situation and typically in the order of several hundred operation hours.

Summary and Conclusion

For machine elements, Condition Monitoring systems are state of the art. Multiple applications are developed and commercially existent. Substantial progress was made measuring the conditions of bearings and gear, typically conducted with accelerometers. Those deliver reliable results for the mentioned and similar components. With specific focus on hydrostatic units, especially axial piston units, this paper presents an alternative approach without additional sensors, based on the analysis of the system performance.

Key element is the prediction of a typical but well-measurable machine performance, e.g. a speed of a hydraulic consumer. This measurement is compared with a model prediction. It was discussed that the best approach for those models is a gray-box approach as white box models do not deliver the necessary accuracy and black-box models require too much data to be trained so that a series usage for mobile machinery is unfavourable. The approach was first tested with simulation data and delivered promising results. The used gray-box approach was able to predict the behaviour of a healthy system as well as detect the induced failures which represent wear in the system. Based on these positive results, the approach was verified against a standard hydrostatic circuit, consisting of a pump and a motor and tested until several failures of the units occurred. The results of these tests demonstrate that the presented approach is working rather well, the failures have been detected upfront with a comfortable warning time when the drive system would be operated in typical vehicle operation conditions.

As a downside of this approach, it needs to be mentioned, that the failures this system can detect are limited. In the given extend, the system focusses on detecting leakage or mispositioning of the hydrostatic units. The later situation is indicating failures in and around the control of the units. Other mechanical problems which do not lead to a decrease in the volumetric efficiency of the units will not be detected. Additionally, the system is also not able to detect the failing unit in simple hydraulic systems, so that during the maintenance both units need to be inspected.

To assess the impact of these downsides, it is helpful to look at the most prominent downtime reasons in hydrostatic circuits. This is typically wear in the rotational group or between cylinder block and valveplate or fractures of the cylinder block neck as that is one of the most loaded areas in swashplate units, see also [2], [15]. The experience around block neck failures reveals, that the cracks in those areas propagate also towards the cylinders. So, this problem also announces itself by increasing leakage. In other words, it is safe to assume that this Condition Monitoring approach will detect most situations when problems is axial piston units occur. The mentioned downside of this approach – to not being able to detect clearly which unit is affected – remains but does not diminish the main goal and effect of a condition monitoring system: To detect an upcoming problem early and thus prevent machine downtime and to schedule maintenance in accordance with the planned machine assignments. This is still achieved, making also this Condition Monitoring approach beneficial. So, with a system like this, the reliability of robust hydrostatic systems like the here tested H1 systems can be extended and maintenance schedules dynamized, which is especially interesting for applications where reliability is extremely important, like mining or when the machines are part of a modern fleet management system, exemplarily demonstrated in Bauen 4.0/Construction 4.0.

Outlook

As this is part of the project Bauen 4.0/Construction 4.0 and the condition Monitoring system is being implemented on the work hydraulics of an excavator, the next activities are to transfer the obtained knowledge to an open circuit system. A closed-circuit system was used for initial tests as such systems were better testable at the development location. Nonetheless, as the principles are the same, only the gray box model needs some modification/new training to better represent the open circuit system. After that step, the system will be optimized and tested with real machine data to demonstrate the usability not just under lab conditions but also in mobile applications. In a research project like this, typically the machine will not be subjected to long and harsh work cycles which have the potential to wear the components. So, for the verification of failure detection, the excavator will be prepared to simulate failures. In such a configuration, the Condition Monitoring system can be extensively tested and the value demonstrated.

Nomenclature

Variable	***Description***	***Unit***
n	Speed	$[min^{-1}]$
p	Pressure	$[bar]$
dp	Differential pressure between high and low loop side	$[bar]$
t	Time	$[s]$
V	Displacement (with indices M and P for Motor and Pump)	$[cm^3]$
ϑ	Temperature (with indices M and P for Motor and Pump)	$[°C]$
η_{vol}	Volumetric Efficiency (with indices M and P for Motor and Pump)	$[1]$
D	Gray box model	-

β	Monitor Model	-
X	Input function	-
w	Weighting parameters	-
Y	Output function	-

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