Condition monitoring on hydraulic pumps – lessons learnt

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ABSTRACT

An overview to the performed analysis and lessons-learnt approach from flight control & hydraulic designers perspective on a condition monitoring (CM) concept for hydraulic pump application for helicopters is given.

At least two levels of maturity could be achieved by application of CM:

- The maturity *Level B* allows to identify and to distiguish failures.
- The maturity *Level A* allowes to predict and to forecast the remaining useful life of the weak parts inside the equipment until major failure.

In the first part some different processing and analysis philosophies for CM data (data driven versus physics based driven) will be discussed for their advantages and disadvantages.

The second part of the analysis focusses on CM for a hydraulic pump. An axial piston machine type with mechanical pressure compensation and variable displacement mechanism was used for this analysis as this type is widely used in helicopter hydraulic systems.

Within the third part, a selection of already performed studies on concepts for possible condition monitoring applications on hydraulic pumps are discussed. The selection criteria for these studies were made to ensure coverage of the different major focuses of CM like:

- the merrits of data processing by artificial neural network,
- the efficiency of generation of failure data on defined pre-damaged pumps for system learning,
- the merrits of usage of noise resistant and acoustic sensors,
- the impact of sensor reliability,
- the efficiency of monitoring changes in global system transformation function,
- the efficiency of event recording versus continous monitoring approach and
- business case evaluation models to identify the necessity of CM on hydraulic pumps.

In the final part, the analysis summarizes the main obstacles as lessons-learnt in the process to implement CM into H/C for hydraulic pumps.
As an outlook, it is possible to lay down a CM concept proposal based on these lessons-learnt.
It is considered as unavoidable to enter the CM concept by a data collecting and processing phase ("Big Data Approach"). Thanks to the continuous maturity improvement of the CM hybrid algorithm by data feeding, the obtained in-service data will be then directly used to correctly identify the failure with a high probability rate in real-time, i.e. to achieve maturity Level B of CM.

In parallel, the analysis of the trend evolution of the data should allow to decide if it can be used also as a predictive element into the CM system for the dedicated failure mode ("Smart Data Approach"). This could lead to achieve maturity Level A of CM.

Similar approaches are currently already applied in several branches of industry and automotive, especially by car OEM like BMW, Mercedes and Tesla [21].

1. CONSIDERATIONS TO CM

1.1 CM maturity level

There are at least two levels achievable by application of CM:

Level B: this level allows to identify and to distinguish failures at an early stage under operation and environmental conditions to avoid un-scheduled repairs/exchanges. Also the governing parameters which indicate the failure of these parts are known.
These informations can be used for design upgrades and improvements of the related equipment.

Level A: this level is based on data and experience accumulated in level B. It allows to predict and forecast the remaining useful lifetime of the weak parts inside the equipment until major failure, taking into account the evolution trend of the governing parameters and the individual influencing environmental conditions. The remaining fault-free operation time of the equipment can be considered by the operator for the maintenance planning of the related system.

An implemented CM system of level B can improve mission / dispatch availability of equipment, which has a direct positive impact on operational costs.
A CM system of maturity level A can even be used as a improvement factor for system safety.

1.2 CM data processing and analysis philosophy

A complete definition of sensor data procession and analysis architecture would be outside the scope of this paper.
A pure data driven approach has the following advantages and disadvantages [1]:

Advantages

- Relatively simple and fast to implement.
- Variety of generic data-mining and machine learning techniques are available.
- Helps gain understanding of physical behaviours from large amounts of data. These represent facts about what actually happened which may not be apparent from theory.

Disadvantages

- Physical cause-effect relationships are not utilized, e.g. different fault growth regimes, effects of overloads or changing environmental conditions.
- Difficulty to balance between generalization and learning specific trends in data.
  Learning what happened to several units on average may not be good enough to predict for a specific unit under test.
- Requires large amounts of data. It is difficult to determine without experience what amount of data can be considered enough. Taking Neural Nets as example, one should keep balance between overly-trained net (i.e. too specialised) and insufficiently-trained net (i.e. unprecise).

A pure physics based approach has the following advantages and disadvantages [1]:

Advantages

- Prediction results are intuitive based on modeled cause-effect relationships. Any deviations may indicate the need to introduce more fidelity for un-modeled effects or methods to handle noise.
- Once a model is established, only calibration may be needed for different cases.
- Clearly drives sensing requirements. Based on model inputs, it is easy to determine what needs to be monitored.

Disadvantages

- Developing models is not trivial. It requires assumptions regarding complete knowledge of the physical processes, the range of manufacturing tolerances and the robustness of the model against modelling errors, disturbances, is also of great importance for the reliability of the diagnosis/prediction.

- Parameter tuning may still require expert knowledge or learning from field data.
- High fidelity models may be computationally expensive to run, i.e. impractical for real-time applications.

2. HYDRAULIC PUMP

2.1 Function

The hydraulic pumps used in most of AH H/C fleet are axial piston machines with an internal swash plate for pressure/flow regulation.

It comprises of a rotatry cylinder barrel (2) in a manifold, which houses and guides a number of pistons (1). The pistons slide with shoes (4) on the hanger (also referred as back plate or swash plate) (3). The shoe retainer plate (4) engages the piston shoes and holds them in the same plane relative to the hanger. The fluid is sucked into the pump from hydraulic reservoir via suction line (8) and displaced back into the circuit by the pistons via the pressure line (9). The cylinder block is driven by a supported internal drive shaft (by bearings, parts of 2 and 5), linked to a supported external drive shaft (5). Rated pressure is controlled by a compensator valve with spring (6) and piston (12) assembly, which actuates the hanger; the compensator setting can be adjusted manually by a screw (7).

All rotating parts are embedded into hydraulic fluid taken from suction line via internal leakages. This "case" fluid is used for lubrication of bearings and piston and piston shoes and circulated via case drain line (10) with the hydraulic reservoir.

(1)	Piston	(7)	Adjustment screw
(2)	Cylinder barrel	(8)	Suction port S (from VBR)
(3)	Hanger	(9)	Pressure port P (to VBR)
(4)	Shoe retainer plate	(10)	Case drain port CD
(5)	Splined shaft	(11)	Seal drain port SD
(6)	Spring	(12)	Pressure compensating valve

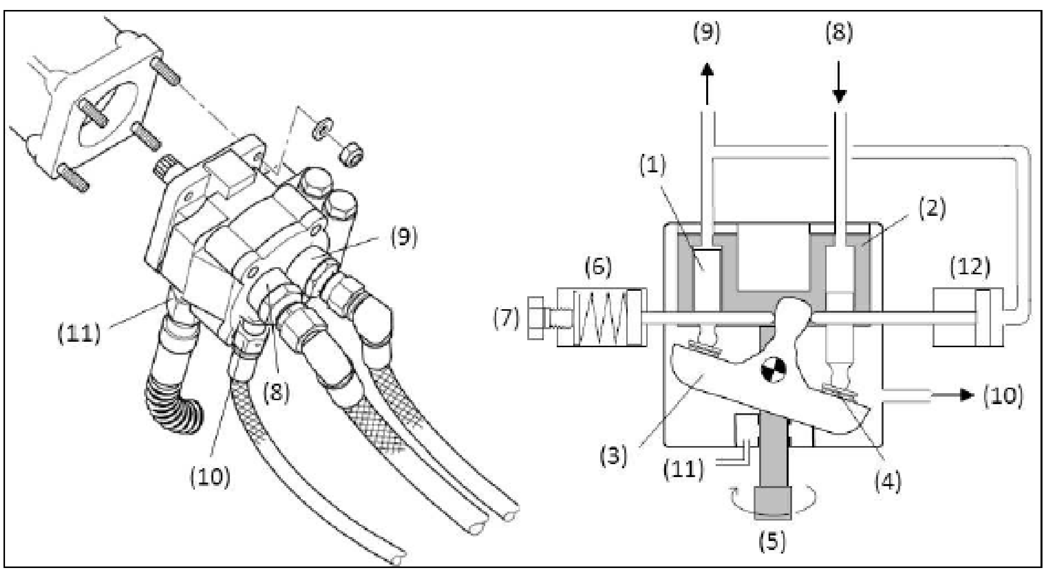

Figure 1 Function of hydraulic pump, © Airbus Helicopters Deutschland GmbH.

2.2 Pump failure modes

The Table 1 gives an overview of pump failure modes (without design errors), the affected system parameters and the effects on the hydraulic system which can be observed from outside. Figure 2 shows some typical damaged pump parts.

2.3 Reminder to safety and reliability requirements

Hydraulic pumps of this type are considered having a reliability in the magnitude of 1 failure per 100,000 flight hours (FH) (rate 10^{-5} /FH).
In order to fulfill the safety requirement in commercial helicopter aerospace of one failure per one billion FH (rate 10^{-9} /FH), today in minimum two hydraulic pumps are used in hydraulic system architectures for flight control systems. The failure of one pump is rated as “mission and safety critical” and leads to an abortion of the mission and to an unscheduled landing.
Taking further mission duration influence to probabilty calculation and mission/dispatch reliabity into account, these are strong drivers to select an architecture with more than two pumps per flight control system, at least for the medium and heavy classes H/C.

2.4 Review of pump data

A review of reliability data for some hydraulic pumps used in AH commercial fleet was performed to identify potential weak pump components.

For a typical hydraulic pump, the reliability report shows MTBF of approximatively 16,600 FH and 20 unscheduled removals over a four year period monitoring, which is in average expectation frame, rated with a “usability caution indicator” of medium (second best rating).
Supplier provided a list showing components affected by frequent exchange/wear during overhaul in Qpa (quantity per annum). The needle bearing and screws seem to be the top leading items.
The pump has no TBO and is maintained “on-condition”.
Bearings are located at pump hanger and screws are located at external drive shaft seal (see Figure 3).

For another typical hydraulic pump, the reliability report shows MTBF of 13,750 FH and 53 unscheduled removals over a five year period monitoring).
Supplier provided a list showing most frequent causes for exchange/wear during overhaul in 2013 (see Figure 4).
According to also performed review on overhaul, worn compensator parts, piston shoes, cylinder bores and external drive shaft seal wear seem to be the top leading items.
This pump has a TBO of 7500 FH.

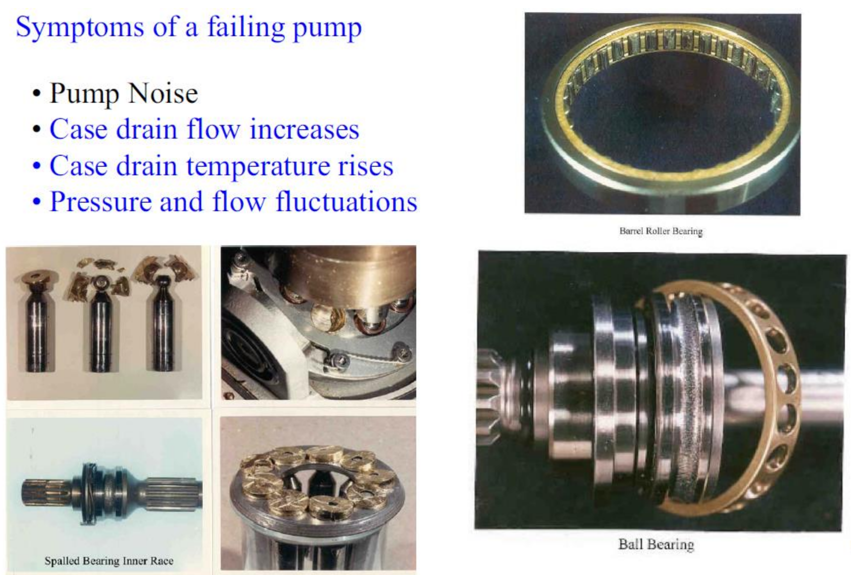

Figure 2 Illustration of failed pump components [8]

Failure mode	Affected parameters	Effect
Wear in compensator valve. Fracture or jam of compensator valve.	Supply pressure. Swash plate position. Flow rate.	Loss of pressure adjustment.
Defective tilting mechanism of swash plate (friction / jam in bearing of swash plate).	Supply pressure. Flow rate. Swash plate position.	Loss of pressure adjustment and/or flow displacement rate. Loss of pressure compensation capability.
Friction / wear of pistons / sliding piston surfaces in cylinder block.	Case drain leakage rate. Debris in case drain and supply pressure line. (Case fluid) temperature.	Increase of (case fluid) temperature. Degradation of pressure / flow rate. Pollution of filter.
Alignment error of internal or external shaft, leading to excessive wear in shaft bearings. Pre-damage of external drive shaft. Friction / jam of drive shaft bearings.	Case drain leakage rate Debris in case drain and supply pressure line. (Case fluid) temperature. Drive shaft speed.	External droplet leakage at drive shaft seal. Jam of internal rotating parts (cylinder block, pistons). Increase of (case fluid) temperature. Fracture or damage of external drive shaft. Pollution of filter.
Wear/loss of seal function at compensator adjustment screw.	None.	External droplet leakage.
Loss of seal functions at plugs/housing seals/pressure port O-rings.	None.	External leakage.

Table 1 Pump failure modes

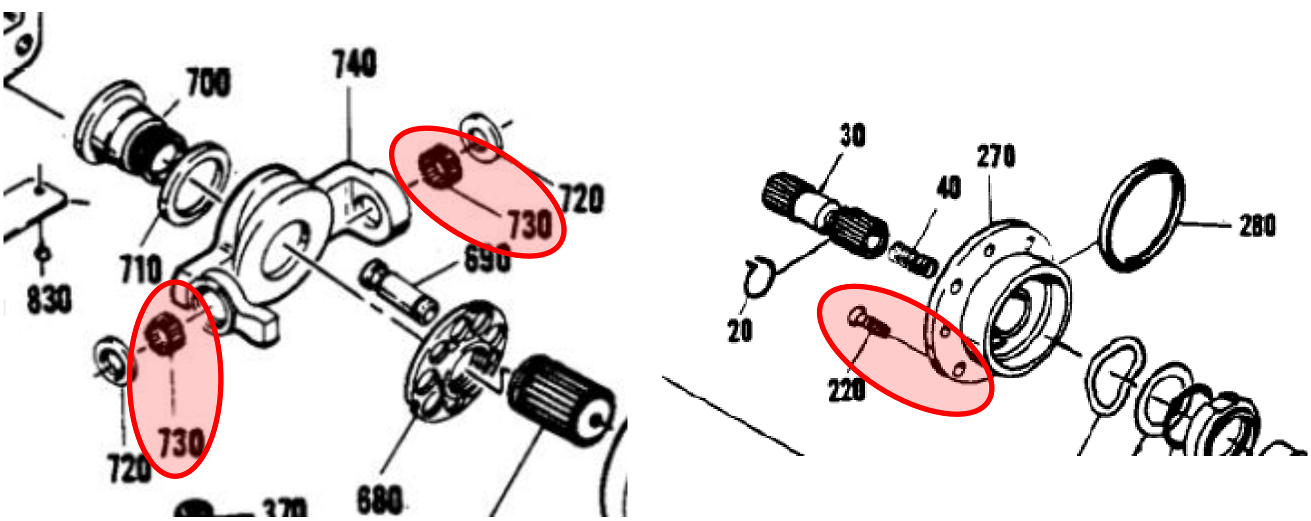

Figure 3 Bearing (item 730) and screw (item 220), © Airbus Helicopters Deutschland GmbH

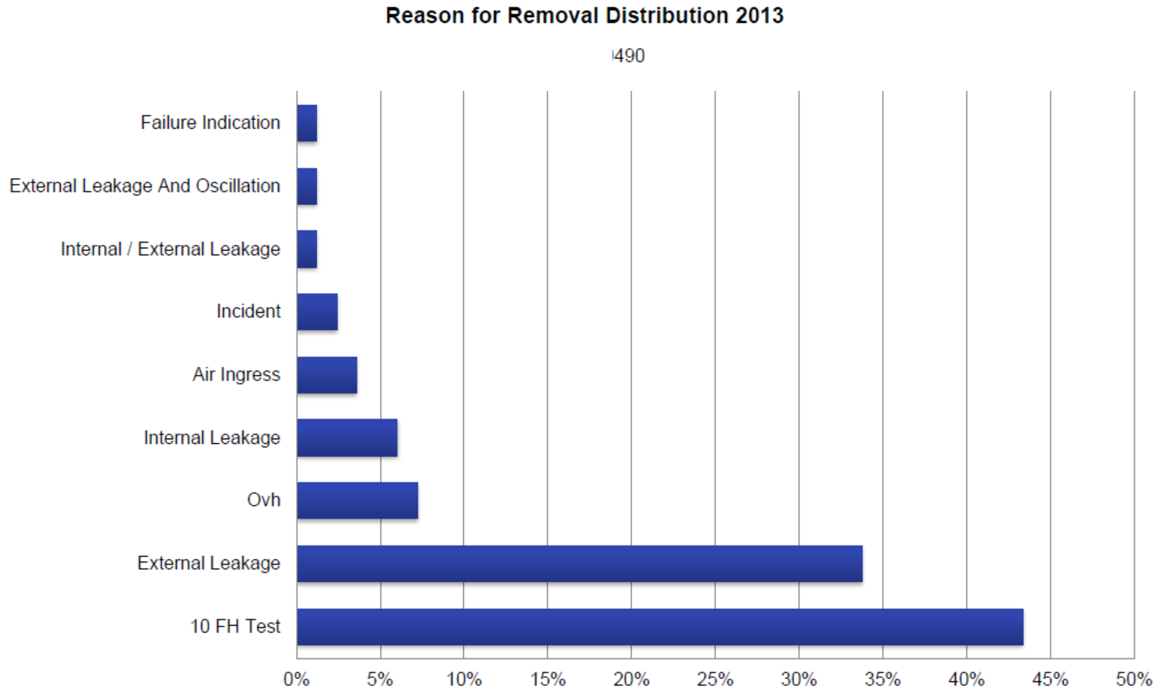

Figure 4 Reason for frequent exchange, © Airbus Helicopters Deutschland GmbH

2.5 Parameters influencing pump performance

The following pump parameters could be subject to monitoring:

- Supply pressure.
- Case drain pressure.
- Inlet pressure.
- Fluid temperature.
- Drive shaft speed.
- Drive shaft and bearing vibration/structure-born noise.
- Flow rate / Position of swash plate.
- Fluid pollution (particles, water, viscosity, total acid number (TAN).

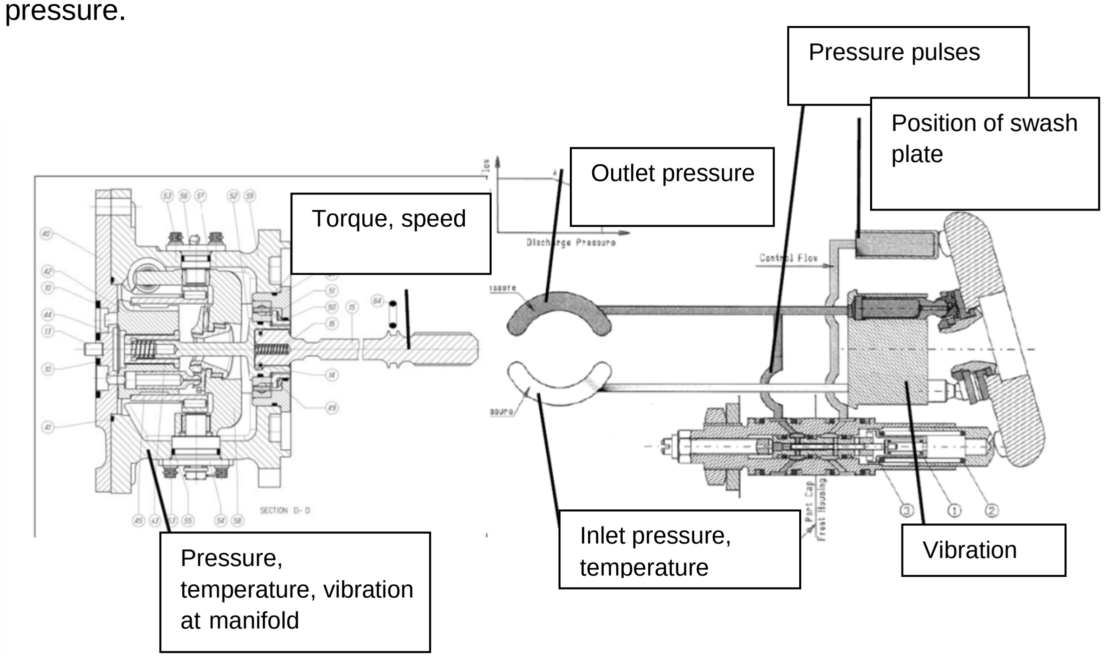

Figure 5 Possible locations for CM sensors in pump, © Airbus Helicopters Deutschland GmbH

3. Review of studies on CM for hydraulic pumps

The following Table 2 gives an overview of the studies subject to review for this paper:

Reference	Short abstract/aim of study	Lesson learnt
[2]	**Neural net analysis for CM.** The authors conclude the measurement of vibration as the only remaining suitable mean for CM. All tests were performed on a bench and not in H/C. Artificial neural networks were used to collect and analyse vibration data on several hydraulic pumps of an SH-60B drive train system. "…	Monitoring pressure & temperature "…provides some monitoring capabilities, generally does not give early indication of incipient faults…" Using vibration measurement for CM, an artificial network with "Adaptive Feature Map", (AFM) algorithm could be effective.
[3, 4, 5, 6]	**"ProReB" study** A study by Airbus and BOSCH dedicated to the impact of CM in a maintenance environment including the relation to added economic value, presented on the 28th international congress of the aeronautical sciences. Identification of components where applied CM could results in benefits for operating costs. Hydraulic pumps beside other components like fluid, filters, external leakage rates and different valves were identified as a potential candidates for CM. Combination of simulation (AMESim and MatLab Simulink software) and hardware test object on test bench with artificial introduced failures. The chosen monitor characteristics were not robust against the installation orientation of the pump (the test results on BOSCH bench could not be reproduced on another test bench with different pump orientation).	The monitoring and diagnostic methods are already used in industry and automotive hydraulics but not yet in aerospace hydraulics. CM contributes to economic added value (net present value, NPV), direct maintenance costs (DMC) only for those applications whose require a high reliability of the applied CM method. Pump internal sensors for pressure and temperature based on SMD- and thin-film technology. Stand-alone simulation model could be not sufficient to design CM algorithm as during comparison of simulation results with test bench results, it was not possible to distinguish doubtless failure influences from model immanent accuracies. The definition of equipment failure behaviour based only on physical model simulation could limit the success, because for such a definition, all physical parameters (e.g. friction coefficients of pump pistons versus cylinder barrel in relation to fluid temperature and used material) which affects the failure have to be known or have to be elaborated in an exhaustive manner of data mining and bench testing. Test bench environment not sufficient for proof of robustness of monitoring approach.
[7]	**Noise resistant sensor** On sensor level, to use triplex redundand sensors for each parameter and to monitor average sensor results. A voting routing rules out by majority decision a deviating sensor.	To consider sensor failures influences in high vibration environment. Adress possibility of common cause failures on sensors / usage of dissimilar sensors.

Reference	Short abstract/aim of study	Lesson learnt
	On analysis level, compensate a sensor malfunction by calculation of probable missing sensor data based on a diagram elaborated from tests and a tolerance range comparision.	
[8, 9]	**In-line CM** Signal/transfer function change behaviour of monitored pumps during occurrence of a failure. Paper included a feasibility study using simulation, collection of data of faulty equipment on test bench and to establish a final concept to be integrated in A/C. The status of this last step of this study could not be found. Three pump parameters were used: outlet pressure, case drain flow rate and case drain temperature. It is postulated that these parameters show failures as bearing degradation via high frequency noise, see Figure 6.	To monitor system signal /transfer function for changes. High sample-rate sensors needed at pump to detect postulated changes. To train algorithms by defined faulty components (same approach as in [3, 4, 5, 6]).
[10]	**CM of axial piston pump** The study focused on wear (and hence leakage) between the pistons and cylinder bores in the barrel.	Wear on pump piston affects the pump output flow and output pressure ripple waveforms statically and dynamically (see Figure 7).
[11, 12]	**Usage of acoustic sensors** It could be shown that with a time synchroneous averaging process, it was possible to allow detection of a gear fault and also CM indicators could be defined. Company SIEMENS offers accoustic sensor CM for hydraulic pump branded SITRANS DA400 [12]. It will be used to monitor internal leakage at the compensator valves of displacement piston pumps, used in heavy industry like oil&gas or water cleaning. The sensor uses the noise generated by cavitation inside the valves, caused by internal leakages.	Alternative sensor concept to acceleration sensors. Robustness in noisy H/C environment to be investigated.
[13]	**Low cost CM algorithm** The proposed CM algorithms (Auto-Correlation and Cross-Correlation) record only events and do no continuously recording. “...The event recorded is not necessarily fault induced. The event could just be an abrupt control input by the pilot (i.e. aircraft manoeuvres). This is where the proposed DI differs from conventional HUMS. While conventional HUMS use algorithms that specifically look for individual faults (or faults in individual gears, bearings,	CM algorithm which aims for changes in transfer function during specific events; related to studies [8] and [10].

Reference	Short abstract/aim of study	Lesson learnt
	etc.), the DI techniques looks for events in terms of changes in transfer functions...”	
[14]	**Fault detection for hydraulic pump based on chaotic parallel RBF network** Use of neural networks in conjunction with chaos theory (here called CPRBF). Construction of a CPRBF model trained with data from a healthy pump. The model proves to be able to reproduce the healthy pump behaviour accurately. Data sets from a test rig in laboratory were used to assess the method’s ability to detect pump failures. Vibration data from healthy and faulty (valve plate wear, swash-plate/slipper wear) axial piston pumps were used. The fault detection is made through residual estimation.	The introduced method (data-driven neural network based approach to model a healthy pump + residual estimation for diagnosis) allows to detect pump failures but not to isolate them (i.e. to tell which part is failing). As the data used was obtained in laboratory, no information available for robustness of process.
[15]	**Wavelet approach for performance monitoring and diagnosis of a hydraulic pump** Investigation of pump performance monitoring methods through outlet pressure signals observation. Pressure measurements give direct information. Comparison of Fast Fourier Transform (spectral analysis method) and wavelet based analysis method, via simulation and experimental results. The method could be “implemented on-line to support real-time health diagnosis without affecting normal operation of the pump”. Tests on three pumps: one healthy, two defected (1 with loose ball-socket, 1 with worn swash plate), using the same hydraulic test rig in laboratory.	Shows that the discharge pressure signal “was not able to provide sufficient information to support pump health diagnosis” because of the too little difference between the signals of the healthy and defected pumps. However, the wavelet transform was able to improve the “capability of diagnosing the health conditions of the piston pumps” thanks to the signal decomposition. The patterns and amplitudes of the wavelet coefficients also provided the possibility to isolate both faults. No discussion about the sensor definition i.e. high sample rated sensor would be needed to correctly interprete the pressure signal.
[16]	**Leakage fault detection method for axial piston variable displacement pumps** Development of a general physics-based nonlinear model in MATLAB/Simulink environment with leakages (between pistons and cylinder bores, at valve plate – barrel interface to case and between two piston chambers). A comparison of simulations without and with the different leakages is made with pump discharge pressure as a basis. An experimental study was also done, comparing pressure measurements of a pump in healthy and simulated faulty states. The faulty	The global model was to be validated against experimental results. However, it was observed that “external leakage [to case] could be discriminated from both piston leakage and internal leakage [from one piston chamber to another]” through investigation of the mean and standard deviation of the discharge pressure in steady state conditions, and that the fault severity could be estimated. The conclusions are in opposite to [15] as also discharge pressure was used as failure indicator and FFT used for identification.

Reference	Short abstract/aim of study	Lesson learnt
	state is obtained exchanging one piston with one with increased radial gap (machined to 30, 60 and 90 microns). The authors suggest comparing the simulated time history under faulty conditions to pump measurement to diagnose the pump state.	
[17]	**Evaluation of analysis methods for fault diagnosis on axial piston pumps** Vibration measurements, taken on a flawless pump and on a pump with various built-in faults, are used for the fault diagnosis. The fault diagnosis method is based on a pattern recognition approach. The author tests its robustness through inspections and modification of the hydraulic system as well as changes in the operating point. Different feature extractions methods and fault classifiers performances are assessed.	All tests made were made in laboratory and for steady state conditions. All of them were short terms tests. Pattern recognition approaches were able to properly detect faults in axial piston pumps “even when assembly and system variations caused high variations in the measured vibration signals”. No evidence for this last statement could be found.
[18]	**Layered clustering multi-fault diagnosis for hydraulic piston pumps** The authors propose a method for multiple fault diagnosis for axial piston pumps based on the layered clustering algorithm. 5 fault types are taken into account: valve plate wear, insufficient inlet pressure, bearing wear, swash plate eccentricity and increased clearance between slipper and piston. To simulate experimentally a multiple-fault occurrence, the 5 type of faults were artificially set on pump.	The proposed algorithm successfully classifies the 5 types of faults considered, using as entry data the discharge pressure, leakage flow, and the axial and radial vibrations. Is it also able to detect progressive faults (e.g. piston-slipper clearance increase) with “higher precision and reliability” compared to the classical Fast Fourier Transform-based method. Tests made in laboratory conditions. An analysis for environmental influences was not performed.

Table 2 Overview to reviewed studies

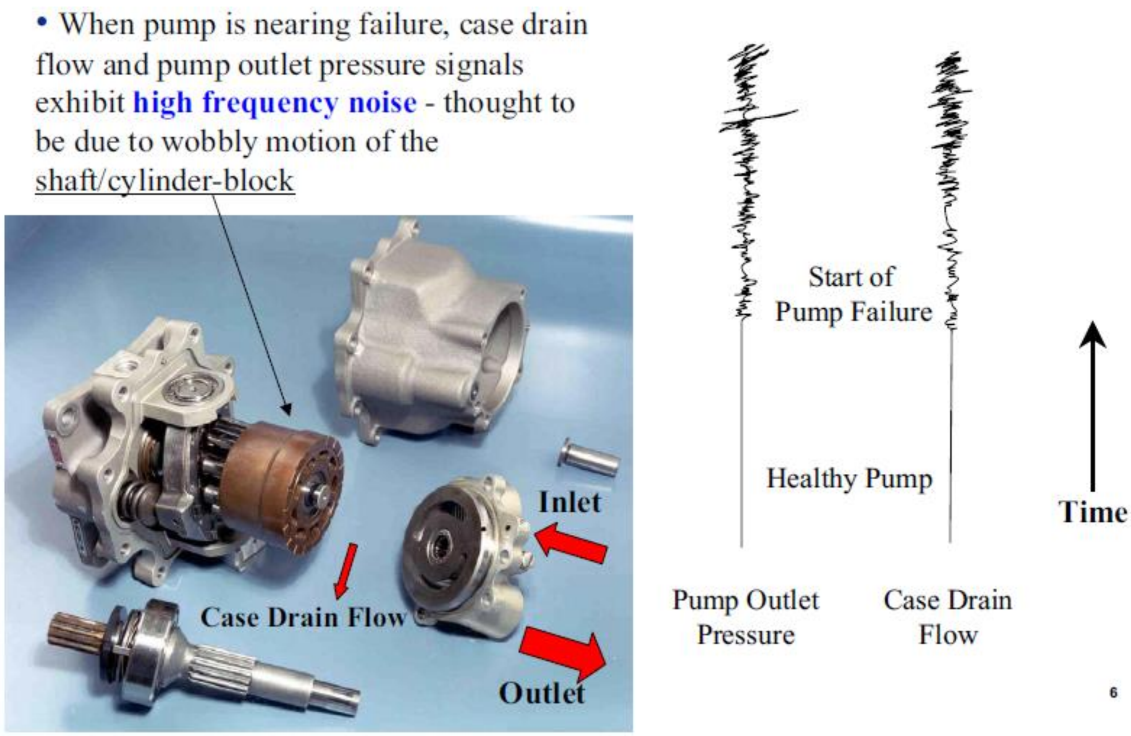

Figure 6 Illustration of indication of pump failure by signal change [8]

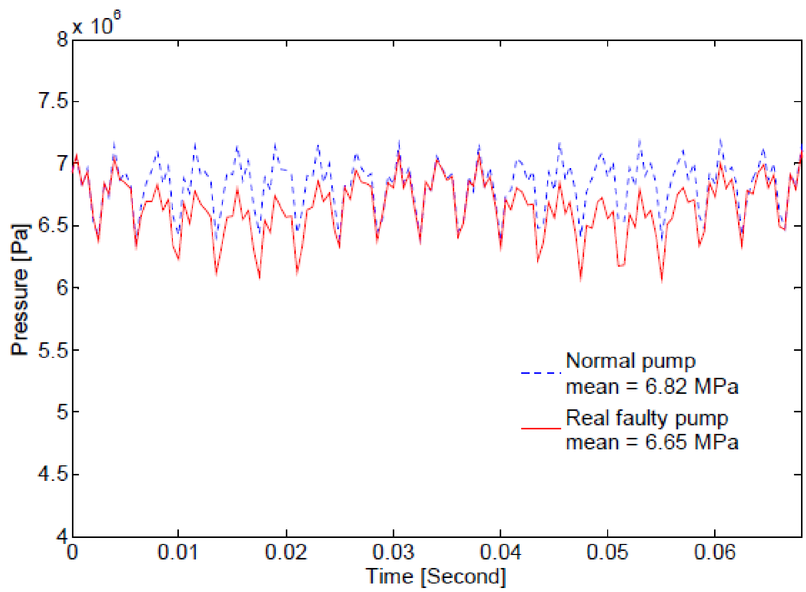

Figure 5.21 Comparison of the experimental pressure waveforms for the pump with a real fault (not artificially created) and a normal pump

Figure 7 Illustration of pump pressure ripple waveform;
Comparison between healthy versus faulty pump (piston wear) [10]

4. Discussion

The review led to the lessons-learnt given in Table 2.

Furthermore, the following main obstacles in the process to implement CM into H/C for hydraulic pumps i.e. to establish maturity level B of CM were identified:

- Either the nonavailabiltiy of in-service data or the missing performed correlation of these data with maintenance/repair/overhaul (MRO) shop findings.
- The non-sufficient consideration of environmental influences.

To overcome the non-availabilty of in-service data, all studies have started on simulation, bench testing with artificial damages or a combination of both. In all reviewed studies, if hardware was used, it was tested in a laboratory environment only.

Despite showing promising results, especially the outcome of the study from BOSCH [6] showed that changes of test benches even under controlled laboratory conditions, not said of real operational environment of an aircraft, can make a CM concept become instable due to missing robustness against external influencing parameters.

The definition of equipment failure behaviour based only on physical model simulation could limit the success. This conclusion is inline with reported experience in NASA report [1]. A hybrid approach to the CM processing (combination of physical model plus real data based training of fault identification algorithm) seems therefore the best promising way ahead.

Outlook: a CM concept proposal

As an outlook, it is possible to lay down a CM concept proposal based on these lessons-learnt. Such concept would require the following items to be defined for each individual hydraulic pump build standard (i.e. specific helicopter hydraulic system):

- A definition of the pump failures which are considered as main drivers for system reliablity.
- A selection of a combination of limited number of sensor types (for reliability, feasibility and economic reasons) and their location for failure identification.
- A definition of suitable operation event conditions for data acquisition.
- A definition and validation of a suitable simulation model.
- To establish an information flow process from involved MRO shops for repair/inspection result data to allow correlation with in-service obtained data.
- A well trained hybrid CM algorithm based on simulation data, bench test data, in-service data and MRO shop finding results.
- A benefit analysis, using the identified efforts above to validate improvement to operating costs/safety by CM concept introduction.

This concept is illustrated in Figure 8.

It is considered as unavoidable to enter the CM concept by a data collecting and processing phase ("Big Data Approach") without immediate benefit/feedback to customer.

Thanks to the continuous maturity improvement of the CM hybrid algorithm by data feeding, the obtained in-service data will be then directly used to correctly identify the failure with a high probability rate in real-time, i.e. to achieve Level B of CM.

In parallel, the analysis of the data evolution trend should allow to decide if data can be used also as a predictive element into the CM system for the dedicated failure mode ("Smart Data Approach").

This could lead to the next phase of CM, where the obtained data will allow predicting the failure mode with a high probability rate in real-time, i.e. to achieve maturity Level A of CM.

Similar approaches are currently already applied in several branches of industry and automotive, especially by car OEM like BMW, Mercedes and Tesla.

How to build a mature CM algorithm?

A hybrid approach as described in [1] is proposed for the processing and analysis step. A pure model based approach turned out to be too complicated and costly [6].

- Use a physical simulation model (e.g. like in [5, 16]) to make prediction and make adjustment based on observed data accumulated from in-service equipment.
  The output of this model will be implemented into the fault identification routines of the CM software.
- Fault identification routine (could make use of artificial neural networks like in [2, 15, 18] and/or a type of FFT like in [15, 16, 18]).
- Learn current damage state from in-service data and propagate using model
- Use knowledge about the physical behaviour to guide learning process from the data.
- Train the process with the in-service data already collected in the first step.

The output of this hybrid approach can be successively introduced into the CM software of the H/C:

- Recognition of defined events and state changes (e.g. using transfer functions) as proposed in [13, 15, 18].
- First focus on one specific failure (e.g. bearing of cylinder barrel).
- Later increase scope to two or more different specific failures.

How to certify?

In terms of certification, the guidelines and requirements of Miscellaneous Guidance (MG) 15 in FAA AC 29-2C [19] have to be considered.
It addresses the most complex/extensive HUMS; for systems of lesser complexity only the parts of this section those are pertinent for the affected H/C could be used.

How to obtain in-service data?

In the first step, only a collecting mode ("Big Data Approach") is proposed to be implemented at customer H/C. Similar approaches as currently already applied in several branches of industry and automotive ("internet of thinks") could be used [20]. Especially, some automobile car OEM like BMW, Mercedes and Tesla are using transmission of maintenance related data for CM purposes [21].
Not all necessary elements of such a provision chain have to be fully elaborated by Airbus Helicopter, as potential business partners for the different tasks (data sampling, data transmission, data storage/data clouds, data analysis, cyber security) could be involved.

The data collection and processing has to ensure "cyber security". Transparent communication to customer and detailed definition of necessary data is recommended to avoid miss-use of data and customer rejection of data collection approach. The data collection approach of automobile industry and its discrepancy to customer expectations was lately uncovered [22].

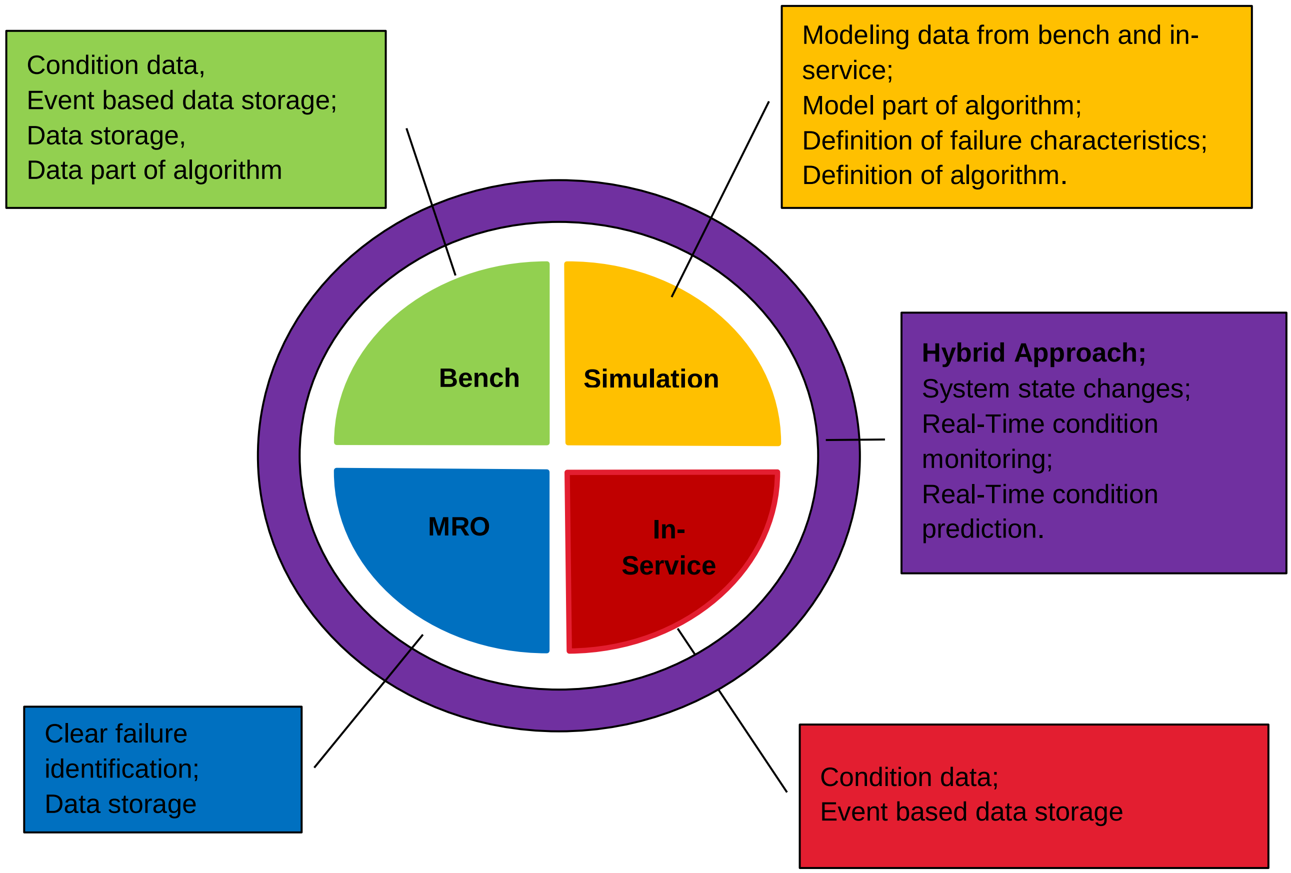

Figure 8 CM Concept graphic, © Airbus Helicopters Deutschland GmbH

5. Conclusion

During the process of reviewing already available research results for the different aspects concerning CM, a CM concept with focus on hydraulic pump used in H/C was created.

It was identified that such a concept could cover the “missing link” of real in-service information from customer and MRO. As such, an approach needs all aspects of bench testing, simulation model and in-service data.

It has to be highlighted that there will be no immediate “profit generation”. The maturity of the CM algorithm will depend on availability and accuracy of data.

The final achievement of level A would require a highly mature CM algorithm, which is not achievable in short time frame.

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List of Abbreviations

AC	Advisory Circular
A/C	Aircraft
AFM	Adaptive Feature Map
AH	Airbus Helicopters
CM	Condition Monitoring
DMC	Direct Maintenance Cost
FAA	Federal Aviation Authority (U.S.)
FFT	Fast Fourrier Transformation
FH	Flight Hour
H/C	Helicopter
MG	Miscellaneous Guidance (Material)
MTBF	Mean Time Between Failure
MRO	Maintenance/Repair/Overhaul
NPV	Net Present Value
OEM	Orignal Equipment Manufacturer
SMD	Surface Mounted Device
TAN	Total Acid Number
TBO	Time Between Overhaul