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Asmussen, Magnus Færing; Liniger, Jesper; Pedersen, Henrik C.

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Review

Fault Detection and Diagnosis Methods for Fluid Power Pitch System Components—A Review

Magnus F. Asmussen [1,2,*] , **Jesper Liniger** [3] **and Henrik C. Pedersen** [2]

1   Hydratech Industries, 9000 Silkeborg, Denmark
2   Department of Energy Technology, Aalborg University, 9220 Aalborg East, Denmark; hcp@et.aau.dk
3   Department of Energy Technology, Aalborg University, 6700 Esbjerg, Denmark; jel@et.aau.dk
*   Correspondence: mas@hydratech-industries.com

Abstract: Wind turbines have become a significant part of the global power production and are still increasing in capacity. Pitch systems are an important part of modern wind turbines where they are used to apply aerodynamic braking for power regulation and emergency shutdowns. Studies have shown that the pitch system is responsible for up to 20% of the total down time of a wind turbine. Reducing the down time is an important factor for decreasing the total cost of energy of wind energy in order to make wind energy more competitive. Due to this, attention has come to condition monitoring and fault detection of such systems as an attempt to increase the reliability and availability, hereby the reducing the turbine downtime. Some methods for fault detection and condition monitoring of fluid power systems do exists, though not many are used in today's pitch systems. This paper gives an overview of fault detection and condition monitoring methods of fluid power systems similar to fluid power pitch systems in wind turbines and discuss their applicability in relation to pitch systems. The purpose is to give an overview of which methods that exist and to find areas where new methods need to be developed or existing need to be modified. The paper goes through the most important components of a pitch system and discuss the existing methods related to each type of component. Furthermore, it is considered if existing methods can be used for fluid power pitch systems for wind turbine.

Keywords: fluid power; wind turbines; condition monitoring; fault detection

1. Introduction

Wind turbines have become a significant part of the global power production and are still increasing in capacity [1]. Especially the offshore wind industry is growing and have increased 87% in installed capacity in 2017 compared to 2016 [1]. The offshore wind industry is expected to cover 23% of EU's total electricity demand in 2030 and is a important factor of EU's long term commitment of reducing the greenhouse gas emissions [2]. A key factor in achieving these long term goals is to reduce the Levelized Cost Of Energy (LCOE) for wind turbines. A way of reducing the LCOE is to reduce the Operational Expenditure (OPEX) which contribute up to 30% of the LCOE. For offshore wind turbines, the OPEX is in general higher compared to onshore wind turbines due to longer lead time, more expensive transportation, and longer downtime of the turbine. A way of decreasing the OPEX is to introduce condition monitoring systems that may increase the reliability.

The LEANWIND project [2] identified condition monitoring systems as one of the subjects to be addressed in order to achieve a reduction of the total cost of energy. The reduction comes from an increased reliability and availability as a result of fewer unpredicted failures and better opportunities for planned maintenance. Hameed [3] and Garcia [4] have earlier made reviews covering some of the existing methods within condition monitoring of wind turbines. Most of the methods aims for monitoring of the structural health, the bearings and the electrical systems. For the pitch system, not much has been presented except for oil analysis and simple check on whether the pitch reference is tracked or not.

However, the pitch system is a very important subsystem of the wind turbine as it is used for emergency shut downs by applying aerodynamic braking to stop the wind turbine. The pitch system can be either an electrical pitch system or a fluid power pitch system where the distribution between them are roughly even. This paper focuses on fluid power pitch systems.

A survey by Carroll et al. [5] analysing a population of 350 offshore wind turbines show that the pitch system is responsible for approximately 13% of the failures of the turbine, making it the sub-system responsible for the largest part of the total number of failures. Another survey by Ribrant and Bertling [6] supports this by stating that the pitch system is responsible for a large number of failures.

Condition monitoring systems does already exist in wind turbines and reviews do exists, e.g., Hammed et al. [3], Garcia Marquez et al. [4] and Jin et al. [7]. As seen in the former reviews, a lot of systems have been implemented, though most of the systems focus on the structural health, the bearings and the electrical systems. The works on fluid power pitch systems are not as comprehensive as for the other areas. However, as stated by Carroll et al. [5], it is an important system as it is part of the safety system of the wind turbine and is subject to a high amount of failures.

Liniger et al. [8] presented a review of existing fault detection and diagnosis methods for fluid power systems. Here it was found that methods do exist for faults like cylinder leakage, internal valve leakage, fluid contamination and sensor faults. However, further work is needed to adapt them to pitch systems. The review is very brief and does not go into detail with each component.

The focus of this paper is to give an overview of fault detection and condition monitoring techniques for fluid power systems, and discuss their applicability related to pitch systems. The overview will include a categorisation of the used methods and the signals used for all the important components of a hydraulic pitch system. The methods are furthermore compared qualitatively and their applicability for wind turbines are discussed. Compared to previous reviews this paper gives a more comprehensive overview of the existing methods and makes a comparison between the methods in relation to fluid power pitch systems. The purpose is to find research gaps where methods needs to be developed and which methods that already exists and can be modified and applied. As fluid power pitch systems are similar to conventional fluid power drives the review may also be relevant for these systems and their components.

2. Pitch System Description

Fluid power pitch systems are used in wind turbines to pitch the blades for aerodynamic braking and thereby regulate the power or to shut down the turbine. In Figure 1, a simplified example of a fluid power pitch system is shown to give an overview of the components and functionality of the system. It may be noted that all hydraulic pitch systems are not identical, which is why some systems vary from the one presented.

The system consists of several valves which are used to control the flow in the system, a hydraulic cylinder as actuator, a supply circuit and an emergency accumulator used for emergency shut down of the turbine. Furthermore, the system consists of different sensors measuring the system states during operation, for both control and monitoring purposes. In Figure 1, a notation of the measured system state is given to each sensor, which will be used throughout the paper. The pitch system is for the most part similar to other conventional fluid power drive systems. The operation of the pitch system can be divided into several modes which dictates the operation of the system and which components are in use. The operation modes are therefore briefly described below.
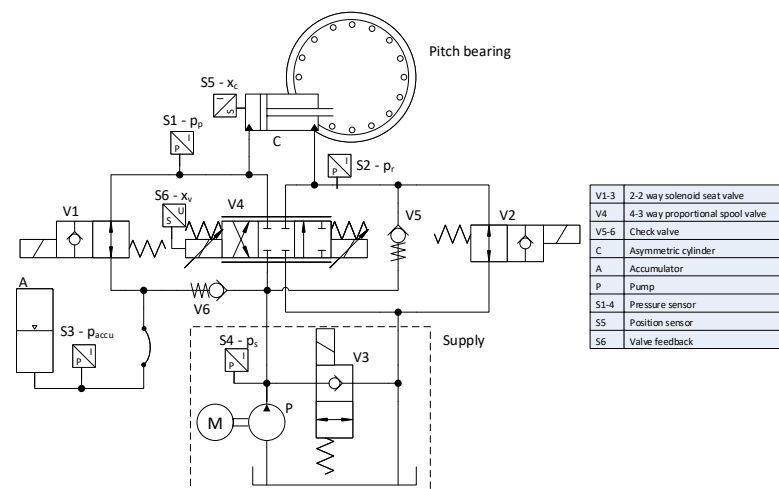
Figure 1. Simplified example of fluid power pitch system.

Start-up

The supply pressure is controlled between two pressure levels by activating and deactivating V3. When V3 is activated pressure is build up and when V3 is deactivated the pump is idling. First the emergency accumulator is charged through the check valve, V6. The blade is then pitched into the wind by retracting the cylinder to the desired position with the proportional valve, V4. Once the desired position is reached the start-up procedure is finished and pitch regulation is enabled.

Pitch regulation

In pitch regulation the proportional valve is used to follow a pitch reference given from the turbine controller. When extracting the cylinder, flow is going from P to A in the proportional valve and flow from the rod side chamber of the cylinder is going through the regenerative check valve back to the supply. When retracting the cylinder, flow is going from P to B and A to T of the proportional valve.

Emergency shut-down

When a emergency shut-down is enabled all valves are de-energised and go to their normal position, i.e., the proportional valve is closed and the two emergency valves are opened. Flow is then going from the accumulator through valve V1 and into the piston side chamber of the cylinder while flow from the rod side chamber is going to the tank, thereby extending the cylinder, i.e., pitching the blades out of the wind.

It should be noted that the system illustrated in Figure 1 is extensively simplified and that a complete pitch system consists of several more components, primarily for safety. This includes additional sensors, redundant components and extra valves for service functions. All main components are though present and gives an understanding of which types of components that are present in a typical pitch system. In the following sections, FDD methods for each component of the system will be reviewed and discussed starting with the cylinder.

3. Hydraulic Cylinder

The fault scenarios related to the hydraulic cylinder addressed in this paper are internal cylinder leakage and external cylinder leakage. Other type of faults include structural damage, slack, etc. but typically to, e.g., mishandling why they are not considered here. Internal leakage is defined as leakage across the piston seal and external leakage is defined as unwanted flow out of the hydraulic circuit. Leakage may be caused by worn seals or by failure in the connection between the cylinder and the hose. Internal leakage is typically

only considered a fault if the levels are so high that the system is not capable of operating. Even small levels of external leakage is critical why no leakage is typically allowed at all.

Internal and External Leakage

In the following an overview is given of the main results related to leakage. An overview table is found is found in the end of the section.

Choux et al. [9] compares an Extended Kalman Filter (EKF) approach and a State Augmented Extended Kalman Filter (SAEKF) approach for detecting internal and external leakage from one cylinder chamber based on pressure and cylinder displacement measurements. Both filters can detect internal leakage and external leakage, though only the SAEKF is estimating the leakage level. The SAEKF estimates the internal leakage level to approximately 0.25 L/min for the test set-up, though the actual leakage level is not given, why the accuracy of the estimate is not evaluated. While promising, the cylinder reference is given as a sinusoidal signal which is not similar to the movement for a pitch system. The non consistent movement in a pitch system may make it hard to apply the EKF approach as the residuals may be dependent on the operating conditions. Furthermore, the external load is applied by a spring-damper system which is not emulating the stochastic behaviour of wind loads.

A similar EKF based method is addressed by An et al. [10] where internal leakage of approximately 0.5 L/min and external leakage of approximately 0.5 and 0.8 L/min are detected. A test setup using a symmetrical cylinder with no load, where the leakage is emulated by needle valves is used for validating experimentally. In An and Sepehri [11], the detection scheme is extended to handle the leakage detection subject to unknown friction forces and unknown loads on the actuator. In addition a spring is attached to the cylinder at the test setup emulating the unknown load. The results of the extended detection scheme shows that the algorithm is capable of handling the unknown factors with similar results as in An et al. [10]. However, the cylinder reference given to the system is a sinusoidal signal which is not necessarily similar to the stochastic movements in a pitch system. This may influence the results as the faults are indicated by average residuals that may be affected by the operation conditions.

Sepasi and Sassani [12] use an Unscented Kalman Filter (UKF) for detecting faults of a hydraulic system including internal and external leakage. Faults are identified by looking at the moving average of errors of the cylinder displacement, the two camber pressures and a ratio between the two cylinder chamber pressures. The system is subjected to three levels of both internal and external leakage which are controlled manually by a needle valve. Experiments show that it is possible to detect all three levels for both internal and external leakage, though the leakage levels are not known. The system is subjected to external load which causes the residuals to increase. As the method relies on evaluating residuals, the method may be hard to implement for a pitch system with varying operation cycles.

Aloize [13] investigates and compares three different signal based methods for detection of internal leakage; autocorrelation of the pressure signal, cross-correlation between pressure signals, cross-correlation between control input and cylinder displacement and ratio of metric length of the pressure signals. All methods successfully detect leakage, though the ratio of metric length methods show better results being able to detect internal leakage down to 0.047 L/min with a change in mean RMS of over 80%. The other methods show slightly less change in mean RMS value but are all able of detecting the same leakage level. The experiments are performed on a valve controlled cylinder attached to a spring load, with a needle valve between the two cylinder chambers to emulate internal leakage. As the method is comparing mean RMS values the results may be affected by the operation conditions.

May et al. [14] describes a method based on cross-correlation between the two chamber pressures to detect internal leakage. The method is tested experimentally on a position trajectory with a series of steps where internal leakage is emulated with a needle valve between the two cylinder chambers. Internal leakage of down to 0.069L/min was found to

be detectable in the experiments. It is unsure how the method would perform in a pitch system with highly varying operation cycles and external loads as this may influence the results of the method.

Goharrizi and Sepehri [15] uses wavelet analysis to detect internal leakage in actuators. Internal leakage down to 0.2 L/min is detected experimentally on the test setup used in May et al. [14]. Goharrizi et al. [16] further uses wavelet analysis to detect external leakage and isolates it from internal leakage. External leakage is detected down to 0.3 L/min experimentally where needle valves are used to emulate external and internal leakage. Goharrizi and Sepehri [17] also describes a method using Hilbert–Huang Transform (HHT) and compare it to a method based on wavelet analysis. Internal leakage of 0.124 L/min when moving the actuator back and forth and 0.23 L/min when following a position trajectory is detected. HHT is found more sensitive to internal leakage, but is also more complex and computational heavy compared to the wavelet approach. The experiments are performed on the same setup used in Goharrizi and Sepehri [15]. Common for these methods is that they are evaluating the leakage level based on obtained coefficients from signal analysis methods, which has to be compared to a fault-free scenario. A disadvantages of this is that tests has to conducted on a system to find a baseline before the methods can be applied. Further, it is unsure how much system changes over time or external disturbances such as highly varying external forces will influence this baseline.

Crowther et al. [18] use a neural network to detect actuator faults including internal leakage which is trained on both simulations and experimental data with different levels of emulated leakage. Both networks was capable of detecting leakage faults, though the network trained on experimental data could be trained with fewer iterations. The leakage level tested for both networks were approximately 0.3 L/min. The used test set-up consists of a valve actuated cylinder drive attached to a mass loaded by a passive cylinder.

Asmussen et al. [19] use a SAEKF approach to detect internal and external leakage. The method is tested in simulations in [19] and later experimentially in [20] on a test set-up similar to a pitch system. During the tests the operating conditions are similar to an actual pitch system as the reference and external load are found from actual turbine scenarios. The results show that internal leakage can be directly estimated down to 0.10 L/min with an estimation error of maximum 0.04 L/min. For external leakage 0.34 L/min can be estimated, though the maximum error is up to 0.43 L/min. A downside of the method is that the valve model used in the SAEKF should be very accurate and uncertainties would lead to worse performance. However, the method could be implemented in an pitch system. It should be noted that the authors are the same as for this paper.

In general internal and external leakage is addressed in the past by several methods, both model based, such as Kalman filters, and signal based, such as wavelet analysis. The signal based methods may be hard to implement in a pitch system as the methods typically rely on a predefined trajectory of the actuator which is not present in pitch systems due to the stochastic behaviour of the wind. Furthermore, the signal based methods typically evaluate the leakage levels by comparing to baseline results obtained by a fault free scenario. However, the baseline may change with the operation cycle and the changing external forces why it may be difficult to use the methods for pitch systems in wind turbines. The model based methods may to some extent be implemented as some of the described methods take external forces and highly varying operation cycles into account. However, some of the model based methods rely on comparison with a fault free scenario why these may be exposed to some of the same problems as the signal based methods. The leakage levels detected by the different methods varies and it is difficult to compare them directly as the influence of a certain leakage level depends on the cylinder size and the total flow rate of the system. When taking the cylinder size of pitch systems, internal leakage of down to 0.2 L/min seems detectable. This may be sufficient for most hydraulic systems as internal leakage typically first becomes a problem at much higher rates. For external leakage none of the presented methods can detect low enough levels to be sufficient in pitch systems, though they could still be used to detect large abrupt

leakages. For very small levels of external leakage other methods should be developed perhaps including other sensor technologies. All the described methods are summarised in Table 1.

Table 1. Covered fault detection methods for actuator leakage failures. The notations of the used signals can be found in Figure 1.

	Fault Type	Method	Used Signals	Validation	Fault Level
Choux et al. [9]	int. and ext.	Model Based	x_c, p_r, p_p	Exp.	unknown
An and Sepehri [10]	int. and ext.	EKF	x_c, p_r, p_p	Exp.	≈0.5 [L/min]
An and Sepehri [11]	int. and ext.	EKF	x_c, p_r, p_p	Exp.	≈0.3 [L/min]
Sepasi and Sassani [12]	int. and ext.	UKF	x_c, p_r, p_p	Exp.	unknown
Aloize [13]	int.	Correlation	p_r, p_p	Exp.	0.047 [L/min]
May et al. [14]	int.	Cross-correlation	p_r, p_p	Exp.	0.069
Goharrizi and Sepehri [15]	int.	Wavelet	x_c, p_r, p_p	Exp.	0.2 [L/min]
Goharrizi et al. [16]	int. and ext.	Wavelet	p_r, p_p	Exp.	0.2 [L/min]
Goharrizi and Sepehri [17]	int.	H-H transform	p_r, p_p	Exp.	0.124 [L/min]
Crowter et al. [18]	int.	Neural Network	x_c, p_r, p_p	Sim.	unknown
Asmussen et al. [19,20]	int.	EKF	x_c, p_r, p_p	Exp.	0.34–0.46 [L/min]

4. Accumulators

The accumulator is used for both storing hydraulic energy for emergency shut-down and for decreasing the maximum flow demand for the pump. The primary failure mode of accumulators is gas leakage, which is also the failure mode considered in this paper. Gas leakage results in lowered pre-charge pressure of the accumulator and thus lowered storing capacity.

Liniger et al. [21] describes a method for detecting the changes in the pre-charge pressure of an accumulator. The method is based on wavelet analysis and uses a measurement of the fluid pressure close to the accumulator. The RMS value of the detail coefficient, corresponding to a frequency range of 0.39–0.78 Hz, is used to quantify changes in the pre-charge pressure. Through simulations it was shown that pre-charge pressure of 180 bar, 100 bar and 50 bar could be isolated from each other in an ambient temperature range of 22 to 60 °C. The method was further validated experimentally showing that levels of 100 bar, 75 bar and 50 bar can be isolated from each other. The method is dependent on excitation of the accumulator why some accumulators in some wind turbines cannot be monitored continuously as they are only used during an emergency shut-down.

In [22], Liniger et al. describes a method for detecting gas leakage by an EKF based algorithm. The method utilise measurements of the fluid pressure and the ambient temperature for estimating the pre-charge pressure of the accumulator. Experiments showed that pre-charge pressure could be estimated when using measurements of the input flow of the accumulator whereas the pre-charge pressure where seen to drift, when instead using a estimated input flow. Flow measurements are in general not present in hydraulic pitch systems why the method may not be applied for continuously monitoring of the pre-charge pressure. However, the pre-charge pressure were estimated during charging of the accumulator with a estimation error below ±2 bar. This may be sufficient to be used in a pitch system as the gas leakage is assumed to be slowly developing over time.

Helwig et al. [23] detects gas leakage, among other things, by multivariate statistics based on multiple signals to extract features related to faults. The method is tested experimentally subject to both fixed and random working cycles and can distinguish between 90, 100, 110 and 115 bar pre-charge pressure for fixed working cycles. However, the method showed decreased performance detecting the change in pre-charge pressure for random working cycles which is what pitch systems are exposed to. Due to this it may be difficult to apply this method without addressing this.

Sorensen et al. [24] describes a method using a bank of EKFs to detect changes in the pre-charge pressure of a piston accumulator. The residuals of the four EKFs with different

assumed pre-charge pressures are analysed using a multi-model adaptive estimation scheme to evaluate the most likely pre-charge level. Through experiments the method is shown capable of isolating 140 bar, 110 bar, 80 bar and 50 bar from each other. However, the method still relies on flow measurement which is not present in common pitch systems.

Nielsen et al. [25] is a patent application that describes a method where the accumulator capacity is evaluated by draining the accumulator through an orifice to the tank. During the decharge period the fluid pressure is monitored and decreased accumulator function can be detected by comparing the decharge time to a predefined value. A drawback of the method is that the wind turbine has to be shut down in order to perform the evaluation of the accumulator function. In a patent application by Minami et al. [26] a similar method is described, though it is not clear how the accumulator is decharged. Furthermore, this method can only be done when the turbine is shut down.

The described methods are summarised in Table 2.

Table 2. Covered fault detection methods for accumulator gas leakage. The notations of the used signals can be found in Figure 1.

	Method Domain	Used Signals	Validation
Liniger et al. [21]	wavelet	P_s	Exp.
Liniger et al. [22]	EKF	P_s, $\dot{x}_p$, T_a	Exp.
Helwig et al. [23]	Neural Network	multiple	Exp.
Nielsen et al. [25]	Signal based	P_s	unknown
Minami et al. [26]	Signal based	P_s	unknown
Sorensen et al. [24]	EKF	P_s, Q_{load}, Q_{pump}	Exp.

In general not many papers has been published within the topic of gas leakage detection. Though most of the methods described in this section are developed with pitch systems for wind turbines in mind. However, most of the applicable methods only work well for periods where the accumulator is either charged or discharged, and not during continuous operation. As gas leakage of accumulators typically happens slowly over time it should be sufficient to only check for this failure once in a while why the methods have potential of detecting such failures. Whether the detectable level of gas leakage is sufficient will depend on the safety factor in the design of the specific system, i.e., how much the system is over-dimensioned. In most systems there will be more than one accumulator, i.e., a bank of accumulators. None of the described methods consider this why it may affect the results of the methods. Furthermore, the method cannot identify which of the accumulators are leaking.

5. Valves

In pitch systems there are several different valves including proportional spool valves and on/off valves which are considered in this paper. Common for the on/off valves and the proportional valve is that they are solenoid actuated. Typically the on/off valves are poppet valves. As the on/off valves and the proportional valve are both solenoid actuated they are considered in the same section. Both signal and model based methods exists for detecting failures in valves. Some of the method exploits that the movement of the valve can be detected in the current response and uses this to detect failures related to the movement of the valve. The current response is then typically compared to a healthy valve to check for failures.

Solenoid actuated valves typically work by applying voltage over a solenoid to create a electromagnetic force that is capable of moving either a spool or a puppet in order to control the flow through the valve. Jameson et al. [27] gives an overview of the failure modes and root causes of solenoid actuated valves by a Failure Mode Mechanisms and Effect Analysis (FMMEA). Here worn or degraded parts, contamination by foreign materials, short circuit

in the coil, and open circuits in the coil where identified as the most important ones with short circuits being the most dominant.

Ramos Filho and Negri [28] describes a model based approach to fault detection of a hydraulic proportional valve. A physical model is used as a reference such that the measured current can be compared to a theoretical value. The method is tested on a healthy valve, a valve with a contaminated spool, and a valve with a degraded spool. It is shown that the faulty valves may be detected. The method is using pressure measurements on the valve ports which may not be present in pitch systems. Though available pressure measurements may be used even if they are not attached directly to the valve ports. Furthermore, the method relies on a known trajectory which may not be possible in a pitch system as the operation cycles are changing continuously due to the wind.

Jouppila et al. [29] describes a model based method for detection increased Coulomb friction of a PWM driven solenoid operated proportional valve. Increased friction was identified by changes in the current gradient compared to normal operation. The results are only simulated and variations in operation conditions such as temperature are not addressed, why the robustness of the method is unclear.

Moseler and Straky [30] uses a model based approach for fault detection of a solenoid valve for hydraulic systems in vehicles. The method is based on estimating the stroke from voltage and current measurements and then use the stroke to detect failures such as blocked spool, increased friction and wrong neutral position by comparing it to a healthy operating valve. The solenoid valve is doing a voltage step which may not be possible to conduct while the pitch system is operating. However, it may be possible to implement such a test sequence when the system is shut down.

Raduenz et al. [31] describes an on-line fault detection method for proportional valves using measurements of the supply current and the spool position. Five different valves with different sizes and from different manufacturers are tested. The method is based on limit checking to see if the current and position is within predefined limits found from tests on healthy valves. The method may detect failures associated with change in the required force such as friction and flow forces. Fault scenarios with spool locking and a broken spring are tested experimentally and are detected successfully. The method may be used in a pitch system dependent on the available measurements of the proportional valve. Typically only position feedback is available, though valves with both position and current measurements do exists.

Adrees [32] uses current signature analysis to detect faults of a solenoid valve. Faults addressed are various quantities of increased load and a damaged spring. It is not clear how effects of operating conditions, such as changing temperatures, influence the results. Due to this it may be not be possible to directly implement the methods in a real system.

Tsai and Tseng [33] describes a diagnostic algorithm based on a neural network to detect deterioration of solenoid valves used in a diesel engine. The neural network was trained on four brand new and two severely worn solenoids and was used to determine either normal or abnormal operation. The diagnostic algorithm was tested on another 18 solenoids, ten reusable and eight broken, where the algorithm were able to classify all reusable solenoids in the normal region and all except one of the broken solenoids in the abnormal region. Each solenoid was tested three times resulting in values close to each other.

Liniger et al. [34] develops a model based scheme for detecting early signs of coil failures in solenoid valves. It is seen that typically, a minimum of five insulation faults occurs before a coil failure. An insulation fault is identified by a resistance change estimated by an EKF algorithm and isolated from thermal effects by use of a thermal model. The method uses measured coil current and voltage and ambient and fluid temperature. Resistance changes of down to 0.26 ohm for a continuous operated coil and 0.36 ohm for a intermittent operated coil was found as minimum detectable. A detection probability of 97% and 99% is found for, respectively, continuous and intermittent operated valves.

A challenge with the many of the above described methods are that operating conditions such as the temperature of the valve may influence the results. Particles or changes in the oil properties may also influence the results. It is thus estimated that the presented methods may be used in controlled and constant environments, but may work with decreased performance in pitch systems for wind turbines. Coil short circuit failure seems to be detectable for both continuous operated valves and intermittent operated valves, though the presented methods use current measurements which are normally not available, why such needs to implemented. The presented methods are summarised in Table 3.

Table 3. Covered fault detection methods for valve failures. i_v, V_v and x_v represent the valve current, voltage and position, respectively.

	Failure	Method Domain	Used Signals	Validation
Ramos Filho and Negri [28]	faulty spool	model based	i_v	Exp.
Jouppila et al., [29]	inc. friction	model based	i_v and V_v	Sim.
Moseler and Straky [30]	inc. friction and blocked	model based	i_v	Exp.
Raduenz et al. [31]	locking and broken spring	model based	i_v and x_v	Exp.
Adrees [32]	broken spring	signal based	i_v	Exp.
Tsai and Tseng [33]	deterioration	neural network	i_v	Exp.
Liniger et al. [34]		model based	i_v	Exp.

6. Sensor Faults

The sensors used in a common hydraulic pitch system typically include pressure transmitters and cylinder displacement sensors. The failures related to sensors can be a bias, drifting, drop out, signal peaks or increased noise.

Helwig et al. [35] presents a signal based condition monitoring system where sensor faults such as constant offset, drifting, noise and signal peaks may be detected and compensated. The method extract features of the signal and using linear discriminant analysis for classification. The detection method is tested on experimental data from a pressure transmitter in a hydraulic setup. Sensor faults are emulated by signal manipulation. Offset of approximately five bars are detected without overlap with no offset. One peak may be detected without overlap. Drifting of 0.25% per hour and noise of 10 dB are detectable. The method is applied to constant operation cycles, and it is unknown whether the method is applicable for unknown and switching operation cycles as for pitch systems in wind turbines.

Garimella and Yao [36] uses an adaptive robust observer to detect velocity sensor faults in a hydraulic actuator. The fault emulated is a drift of 10^{-7}ms^{-1} in the sensor signal and the fault is detected after approximately 40 s. A threshold is compared to the estimation error to indicate when a fault is present. The method is validated by simulation of a hydraulic drive system consisting of an asymmetric cylinder attached to a mass.

Mosallaei and Salahshoor [37] investigates a data fusion technique for sensor fault detection and diagnosis. The method is based on an Adaptive Modified Extended Kalman Filter (AMEKF) and is tested on simulations of a continuous stirred tank reactor and detects bias and drift sensor faults.

In general, there is not much literature available on sensor faults of hydraulic systems. More work is thus needed if such failures should be detected. The methods described are summarised in Table 4.

Table 4. Covered fault detection methods for sensor failures.

	Method Domain	Used Signals	Validation
Helwig et al. [35]	Statistical	Pressure	Manipulated Data
Garimella and Yao [36]	Robust Observer	P_s, $\dot{x}_p$, T_a	Simulation
Mosallaei and Salahshoor [37]	Kalman Filter	-	Simulation

7. Fluid Faults

Fluid faults in hydraulic systems includes air contamination of the oil, oil additives breakdown and particle contamination. Fluid faults may change the properties of the fluid and be a source to more failures. A change in fluid properties may also be an indication of faults in the system such as worn out seals resulting in air and particle contamination of the oil. Pitch systems have high demands for the oil cleanness compared to many other hydraulic systems due to the life time and service requirements of pitch systems. In hydraulic systems preventive actions such as filters is used to prevent fluid contamination. Furthermore, commercial available monitoring systems for fluid contamination including particle counters and off-line monitoring do exist. In this section, only on-line monitoring methods that deal with fluid contamination in a hydraulic system is described.

Garimella and Yao [36] uses an adaptive robust observer to detect oil contamination in a hydraulic actuator among other failures. This is done by estimating the effective bulk modulus of the fluid by the observer, as an indicator for air contamination, and comparing it to a found threshold indicating a fault. The method is only tested in simulations why it is unknown how the method performs in a real system. The uncertainties in the model combined with external disturbances may influence the results.

Salguerio et al. [38] describes a method for on-line oil analysis measuring multiple oil properties such as temperature, water content, chemical and oil contamination. The oil contamination is measured by particle counters, both ferrous and non-ferrous. Faults are detected from changes in the oil properties. Detection of ferrite particle and water content in the oil are experimentally validated in a hydraulic setup with a gearbox lubricated with hydraulic oil. The method relies on particle counters which in general are not present in pitch systems due to their high price.

The described methods are either relying on expensive sensors or have only been tested in simulations. More work is thus needed if on-line monitoring of the oil could be used without the use of particle counters. The methods described are summarised in Table 5.

Table 5. Covered fault detection methods for fluid failures. The notations of the used signals can be found in Figure 1.

	Failure Type	Method Domain	Used Signals	Validation
Garimella and Yao [36]	air cont.	Adaptive Observer	P_s, $\dot{x}_p$, T_a	Sim.
Salguerio et al. [38]	multiple cont.	Direct measure	Particle counters	Exp.

8. Supply

A hydraulic pitch system is typically supplied by a hydraulic power unit containing several components, such as pumps, valves, accumulators, etc. As valves and accumulators have already been treated in previous sections only the pump is considered as a component itself. In addition detection of lowered supply pressure have been dealt with by a number of papers why these are considered as well.

8.1. Pump

Gao et al. [39] investigate a wavelet analysis approach of the outlet pressure of a hydraulic pump for fault detection. The analysis is done for a fault-free pump, a pump with loose piston shoes and a pump with worn swash plate. Experimental test showed that the wavelet coefficients where higher for the malfunctioning pumps compared to the fault free pump, which then can be used to identify a defect pump. Gao et al. [40] further investigates a wavelet analysis approach of the outlet pressure of a hydraulic pump for fault detection and compares it to a FFT approach. The methods are tested on the same pumps as in [39]. The FFT approach compares the summation of the power spectra 10–40 Hz for each pump while the wavelet approach applies a three level wavelet transform giving eight

coefficients to compare. Experimental tests showed that the wavelet approach where better suited for diagnosis of the pump.

Ramden et al. [41] uses vibration measurements to do condition monitoring of a hydraulic pump. The fault is introduced on the bearing plate where four different plates where tested. One from a working pump and three from damaged pumps. One of the damaged plates caused decreased efficiency of 20% while the remaining two are only beginning to wear out with no decrease in efficiency. The damaged plate was detected by RMS of the time signal of the vibrations. The frequency spectrum further detects the worn plates. Furthermore, it was shown that the placement of the accelerometer was not important as long as it was on the housing of the main pump.

Johnston and Todd [42] uses pressure and flow ripple measurements to identify worn bearings using RMS and the first harmonic amplitude of the pressure and flow ripple. The method is tested on "good", "worn" and "bad" bearings and for different pump speeds. It is shown that it is possible to distinguish the bearing condition from each other, though with some overlap between "worn" and "bad".

In addition to the available literature commercially available condition monitoring solutions do exist. Typically they use measurements, such as vibration and temperature, directly on the pump or motor driving the pump. As condition monitoring systems already do exist it could also be possible to implement such solution in wind turbines. The mentioned methods also indicates that it is possible to detect pump failures in pitch systems. In Table 6, the described methods for pump faults are summarised.

Table 6. Covered fault detection methods for pump faults. The notations of the used signals can be found in Figure 1.

	Method	Used Signals	Validation
Gao et al. [39]	Wavelet	p_s	Exp.
Gao et al. [40]	Wavelet and FFT	p_s	Exp.
Ramden et al. [41]	Frequency analysis	Vibrations	Exp.
Johnston and Todd [42]	Direct measure and frequency	p_s and pump flow	Exp.

8.2. Supply Pressure Faults

An and Sepehri [43] uses an EKF based method to detect changes in the supply pressure. This is done by looking at a moving average of the residuals which can detect changes in the supply pressure. The method is tested experimentally which shows that the method respond to changes of down to 10% of the normal operating pressure.

Crowther et al. [18] describes a neural network detecting lowered supply pressure among other faults. The network is feed with measurements of the cylinder pressures and displacement and the current of the proportional valve. The approach is to train the network on simulated data and validate the network on experimental data. From the results it seems possible to detect faults though the exact size of the fault seems hard to determine.

Chen et al. [44] develops an active FTC scheme, redesigning the controller on-line, for a hydraulic pitch system of a wind turbine. The controller here compensates for a drop in the supply pressure. The quantity of the pressure drop is not stated, but it is seen from simulated results that the fault may be detected and that the FTC scheme may reduce unwanted oscillations due to drop in supply pressure.

Khan et al. [45] uses a non-linear observer based fault detection scheme. The cumulative sum of residuals of the cylinder velocity is used to determine faults by predefined thresholds. Drop in supply pressure from 57 to 50 bar and 77 to 57 bar is detected after approximately 1–2 s.

Shi and Patton [46] describes a method based on a robust adaptive observer. The method detects faults by estimating the response of the pitch system and then relates that to certain

faults. The method is validated by simulations where lowered supply pressure of 50% is shown to result in a significant decrease in the natural frequency of the pitch system.

Tan and Sepehri [47] describes a model based fault detection method. The method is based on estimating parameters of a Volterra model and use that to detect faults by comparison with thresholds. Decreased supply pressure is detected in the range of 12–40% and increased supply pressure is detected in the range of 20–40%, based on experimentally tests.

In general some work has been done on detecting decreased supply pressure for hydraulic systems. For fluid power pitch systems the supply pressure is though not constant as described in Section 2. Due to this it may be difficult to use the described methods as the supply pressure will decrease naturally in a pitch system. However, the methods may be applied for systems with a more constant supply pressure. In Table 7, the described methods for supply pressure faults are summarised.

Table 7. Covered fault detection methods for supply faults. The notations of the used signals can be found in Figure 1.

	Method	Used Signals	Validation
An and Sepehri [43]	EKF	P_s, x_p	Exp.
Crowther et al. [18]	Neural network	P_s, $\dot{x}_p$ and valve current	Exp.
Chen et al. [44]	FTC scheme	Pitch angle	Sim.
Khan et al. [45]	Nonlinear observer	$\dot{x}_p$	Exp.
Shi and Patton [46]	adaptive observer	Generator speed and pitch angle	Sim.
Tan and Sepehri [47]	model-based	P_s, x_p	Exp.

9. Discussion

Most of the methods described in this paper are not aimed directly for pitch systems, but for hydraulic systems in general. The main difference is the operating conditions where a pitch system is subjected to both highly varying trajectories and external forces. Many other hydraulic systems work under more constant working conditions. Many of the methods described detect faults by either residuals generated from a physical model or by comparing signal attributes to a healthy system. When the operating conditions are varying the residuals or the signal attributes of a healthy system may change which may influence the performance of such methods. It may be that the methods are still capable of detecting failure, however, it is unknown as it has not been addressed in most papers. In few papers the system considered is a pitch system, which indicates that the methods can be adapted to pitch systems. Furthermore, some of the methods rely on sensors that are typically not present in pitch systems why the use of these method do require additional sensors which may increase the total cost of the system.

Methods related to internal cylinder leakage can be used in pitch system and acceptable leakage levels can be detected. However the methods that have shown these results do require an accurate valve model which may be found from experiments. Furthermore, methods for detecting gas leakage in accumulators seems applicable, though they can only be used in certain operation cycles such as start-up. Furthermore, many usable methods for detecting valve failures exits, however, they rely on current measurements which is normally not present in pitch systems. It should be noted that many of the methods may be applicable for other hydraulic systems where the operating condition are more constant.

For some critical faults like external leakage, the methods available are only capable of detecting high leakage levels, and it is questionable whether the described methods may ever be capable of this. To deal with this method it may be needed to look in other directions such as new sensor technologies, new methods etc. In general applicable methods for fault detection and condition monitoring do exist. However, more work is needed if all potential faults in a pitch system should be covered. Furthermore, additional sensors may need to be implemented, though resulting in a more expensive system.

In addition to the methods mentioned in this paper it is worth noting that other fault detection methods used in other industries or addressed in other research communities do exits. As an example Ding [48] mentions methods from data science which may be used for wind turbine systems. As the amount of gathered data increases over time such data driven methods may be more widely used. The industry may already be utilising such methods as they already have large amounts of data that could benefit the use of such methods.

10. Conclusions

This paper has presented a state of the art review of fault detection and diagnosis methods for fluid power pitch systems. The review is based on published methods including scientific publications and patents. In general, a lot of methods exists on different components of the system which may be applicable for specific systems. Many of the methods may be suited for systems with fixed operation cycles while it may be harder to achieve sufficient results with systems similar to the fluid power pitch system. This is due to the stochastic position trajectory and stochastic external load applied to the system due to the behaviour of the wind. Very few methods are directly aimed towards such systems why more work needs to be done before the methods may cover all potential failures of the fluid power pitch system.

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