PREDICTIVE MAINTENANCE FOR AXIAL PISTON PUMPS: A NOVEL METHOD FOR REAL-TIME HEALTH MONITORING AND REMAINING USEFUL LIFE ESTIMATION

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ABSTRACT

In this paper, a novel method to estimate and predict the condition of an open circuit piston pump is presented. We introduce the concept of the 'Pump health index' which can assess the health of the pump in real time and use it to estimate the remaining useful life of the pump. The solution is agnostic to pump size, make, and application duty cycle. The solution has been tested with different levels of degradation that were simulated on the physical pump. The algorithms were implemented on multiple embedded platforms to illustrate the agnostic nature of the developed technology.

Keywords: Open circuit axial piston pump, pump health index, edge computing, predictive analytics, machine learning, pump health monitoring, remaining useful life.

1. INTRODUCTION

Piston pumps – the heart of any hydraulic application is critical to various industrial and mobile applications. Condition monitoring of piston pumps has been a key area of industrial research for many years. A detailed customer profile and value chain analysis is shown in Figure 1, which indicates that health monitoring solution for piston pumps offers incentive for each stakeholder in the value chain.

Figure 1: Market potential and customer profile for solution (*All the images are copyrighted to their respective owners)

1.1. Objectives and scope

Piston pumps find applications in mission-critical areas like marine engines, tunnel boring machines, steel manufacturing, and discrete manufacturing to name a few. Piston pumps operate under adverse environments and can operate without any discernible change in performance under incipient fault conditions. However, with continual operation, the fault condition deteriorates and can cause major disruption and downtime [1]. Any downtime on these machines incurs huge losses to the customers. The customer challenges related to these machines could be:

1. Revenue loss due to pump failures: As the pump is the heart of any hydraulic system, failure related to the pump causes non-operation of the machine and hence loss of revenue.
2. Operational cost increase: As customers do not have a mechanism to access pump health status, they may continue using the same pump irrespective of its degradation status. Due to the usage of a degraded pump, the amount of energy consumed is higher than a new pump, for the same amount of useful work. Hence operational cost increases due to the usage of degraded pump.
3. Unplanned system stoppage: Continual operation of degraded pumps can result in pump failures, causing severe downtime for the entire machine. The unplanned system stoppage is a huge challenge for customers.

To overcome these challenges, some of the existing strategies are 1. backup & redundancies, 2. periodic maintenance, and 3. reactive maintenance. All these strategies would be costly and would not solve the problem completely. Hence there is an unmet need to provide real-time health indications for a critical component like a pump.

The objective of the paper is to develop a technology that analyses fundamental signatures from hydraulic pumps and provide insights for continuous monitoring of pump performance as shown in **Figure 2**. For this solution, key signatures from a pump are captured through sensors and their real-time analysis is carried out on a controller. The processed output of the algorithms is in the form of Pump Health Index (PHI), shown as the hypothetical curve with respect to operating hours. The PHI is estimated till current time and using the previously computed values, a forecast is performed.

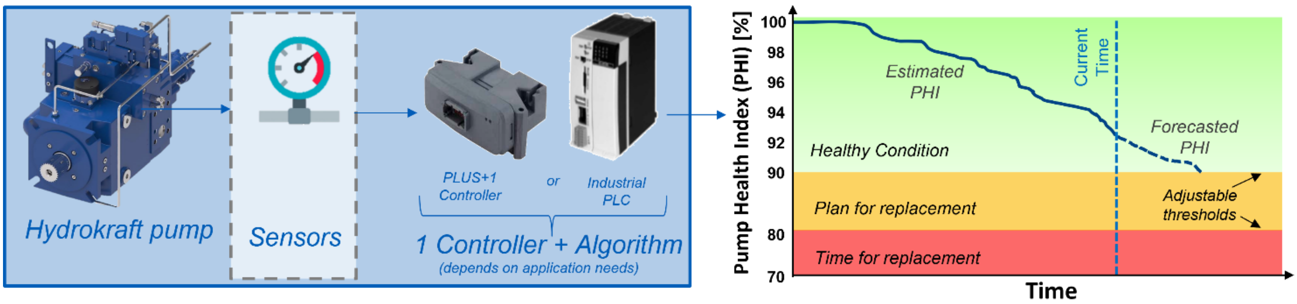

Figure 2: Pump health monitoring solution with the indicated health index

1.2. Literature review and state of art

Most methods estimate volumetric efficiency using outlet flow. However, measuring the main flow affects the output of the pump. Multiple papers have proposed methods that use pressure [2] and vibrations [3] signals to derive fault features. Some of the previous works from Danfoss also show promising results [4]–[6], where grey box modeling is used to predict system performance in the form of motor speed. This work evaluates the pump performance as a standalone product when rotary or linear velocity is not available. Recent advances in machine learning (ML) have been widely used for detecting the defects of piston pumps [7]. As the evolution of ML techniques is rooted in domains other than industrial applications (like computer science), application-specific tuning and capturing application-specific domain knowledge is not warranted. An attempt to integrate the knowledge into neural networks has been made by Kulkarni and Guha [8]. Most of the ML algorithms require specialized embedded hardware for their implementation. Machine learning-based methods assume the generalizability of the trained models as fault class data are not always present for the pump under test. Apart from the development of these advanced techniques, their deployment strategies concerning computational architectures are also critical. A recent review of condition monitoring of axial piston pumps for mobile applications can be found in [9].

Many researchers have evaluated computational architectures from various perspectives [10], [11]. Particularly for PHM (Pump Health Monitoring) solutions, [12] indicated critical points to be considered like, data processing and storage capability [13], asset overview, domain knowledge, and robustness for estimating the 'Remaining Useful Life (RUL)' [14]. This work also proposes computational architectures for the effective deployment of condition monitoring solutions. The work focuses on the aspects of effective implementation, including the time of response from data acquisition to decision-making and computational resources for data processing in real-time.

Alternatively, residue-based methods can be used to fix a baseline model under the healthy state of the pump, but it requires online training of the models on resource-constrained embedded systems. The condition monitoring of axial piston pumps has matured in the last two decades from a signal processing problem to a data science problem. In [15] spectral analysis and wavelet transformation of outlet pressure were used for pump signature analysis. RUL prediction using different leakage models was proposed in [16] using case flow measurement and Weiner filter. Low and high Reynolds flow losses are estimated as states of the pump model using an extended Kalman filter (EKF) with pressure as a measurement for RUL prediction [17]. The use of particle filters for estimating the RUL was proposed in [18]. A non-linear unknown input observer using swash-plate angle and outlet pressure input was proposed in [19]. However, the lack of correction due to unavailable future data leads to linear regression-type estimation with state estimators. The volumetric efficiency can be estimated using such a state estimator. However, the prediction method will remain unchanged.

The relation between oil contamination and the RUL of the pump was established in [20]. Fault isolation for different parts of the pump like cylinder, valve plate, slipper, sliding boot, and spring wear in the lab environment using vibration signature was demonstrated in [21]. The classification of the faults was carried out with a convolutional neural network. However, the absence of adequate and publicly available data on the fault classes makes it challenging for the implementation of such machine learning-based methods in industrial cases for generalized fault classification. Degradation characteristics of port plate pairs extracted from flow by monitoring the volumetric efficiency were exhibited in [22]. The use of compressed sensing for fault detection was proposed in [23]. However, the spectral estimation of reconstructed, compressively sensed signal is lossy and may lead to loss of fault information. The use of Eigenvectors as indicators of pump degradations using a pre-filtered vibration signal was demonstrated in [24].

Case-flow of an axial open circuit piston pump indicates tribological interface component of wear. However, methods based solely on the case flow can't determine the condition of the pump. Case flow is dependent on the pressure, swash-angle, speed, and fluid viscosity of the pump. In this paper, we propose a method that considers these factors to determine the condition of the pump. The solution is agnostic to pump size, make, and application duty cycle, which has been tested with different levels of degradation that were simulated on the physical pump. The prediction has been tested using different degradation patterns generated mathematically and from actual pump data. The overall estimation error is less than ±2%.

The estimated PHI values are used for predicting the future health of the pump. Estimating the pump health as one unique number has provided the possibility to use a machine learning model, which can be deployed through resource-constrained edge hardware. This unique number (PHI) is fed to the prediction model, which gets updated for every new value. This provides the health predictions which are updated as per the previous degradation pattern.

This continuous learning methodology using machine learning models provides not only real-field pump degradation but also its variation and prediction to reach certain thresholds set by customers as per application needs. To deploy the methodology for customer application, non-linearity should be handled carefully. The non-linear behaviour of PHI is taken care through continuous learning methodology. An advanced outlier removal method provides the required robustness for actual field deployment.

The estimation and forecast algorithms were implemented on various controllers including Danfoss's Plus+1® MC024™ [25]. The validation has been carried out in two phases. In the first phase, a piston pump has been artificially degraded in the lab by artificially wearing the valve plate. In the second phase, different tests have been carried out using a wide range of pumps (low to high displacement) to validate the algorithms. The overall system is ready to be deployed as a prototype solution at customer sites.

2. METHODOLOGY

One of the challenges faced by the operator/plant manager is the evaluation of the present health status of the pumps and how the performance of the pump might degrade in the future. The proposed method works by calculating the PHI in real-time, storing historical data of the PHI, and predicting the values of PHI up to a certain interval in the future. The PHI is related to the volumetric efficiency of the pump and can be estimated using the leakage flow. However, it is well known that the leakage flow is also correlated with the outlet pressure, fluid viscosity, and speed of the pump. To develop an index that is only affected by the degradation of the pump we measure the correlated sensors for normalization. The overall method is shown in Figure 3.

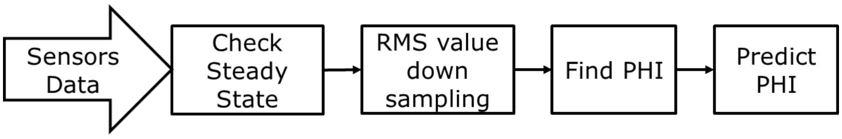

Figure 3: The algorithmic block diagram

Assuming the theoretical flow to be Q_{Th}. The main flow is a fraction of Q_{Th} given by $Q_m = \eta Q_{Th}$. Therefore, the rated case flow or the leakage flow is given by $Q_c^{rated} = (1-\eta)Q_{Th}$. The case flow is directly proportional to the outlet pressure [26]. Therefore, $Q_c \propto P$. Therefore,

$$\frac{Q_c}{Q_c^{rated}} = \frac{P}{P^{rated}} \tag{1}$$

$Q_c = Q_c^{rated} P / P^{rated}$. Using the relation of Q_c^{rated}, we get the leakage flow as

$$Q_c = \frac{P}{P^{rated}}(1-\eta)Q_{Th} \tag{2}$$

Now $Q_{Th} = \omega d$, in which, ω is the rotational speed per minute of the pump and d is the displacement in cubic centimeter of the pump. Therefore, Q_c is given as follows:

$$Q_c = \frac{P\omega d}{P^{rated}}(1-\eta). \tag{3}$$

The total leakage flow is solely not due to degradation. There is control flow which is represented as a fraction of the theoretical flow given by βQ_{Th} [26]. Hence,

$$Q_c^{act} = \frac{P}{P_{rated}} [\omega d(1-\eta) - \beta Q_{Th}] \tag{4}$$

The quantity β can be obtained empirically from initial data or end-of-line testing of the pump. Once we obtain the actual case flow due to leakage given by Q_c^{act}, we find the relation between the outlet pressure and Q_c^{act} for a window of data. The PHI is a function of the slope of the fitted curve for that window of the data.

3. EXPERIMENTAL SETUP

With the introduction of the novel concept of 'pump health index', it is imperative to verify and validate the method with situations replicating real-field duty cycles and data. For this purpose, an experimental test bed in our facility has been utilized. The experimental test bench schematic with Danfoss Plus+1 controller and display is shown in Figure 4. In this setup, the hydraulic pump is driven by an electric motor. Different loading conditions on the pump were experimented using relief valves.

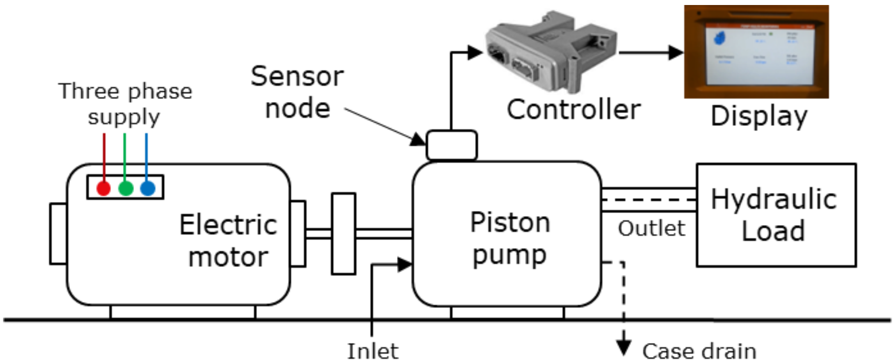

Figure 4: Schematic representation of the experimental test bench

The sensor data is communicated through CAN protocol to the edge hardware from the test-bed programmable logic controller (PLC), where the algorithm is deployed. The output of the algorithm was displayed on the display. A photograph of the pump, driven by the electric motor is shown in Figure 5. Real-field duty cycle is replicated in this setup. Five sensor measurements were captured, i.e., pump discharge pressure, case flow, swash angle, fluid temperature, and speed as shown in Figure 6.

Figure 5: One of the pumps under test

Pump discharge pressure shows the loading of the pump with respect to time. Real-field dynamic duty cycle was achieved, which shows the variation from 20 bar to 210 bar. Case flow values captured in real-time show the variation as indicated in Figure 6. The swash angle sensor shows a variation of 0 to 18.5 degrees, which is the maximum swash angle for this pump. These variations are as per pump controls. Fluid temperature variation is not dynamic in nature, as the same is expected in field operations. Hence experiments have been conducted at 50 °C, 75 °C, and 93 °C fluid temperature.

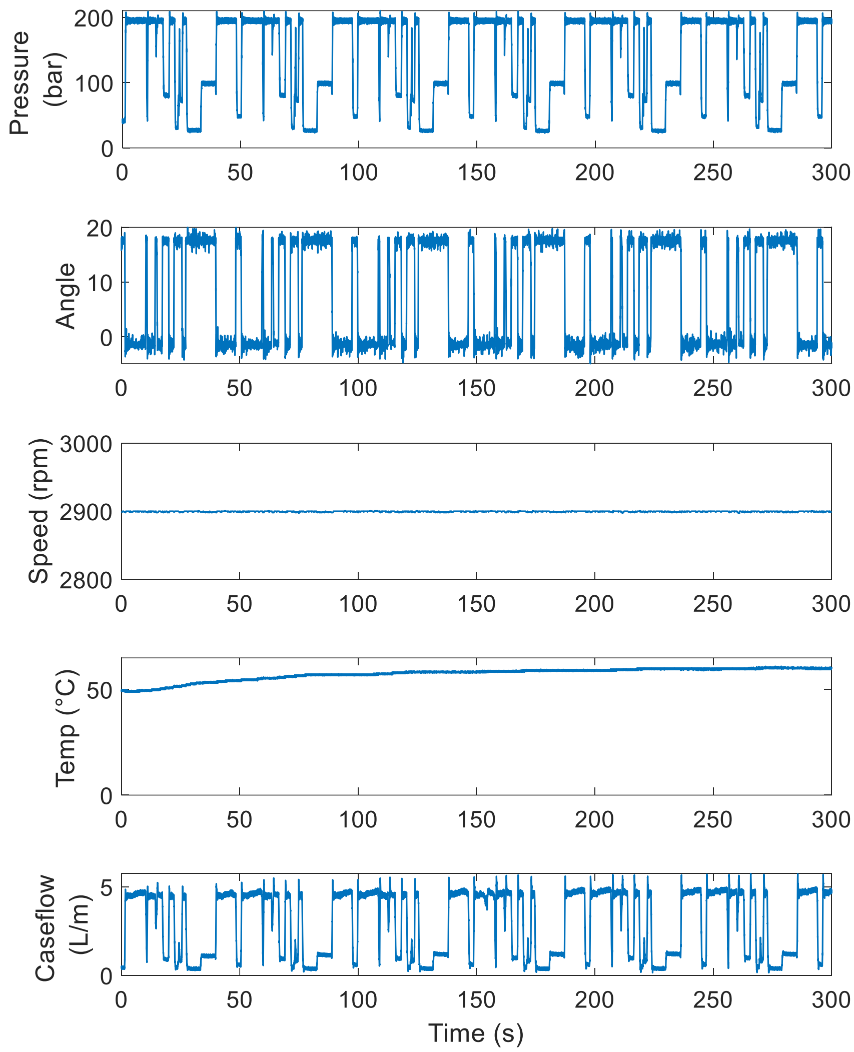

Figure 6: Visualization of different recorded signals of the pump. From top: Pressure, Swash-angle, pump-speed, temperature, and case-flow.

Many industrial applications run the pump at constant speed, with the possibility of changing speed as needed. Hence, PHI algorithms have been tested at constant speed and the same experiment has been repeated with variation in speed at 1000 rpm, 1500 rpm, 2200 rpm, and 2900 rpm. Generally degraded pump has lower efficiency. To collect the data of degraded pumps, tribological parts were degraded and then data was collected. The data is used to estimate and predict the performance of the pump.

4. RESULTS AND DISCUSSIONS

With the experimental setup described in Section 3, detailed test scenarios have been formulated to capture and test the robustness of the solution. The purpose of this testing is to capture the performance of the algorithm with real-field scenarios. The different test scenarios with a variety of pumps are described below. The actual and estimated PHI has been compared.

a. Piston pump sizes (cc): 250 cc, 90 cc, 66 cc, and 28 cc.
b. Speed (rpm): Speed variations have been tested from 500 rpm to 2900 rpm.
c. Temperature (°C): Temperature variations have been captured from 50°C to 93°C.

PHI (Actual): This is the volumetric efficiency of the pump at the rated condition at 50°C. To capture this index, volumetric efficiency is calculated, using the main flow measurement of the pump.

PHI (Estimated): This is the estimated PHI as an output from the developed algorithm, without using the main flow. Calculation of estimated PHI is taking place using the actual sensor data with dynamic variations with time, like the real field scenario.

4.1. End-of-line Testing with Production Pumps

To validate the proposed method statistically, the algorithm was tested on multiple Hydrocraft pumps with end-of-line test data. A total of 13 PVX-66 pumps were tested. The maximum error observed was 1.808 %. Similar tests were carried out with 85 number of 90 cc PVX-90 pumps and 15 number of 250 cc PVX-250 Pumps. The actual versus the estimated PHI are shown in Figure 7. The mean percentage error with PVX-250 was found to be 1.54 %. The higher error was expected for end-of-line test data as this data serves as the baseline for the control flow as discussed in Section 2.

Table 1: Estimation performance of 66 cc Hydrocraft pump

Pump #	Speed (RPM)	Temperature (°C)	Estimation Error (%)
1	1500	44	0.75
2	1500	44	0.87
3	1500	40	0.37
4	1500	40	0.72
5	1500	44	0.14
6	1500	40	0.13
7	1500	40	1.57
8	1500	40	1.16
9	1500	44	0.16
10	1500	40	1.79
11	1500	44	0.17
12	1500	44	**1.80**
13	1500	44	0.87

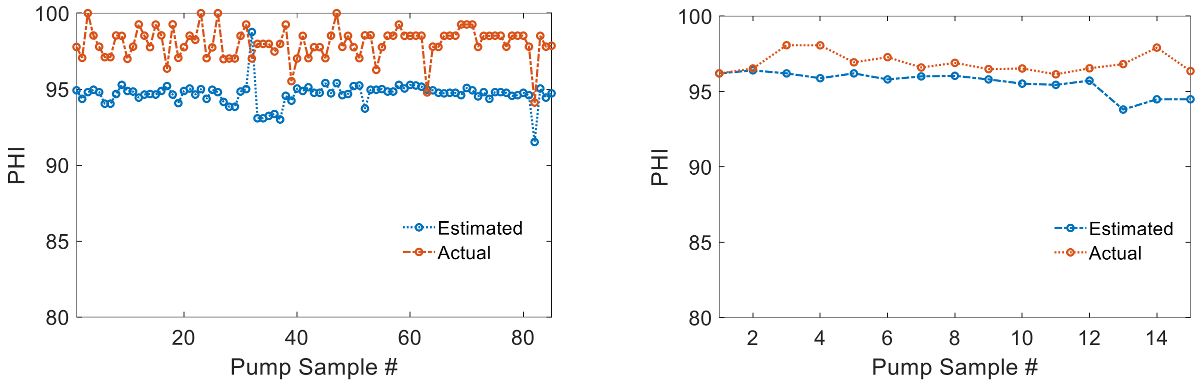

Figure 7: End-of-line validation of the PHI with Hydrocraft pumps. Left: PVX-90, Right: PVX-250

4.2. Validation with different speeds and temperature in laboratory condition:

A total of 12 different data sets have been captured with different testing scenarios of speed and temperature. The error between the estimated and actual PHI is less than 2%, as shown in Table 2 to demonstrate the robustness of the developed algorithms.

Table 2: Estimation performance of 28 cc pump

Dataset	Speed (RPM)	Temperature (°C)	Estimation Error (%)
1	1500	50	1.13
2	2200	50	0.33
3	2900	50	0.67
4	1500	50	1.33
5	2200	50	0.53
6	2900	50	0.87
7	1500	93	**1.53**
8	2900	93	0.27
9	1500	75	1.33
10	2900	75	0.27
11	1500	60	1.33
12	2200	60	0.27

4.3. Validation with Degraded Pump under Laboratory Conditions:

The robustness of the solution also needs to be validated for new pumps, as well as for the old pumps. Pump degradation is emulated in the lab environment by deliberately removing the material from the valve plate. The artificial wearing of the valve plate is carried out using diamond paste & sandpaper. The valve plate has been weighed and a pump performance test has been carried out after each iteration. Validation of the algorithm is carried out at different levels of pump degradation (D1 – D5) with some instances where the pump was run under corner horsepower (CHP) ratings as shown in

Figure 8. The validation results with various levels of pump degradation show an estimation error of less than 2%. This confirms the solution validity for new as well as degraded pumps.

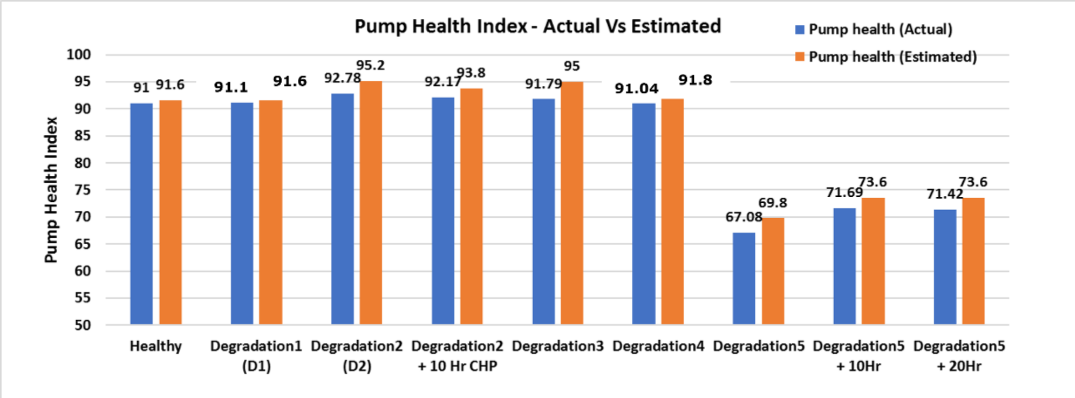

Figure 8: The PHI estimation performance for different test cases

4.4. Hydrocraft Piston Pump Health Prediction

Once the PHI is estimated, the values are stored and are used for predicting the next 'm' PHIs. The stored PHIs are modeled parametrically, and the next 'm' values are predicted using this model. With every incremental instance, a new PHI is obtained. The predicted PHIs are updated accordingly. The remaining useful life is estimated for the predicted PHI, once it approaches the set threshold.

The PHI is calculated every second. As a result, the model fitting, and the prediction are accomplished at the same rate at which the PHI is calculated. However, the horizon of the forecasting algorithm is dependent on the number of samples to be predicted in the future. The accuracy of the forecast is also dependent on the predicted terms. The accuracy decreases with increasing predicted samples. The predictive algorithms are evaluated using historical data. The scheme to test the algorithms is demonstrated in Figure 9.

Figure 9: Predictive algorithm evaluation schema

The performance of the predictive algorithm was validated for two horizons (35 days and 150 days) using the data from a 66 cc Hydrocraft pump which was recorded for a long duration. The prediction accuracies for two horizons are shown in Figure 10 and Figure 11, respectively. The mean errors are 0.69% and 1.14%, respectively. The error increases with increasing the prediction horizon.

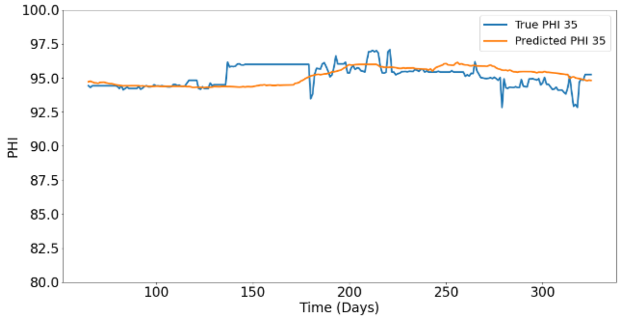

Figure 10: Prediction of PHI for 35 days compared to actual PHI (Mean percentage error = 0.69%)

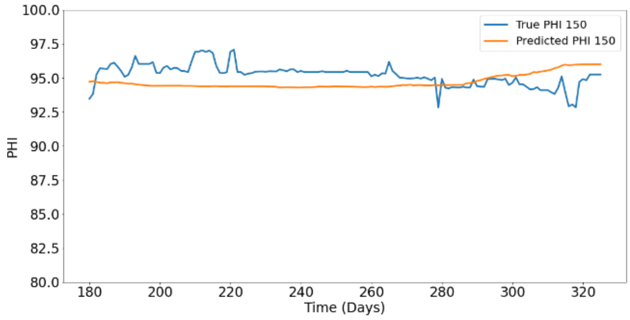

Figure 11: Prediction of PHI for 150 days compared to actual PHI (Mean percentage error = 1.14%)

5. EMBEDDED SYSTEM DEVELOPMENT AND CLOUD ARCHITECTURES

The advent of Industry 4.0 is enabling industries to migrate to IoT-based cloud infrastructures. Deriving actionable inferences from sensor data with estimation and prediction capabilities drive the success of Industry 4.0. However, these solutions require cloud connectivity to enable easier implementation of algorithms and hence add complexity, cost, data insecurity, and latency. For a real-time application, edge hardware is still the preferred mode due to the lower latency of data transfer and the possibility of real-time computation. However, edge computation limits the usage of a plethora of advanced algorithms that can be implemented on cloud-based servers.

To leverage the real-time and on-premises computation capability of edge hardware, we use classical algorithms. However, the PLC coders support the IEC 61131 international standard. As a result, the available predictive model was not usable. Furthermore, due to the limited available computational resources of such devices, the developed algorithms needed to be fast and efficient. The developed algorithms were implemented on different embedded controllers. The implementation framework with the Danfoss Plus+1® MC024™ controller is shown in Figure 12. For this implementation, we acquired data from the PLC of an existing test stand at our facility using a controller area network (CAN). The controller computes the current value of the PHI, along with its forecast after 30 days and 150 days. The current value along with the predicted values are then sent to Danfoss Plus+1® DP730 display for visualization.

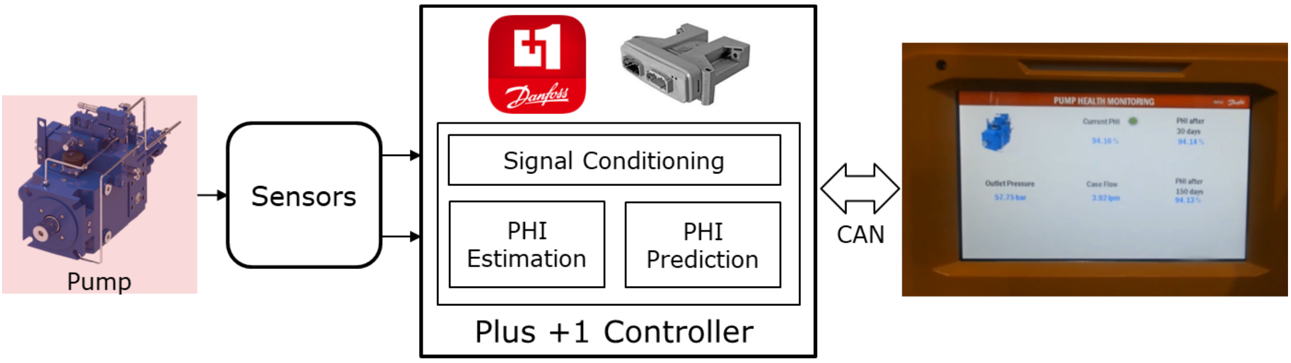

Figure 12: Implementation of the algorithm on Danfoss controller

6. CONCLUSIONS AND FUTURE SCOPES

In this article, we present a system for estimating and predicting the health of open-circuit piston pumps. The developed algorithms are suited for embedded applications that have constraints in terms of both space and computational capability. The concept of PHI is introduced in this work, which can indicate the comprehensive health of the pump. The verification of the proposed algorithms has been carried out in the lab by recreating the real-field scenarios. Exhaustive validation testing was carried out to demonstrate the efficacy of the method. The error of the algorithms is below the 2% limit for all the tests.

With the recent technological advancements, there is scope for improvement of the accuracy further using advanced time-series and machine learning tools. The PHI is unique and can be computed in real-time. It can also predict the future health state of the pump. Additionally, it is also envisaged to develop algorithms that can identify the defects of piston pumps. This solution would play a critical role in reducing the total cost of ownership and enable benefits from predictive maintenance.

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NOTATIONS

Variable	Description	Units
Q_{Th}	Theoretical flow	$[\mathrm{m}^3\mathrm{min}^{-1}]$
Q_m	Main flow	$[\mathrm{m}^3\mathrm{min}^{-1}]$
Q_c	Leakage flow	$[\mathrm{m}^3\mathrm{min}^{-1}]$
η	PHI	[1]
P	Pressure	[bar]
P^{rated}	Rated pressure	[bar]
ω	Speed	$[\mathrm{min}^{-1}]$
d	Displacement	$[\mathrm{cm}^3]$
β	Coefficient of control flow	[1]

REFERENCES

[1] A. K. Samanta, A. Routray, S. R. Khare, and A. Naha, "Minimum distance-based detection of incipient induction motor faults using Rayleigh quotient spectrum of conditioned vibration signal," *IEEE Trans Instrum Meas*, vol. 70, pp. 1–11, 2021.

[2] S. Tang, Y. Zhu, and S. Yuan, "An adaptive deep learning model towards fault diagnosis of hydraulic piston pump using pressure signal," *Eng Fail Anal*, vol. 138, p. 106300, 2022.

[3] W. Jiang, Z. Li, S. Zhang, T. Wang, and S. Zhang, "Hydraulic pump fault diagnosis method based on EWT decomposition denoising and deep learning on cloud platform," *Shock and Vibration*, vol. 2021, pp. 1–18, 2021.

[4] A. Schumacher, D. Weiss, and R. Rahmfeld, "Condition Monitoring of an Axial Piston Pump based on Graybox Modelling," in *13th International Fluid Power Conference*, 2023.

[5] I. Baus, R. Rahmfeld, A. Schumacher, and H. C. Pedersen, "Development of Methodology for Lifetime Calculation for Axial Piston Units," in *2018 Global Fluid Power Society PhD Symposium (GFPS)*, 2018, pp. 1–7.

[6] I. Baus, R. Rahmfeld, A. Schumacher, and H. C. Pedersen, "Lifetime Impact Prediction of Component Modifications in Axial Piston Units by the Failure Likelihood Assessment," in *12th International Fluid Power Conference*, 2020, pp. 323–331.

[7] C. Li, S. Zhang, Y. Qin, and E. Estupinan, "A systematic review of deep transfer learning for machinery fault diagnosis," *Neurocomputing*, vol. 407, pp. 121–135, 2020.

[8] S. Kulkarni and A. Guha, "Equation-based domain knowledge utilization into neural network structure and learning," *Proceedings of the Institution of Mechanical Engineers, Part I: Journal of Systems and Control Engineering*, vol. 232, no. 10, pp. 1275–1291, 2018.

[9] N. J. Keller, "Condition Monitoring Systems for Axial Piston Pumps: Mobile Applications," Purdue University, 2020.

[10] S. Kulkarni, A. Guha, S. Dhakate, and T. R. Milind, "Distributed Computational Architecture for Industrial Motion Control and PHM Implementation," in *2019 IEEE International Conference on Prognostics and Health Management (ICPHM)*, 2019, pp. 1–8.

[11] S. Kulkarni and A. Guha, "Industrial Internet of Things (IoT) Computational Architectures and Novel Neural Network for Smart Computing," in *2019 International Conference on Smart Systems and Inventive Technology (ICSSIT)*, 2019, pp. 925–930.

[12] S. Meraghni, L. S. Terrissa, S. Ayad, N. Zerhouni, and C. Varnier, "Post-prognostics decision in cyber-physical systems," in *2018 International Conference on Advanced Systems and Electric Technologies (IC_ASET)*, 2018, pp. 201–205.

[13] S. Meraghni, L. S. Terrissa, N. Zerhouni, C. Varnier, and S. Ayad, "A post-prognostics decision framework for cell site using cloud computing and internet of things," in *2016 2nd International Conference on Cloud Computing Technologies and Applications (CloudTech)*, 2016, pp. 310–315.

[14] S. Chrétien, N. Herr, J.-M. Nicod, and C. Varnier, "A post-prognostics decision approach to optimize the commitment of fuel cell systems in stationary applications," in *2015 IEEE Conference on Prognostics and Health Management (PHM)*, 2015, pp. 1–7.

[15] Y. Gao, Q. Zhang, and X. Kong, "Comparison of hydraulic pump faults diagnosis methods: Wavelet vs. spectral analyses," in *ASME International Mechanical Engineering Congress and Exposition*, 2005, pp. 73–78.

[16] X. Wang, S. Lin, S. Wang, Z. He, and C. Zhang, "Remaining useful life prediction based on the Wiener process for an aviation axial piston pump," *Chinese Journal of Aeronautics*, vol. 29, no. 3, pp. 779–788, 2016.

[17] T. Shinn, R. Carpenter, and R. C. Fales, "Pump Efficiency Parameter Estimation," in *Fluid Power Systems Technology*, 2016, p. V001T01A030.

[18] L. I. Tongyang, W. Shaoping, S. H. I. Jian, and M. A. Zhonghai, "An adaptive-order particle filter for remaining useful life prediction of aviation piston pumps," *Chinese Journal of Aeronautics*, vol. 31, no. 5, pp. 941–948, 2018.

[19] M. A. Zhonghai, W. Shaoping, S. H. I. Jian, L. I. Tongyang, and W. Xingjian, "Fault diagnosis of an intelligent hydraulic pump based on a nonlinear unknown input observer," *Chinese Journal of Aeronautics*, vol. 31, no. 2, pp. 385–394, 2018.

[20] X. Wang, S. Lin, and S. Wang, "Remaining useful life prediction model based on contaminant sensitivity for aviation hydraulic piston pump," in *2016 IEEE International Conference on Aircraft Utility Systems (AUS)*, 2016, pp. 266–272.

[21] J. Yan, H. Zhu, X. Yang, Y. Cao, and L. Shao, "Research on fault diagnosis of hydraulic pump using convolutional neural network," *Journal of Vibroengineering*, vol. 18, no. 8, pp. 5141–5152, 2016.

[22] R. Guo, J. Zhou, C. Zhang, J. Zhao, and Y. Zhang, "Reliability evaluation of axial piston pump based on degradation failure," in *2017 International Conference on Sensing, Diagnostics, Prognostics, and Control (SDPC)*, 2017, pp. 204–209.

[23] W. Jiang, Y. Lei, Z. Ren, Z. Li, and S. Zhang, "Application of compressed sensing in remote fault diagnosis of hydraulic pump," 2018.

[24] X. Huang, Z. Yao, S. Huang, and D. Liu, "Performance Degradation Analysis of Axial Piston Pumps Based on Self-Organizing Map," in *2019 Prognostics and System Health Management Conference (PHM-Qingdao)*, 2019, pp. 1–6.

[25] "PLUS+1 Controllers: MC024-110 and MC024-112," no. AI00000011en-US0302. Oct. 2017. [Online]. Available: https://assets.danfoss.com/documents/150228/AI152886481001en-000403.pdf

[26] Danfoss Vickers, "EATON Vickers Hydrokraft Open Loop Piston Pumps Technical Catalog," 2003.