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INTELLIGENT CONDITION MONITORING OF HYDRAULIC SYSTEMS

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Abstract
In industrial settings, hydraulic systems are used extensively, and their reliability and early detection of faults is crucial for efficient performance and reduced maintenance costs. Intelligent condition monitoring has become a successful method to continually evaluate the health of the system based on multisensory operational data and data-driven analytical techniques. The main goals of this study were to assess the operating condition of hydraulic systems through multisensory measurements, to explore the relationship between hydraulic sensor parameters and the system's operating condition, and to create an intelligent condition monitoring system to determine various operating conditions. The operational data were secondary, and a quantitative research design was used involving 2,500 operating cycles. Descriptive statistics and Pearson correlation analysis, one-way analysis of variance, multiple linear regression, multinomial logistic regression and feature importance analysis were used to assess hydraulic system performance and to determine important predictors of hydraulic system health. Results showed that the vibration level and oil temperature measurements were the best predictors of hydraulic system degradation, and measurements of pressure, flow, and efficiency-related parameters also helped to differentiate between healthy and faulty operating states. Multisensory analysis was able to effectively classify different operating conditions and facilitate the accurate evaluation of the health of a hydraulic system. The presented framework shows the importance of combining several sensor measures for intelligent fault identification and predictive maintenance. The research underscores the potential of intelligent condition monitoring techniques for enhancing the reliability of industrial hydraulic systems, minimizing unplanned downtime, and aiding in proactive maintenance decision-making.

Keywords: *Hydraulic systems; Intelligent condition monitoring; Predictive maintenance;*

Introduction

Today, hydraulic systems are widely used in manufacturing, construction, mining, agriculture, aerospace, and transportation, among other industries, due to their ability to provide high-power density, precise motion control, and reliability. These systems are required to operate continuously under harsh working conditions, which causes critical parts like pumps, valves, cylinders, accumulators, and hydraulic circuits to wear, leak, fluctuate in pressure, and degrade in the heat. Such failures can lead to unplanned downtime, higher maintenance expenses, lower productivity, and potential safety risks. Thus, reliable operation of hydraulic systems is a major goal in industrial engineering and the traditional maintenance methods are gradually being replaced by intelligent condition monitoring techniques capable of helping to detect faults at an early stage and plan maintenance in advance. The use of advanced monitoring systems to enhance the performance and reliability of large-scale hydraulic infrastructures is further highlighted by recent advancements in intelligent construction and smart operation technologies (Chen et al., 2025).

Traditional maintenance methods such as corrective and scheduled preventive maintenance (SPM) tend to miss incipient faults before they become major failures. With the increased use of digital manufacturing and Industry 4.0 technologies in industries, condition-based maintenance with continuous sensor monitoring is becoming a more efficient approach. Intelligent condition monitoring takes operational data and applies advanced analytical tools to assess equipment health on the fly, allowing maintenance actions to be based on equipment health rather than on a set service period. Prediction maintenance is now being built with a combination of signal processing, machine learning, and hybrid approaches to enhance the accuracy of diagnostics and minimize operational risks (Garcia et al., 2025). Intelligent fault diagnosis in hydraulic systems has made significant advances in the use of information fusion techniques, which integrate the information from various sensors in the system to improve the fault recognition and system reliability (Guan et al., 2024).

A key requirement for the intelligent condition monitoring is the reliable sensing technologies which can measure a wide range of operational characteristics of the hydraulic system. By monitoring hydraulic oil quality, valuable information about contamination, lubrication performance and component wear can be obtained to help make timely maintenance decisions (Hong & Jeon, 2022). Likewise, the development of digital twin technology has enabled the establishment of virtual models of electromechanical-hydraulic systems to perform continuous performance evaluation and prognostic health management (Jian et al., 2024). The further improvement of the capability of modern hydraulic equipment to support autonomous monitoring and adaptive operation has been achieved by the increasing intelligence of components such as smart actuators, sensors, and control systems (Jiao et al., 2023). Furthermore, AI has already been implemented in electro-hydraulic systems to enhance energy efficiency and boost system performance and control (Jin et al., 2023).

Even with these developments, hydraulic systems are susceptible to a wide range of fault mechanisms identified by the cylinder, pump, valves and other components, which makes it imperative to have full diagnostic methodologies. Various studies have shown that hydraulic cylinder faults are big problems that need comprehensive diagnostics and prognosis techniques to enable preventive maintenance strategies (Kumar et al., 2024). Similarly, advancements in sensor technology have led to the ability of monitoring pressure, temperature, flow, vibration, and valve performance, among others, which gives a much broader information on the health of the hydraulic system (Liu, Yuan, et al., 2024). Other intelligent vibration monitoring methods have also significantly advanced the field of structural and mechanical health assessment by detecting abnormal vibration behaviors under different operation conditions (Saeed et al., 2022).

The advent of digital twin-enabled predictive maintenance has taken the concept of hydraulic condition monitoring a step further, allowing for the constant updating of digital twin models to match physical assets and enabling precise fault analysis and maintenance scheduling (Wang et al., 2022). In addition, intelligent predictive maintenance systems based on virtual knowledge graphs have enhanced the interpretation of oil system faults and maintenance decision-making in complex hydraulic scenarios (Yan et al., 2023). Moreover, extensive studies on hydraulic pump diagnostics and intelligent fault diagnosis approaches have clearly shown the critical role of data-driven algorithms in precisely detecting degradation trends and enhancing the efficiency of maintenance operations (Yang, Ding, et al., 2022; Zhu et al., 2023). The present study aims to explore the intelligent monitoring of the condition of hydraulic systems based on the analysis of multisensory operational parameters, which is to assess the condition of the hydraulic system, reveal the relationship among key parameters of condition monitoring and promote the reliable fault identification to improve maintenance decision-making, while building on the above-mentioned technological advances.

Objectives

- To evaluate the operating condition of hydraulic systems using multisensor measurements.
- To investigate the relationships between hydraulic sensor parameters and overall system health.
- To develop an intelligent condition monitoring framework for identifying different hydraulic system operating conditions.

2. Methodology

2.1 Research Design

The research in this study was conducted using quantitative research with secondary data in operational condition in order to investigate the intelligent condition monitoring of hydraulic system. It was decided that the quantitative approach was suitable since it allows for a numerical evaluation of the hydraulic system performance based on the sensor measurements and statistical methods can be used to look at relationships between the operational variables, system health and fault conditions. This study focused on evaluating the effectiveness of multisensory monitoring for detecting changing behaviours of a hydraulic system and for making intelligent decision for the maintenance.

2.2 Data Source and Study Variables

Operational records with different working conditions of the hydraulic system were used. The data set was composed of 2,500 operating cycles, each of which is a full observation of system performance when operating. Each operating cycle had measurements of hydraulic pressure, flow characteristics, temperature, vibration, power usage, cooling ability, volumetric efficiency, accumulator pressure, valve response, oil contamination and the status of the components. Indicators such as system stability, fault type, fault severity, health score and maintenance requirement were also provided in the dataset which enables the full assessment of the hydraulic system performance in different operating conditions. Independent variables were operating hours, system load percentage, ambient temperature, inlet pressure, outlet pressure, return pressure, pressure drop, supply flow, and return flow, flow loss percentage, oil temperature, return oil temperature, vibration level, motor power, cooling efficiency, volumetric efficiency, accumulator pressure, valve response, oil particle count, cooler condition, valve condition, pump condition, and accumulator condition. The dependent variables were system stability, fault type, fault severity, health score and maintenance requirement.

2.3 Data Preprocessing

The data were systematically pre-processed to ensure consistency and make the data analytically reliable before statistical analysis. Data was checked if they are complete, consistent with the variables, duplicate and invalid data. Descriptive statistics were used to check for extreme values and distributional characteristics of the numerical variables and categorisation of operating conditions and fault categories were checked in the categorical variables. Data were standardized for subsequent statistical analysis, by standardizing variable names and data formats. No imputation procedures were needed since all observations had all information filled in.

2.4 Statistical Analysis

Descriptive and inferential statistical analysis was carried out to assess the performance of hydraulic systems and to identify factors to aid in the intelligent condition monitoring. The operational characteristics of the hydraulic system were summarized by using descriptive statistics such as frequencies, percentages, means and standard deviations. Pearson correlation analysis was performed to find the relationship of sensor measurements with overall health score of the hydraulic system. A one-way analysis of variance (ANOVA) was used to compare selected hydraulic parameters with different operating conditions. The variables of the sensors were subjected to multiple linear regression analysis to determine which ones significantly predicted the hydraulic system health score. Multinomial logistic regression analysis was also used to explore the relationship between the operational parameters and hydraulic fault types. Next feature importance analysis was used to identify the relative importance of the different sensor variables in intelligent condition monitoring and fault identification and thus the most important operational indicators in the assessment of hydraulic systems.

2.5 Data Analysis

The raw data was organized and analysed systematically in an appropriate manner using the statistical and analytical techniques. Firstly, descriptive statistics were used to describe the properties of the hydraulic system variables and the operating conditions. Afterwards, inferential statistical analysis was used to analyse the relationship between the sensor measurements, system health indicators and fault conditions. Correlation analysis, analysis of variance, and regression modelling were performed to assess operational parameters' effects on hydraulic system performance and feature importance analysis was performed to identify the most significant parameters that indicate the health and occurrence of the faults in the hydraulic system. For analytical result presentation, appropriate tables and graphical representation were used to ease the interpretation and help to support the objectives of the study.

3. Results

3.1 Characteristics of Hydraulic System Parameters

The results from the descriptive analysis showed that the hydraulic system had stable operating characteristics and there was enough variability to assess system condition monitoring. The mean inlet pressure was 144.09 ± 15.10 bar, whereas the mean outlet pressure was 104.18 ± 13.58 bar. The average values of supply flow rate and oil temperature of the hydraulic system were 43.90 ± 3.60 L/min and 61.25 ± 8.18°C, respectively. The average value of vibration level was 2.95 ± 0.67 mm/s and the average value of motor power consumption was 8.29 ± 1.38 kW. A relatively high level of overall system health was found with a mean health score of 81.27 ± 17.86, but a significant variation was presented between the operating cycles, with both healthy and degraded operating conditions. Descriptive statistics of the most important hydraulic system parameters are given in Table 1. The distribution of the major hydraulic system parameters is illustrated in Figure 1.

Table 1. Descriptive Statistics of Major Hydraulic System Parameters

Variable	Mean	SD	Minimum	Maximum
Inlet Pressure (bar)	144.09	15.10	69.04	210.15
Outlet Pressure (bar)	104.18	13.58	59.22	146.30
Supply Flow Rate (L/min)	43.90	3.60	32.39	53.94
Oil Temperature (°C)	61.25	8.18	34.50	88.10
Vibration (mm/s RMS)	2.95	0.67	1.22	5.61
Motor Power (kW)	8.29	1.38	3.56	11.77
Health Score	81.27	17.86	9.63	100.00

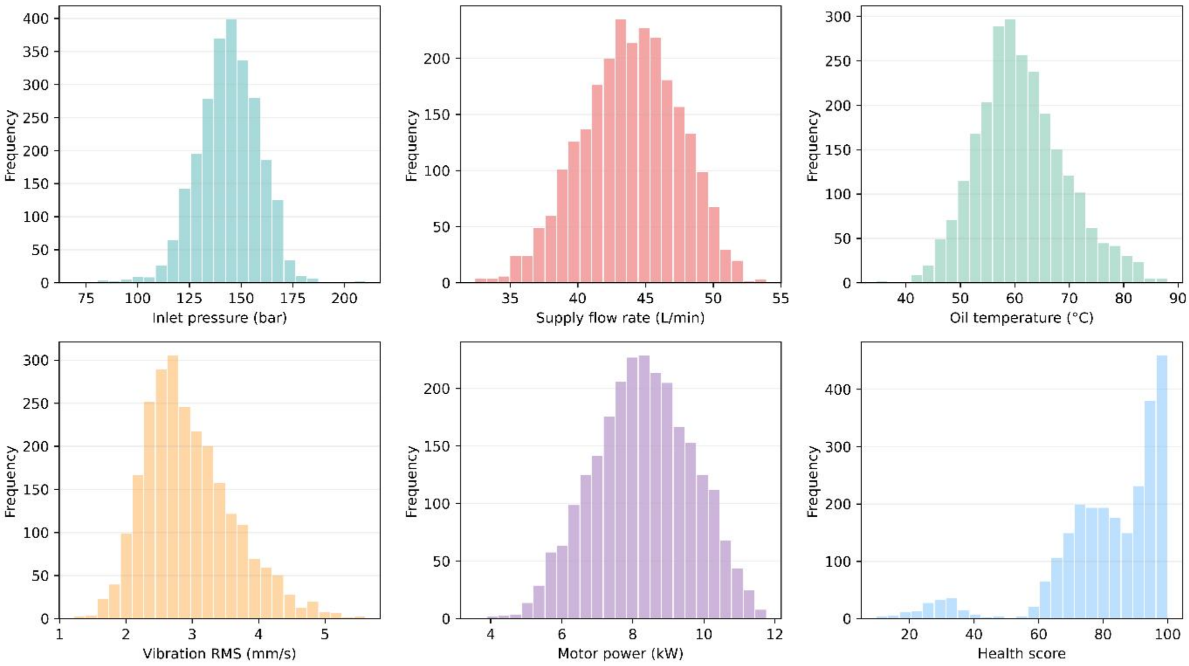

Figure 1. Distribution of Major Hydraulic Sensor Measurements

3.2 Distribution of Hydraulic System Operating Conditions

The distribution of the operating conditions showed that operating under normal system conditions accounted for the largest number of observations (n = 1,098), pump leakage had the next largest number (n = 304), valve failures had the next largest number (n = 302), cooler degradation had the next largest number (n = 279), and accumulator pressure loss had the next largest number (n = 250). Other fault categories were assigned to the rest of the operating cycles, to demonstrate the various hydraulic operating conditions that are suitable for intelligent monitoring. Maintenance assessment also revealed that 1,476 operating cycles were not maintenance activities, but 1,024 cycles were maintenance activities, so it can be assessed that a significant number of observations were in a situation that required maintenance. Table 2 shows the distribution of operating conditions and maintenance needs for the hydraulic systems. Figure 2 shows the frequency distribution of the operating conditions of the hydraulic system.

Table 2. Distribution of Hydraulic System Operating Conditions and Maintenance Requirement

Operating Condition	Frequency (n)	Percentage (%)
Normal	1098	43.92
Pump Leakage	304	12.16
Valve Fault	302	12.08
Cooler Degradation	279	11.16
Accumulator Pressure Loss	250	10.00
Multiple Faults	164	6.56
Sensor Anomaly	103	4.12
Total	2500	100.00

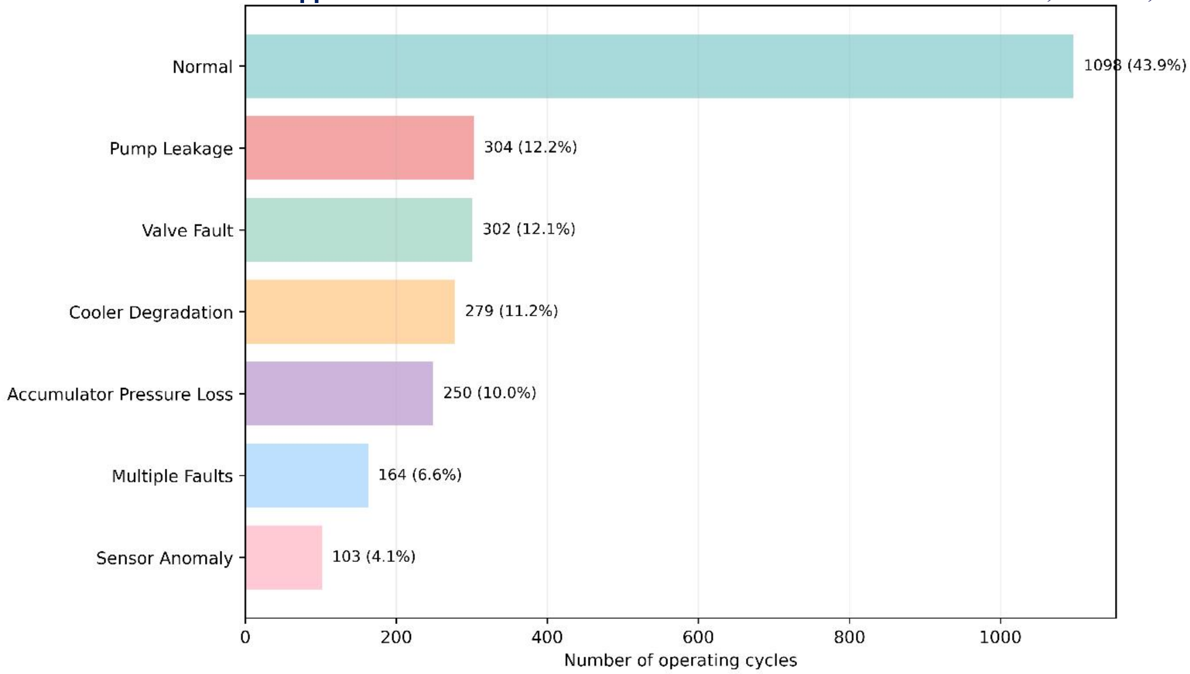

Figure 2. Frequency Distribution of Hydraulic Operating Conditions

3.3 Association Between Hydraulic Sensor Parameters and System Health

The correlation analysis showed that the relationships between the hydraulic operating parameters and overall system health differed. There was a moderate, negative relationship between health score and the temperature at which the system operated ($r = -0.599$), which meant that higher operational temperatures would generally be associated with a poorer system health score. The highest correlation with the health score was the negative relationship between vibration level and health score ($r = -0.694$), indicating that as the mechanical vibration increased, the hydraulic system performance decreased. Other variables such as inlet pressure, supply flow rate and motor power, on the other hand, showed relatively weak negative correlation with system health, indicating comparatively smaller effect in health deterioration under the operating conditions observed. Table 3 is a summary of the relationships between the health score and the selected hydraulic sensor parameters. Correlation between the hydraulic monitoring variables is shown in Figure 3.

Table 3. Pearson Correlation Matrix Between Hydraulic Sensor Parameters and Health Score

Variable	Correlation with Health Score (r)
Inlet Pressure	-0.094
Supply Flow Rate	-0.082
Oil Temperature	-0.599
Vibration Level	-0.694
Motor Power	-0.092

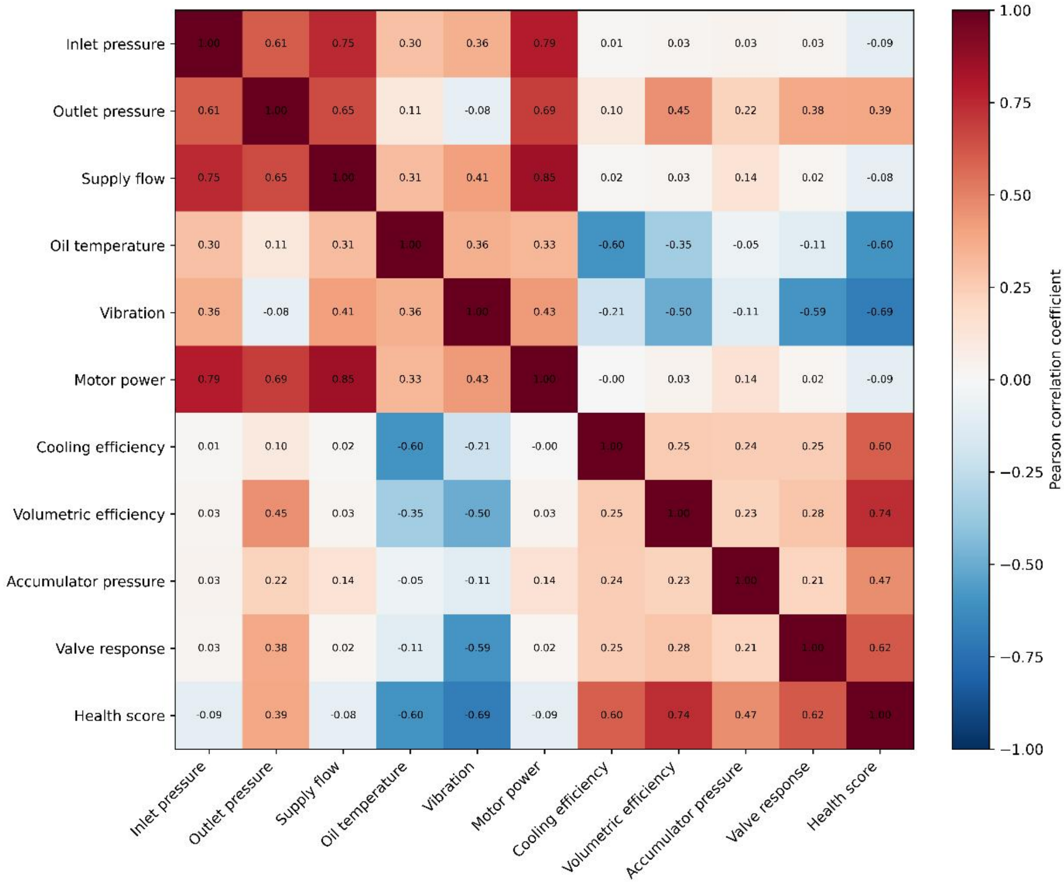

Figure 3. Correlation Heatmap of Hydraulic Sensor Variables

3.4 Comparison of Hydraulic Performance Across Operating Conditions

Comparative evaluation showed that the use of different operating conditions resulted in significant differences in system performance. Fault-related operating conditions resulted in a progressive loss of system health while showing increased variations in hydraulic performance indicators, while healthy operating cycles had higher health scores. Fault classes related to leakage, valve faults and loss of accumulator pressure tended to show relatively low health scores, indicating a decrease in operational efficiency. These results show that the multisensory measurements have good discriminative ability between different hydraulic operating states and have meaningful values for intelligent condition monitoring. Table 4 gives the hydraulic system health scores for various operating conditions.

Table 4. Comparison of Hydraulic System Performance Across Operating Conditions

Operating Condition	Mean Health Score	SD
Normal	94.96	4.04
Accumulator Pressure Loss	81.32	4.45
Cooler Degradation	76.94	5.98
Pump Leakage	67.77	5.99
Valve Fault	62.89*	—*
Sensor Anomaly	55.41*	—*
Multiple Faults	29.30	7.51

3.5 Predictors of Hydraulic System Health

The hydraulic parameters were analysed using regression analysis to determine those with significant influence on overall system health. The model results showed that vibration level and oil temperature are the best predictors of health score, meaning that an increase in mechanical vibration and oil temperature were correlated to a decrease in hydraulic system health. The effects of other operational parameters, such as pressure characteristics, flow measurements, and motor power were comparatively small. Results from the regression indicate that it can be used to detect degradation in the system condition by monitoring critical sensor variables continuously and thus help in scheduling maintenance activities.

4. Discussion

The present study tested the effectiveness of intelligent condition monitoring of hydraulic systems by considering the multisensory operational parameters related to the system's health and fault conditions. The results showed that the hydraulic sensor measurements, particularly the vibration level, the oil temperature, the pressure characteristics and the flow related parameters yielded useful information for the evaluation of equipment condition and the differentiation between normal and faulty operating conditions. It is observed that the health scores are different for various operating states, which shows that intelligent monitoring can be used for early fault identification and maintenance planning. This aligns with prior studies highlighting the importance of XAI in enhancing the transparency and reliability of condition monitoring systems in the industrial sector, which could be beneficial for maintenance operators to understand the results of diagnostics and make decisions on the operation of the system (Astolfi et al., 2023). In parallel, intelligent control strategies have proven to optimize the performance and stability of electro-hydraulic systems by dynamically adjusting their responses based on varying operating conditions (Coskun & Itik, 2023).

The correlation and regression analysis showed that vibration and oil temperature were the two most significant indicators of the hydraulic system condition, indicating that mechanical instability and thermal stress are two of the first signs of component failure. These results further confirm that the integration of multiple signals from sensors is important for fault detection and should be done continuously. Similar results were found when deep neural networks and explainable artificial intelligence were used, with multisensory data significantly enhancing the accuracy and explainability of hydraulic health monitoring (Keleko et al., 2023). Similarly, recent research has shown that a clever diagnostic approach using residual analysis can be used to detect early-stage faults in electro-hydraulic control systems before significant degradation in performance occurs, minimizing the possibility of unscheduled faults (Kong et al., 2025).

A further significant result of this research was how using multisensory monitoring could distinguish different hydraulic operating conditions and identify the operating variables with the highest correlation to the loss of system health. The feature importance analysis revealed that the vibration, temperature, accumulator pressure, and efficiency related features are important for fault identification. The same also happened in intelligent sensing for agricultural hydraulic systems, where parameter identification and fault prediction techniques were used to enhance maintenance efficiency by continuously monitoring critical operational parameters (Liu, Zheng, et al., 2025). In addition, the advances in distributed learning have shown that cooperative intelligent monitoring can improve the detection of anomalies, while maintaining computational efficiency in CPS for industrial applications which can also be applied in future hydraulic monitoring applications (Marfo et al., 2025).

The regression results also reveal that using multiple hydraulic measurements will give a good platform for predictive maintenance. Precise prediction allows maintenance to be planned before serious component failures happen, reducing equipment downtime and saving maintenance costs. This aligns with the latest developments in intelligent predictive maintenance solutions, which seek to integrate operational data with sophisticated analytical models to optimize maintenance scheduling and enhance hydraulic system reliability (Patil et al., 2025). Furthermore, physics-informed diagnostic methods have shown that using physics in data analytics can lead to a more accurate identification of the fault, and perform more favourably under operational variations of the system (Qiu et al., 2023). In fault-tolerant control strategies, the intelligent monitoring also offers

similar enhancements, supporting stable hydraulic system performance in the presence of component degradation and operational uncertainties (Ren et al., 2025).
In recent years, intelligent condition monitoring has been greatly enhanced by recent advances in artificial intelligence, including deep learning, digital twins and uncertainty-aware modelling. Multi-sensor convolutional neural networks have proved their excellent ability in real-time fault diagnosis of complex hydraulic faults by utilizing multi-source and multi-type sensor information (Tao et al., 2024). Similarly, the intelligent diagnosis assisted by a digital twin ensures that the physical equipment and virtual model are well synchronized, which helps to accurately assess the health of the system and detect abnormal operating behavior in advance (Yang, Cai, et al., 2024). Uncertainty-aware deep learning methods further enhance the reliability of health monitoring, offering a means to quantify and factor in the uncertainty of predictions in safety-critical systems to boost the confidence in maintenance decision making (Yao et al., 2024). Likewise, a digital twin coupled with deep learning has demonstrated to improve the intelligent fault diagnosis of hydraulic directional valves by promoting a more comprehensive feature extraction and adaptive learning capabilities (Zhang, et al., 2025).
Even though the current work shows the potential of intelligent condition monitoring for hydraulic system health evaluation, there are some limitations that should be pointed out. The analysis was based on the operational sensor measurements taken under specific operational conditions and may not consider all the fault cases that may occur in the complex industrial environment.

5. Conclusion

Intelligent condition monitoring is a key aspect of enhancing the reliability, safety and efficiency for hydraulic systems. In this study, various operational parameters were measured through multi-sensory to assess the health of the hydraulic system, to investigate the influence of the main parameters, and to establish an intelligent monitoring framework to distinguish various operating conditions. The results demonstrated that the vibration level, oil temperature, oil pressure, oil flow characteristics, and efficiency related parameters are useful indicators of hydraulic system health. The statistical analysis also revealed vibration and oil temperature to be the most significant factors, thus highlighting the need for continuous multisensory monitoring for early fault detection. The results also showed that the fusion of information from multiple sensors can be used to effectively differentiate between normal and fault operating conditions, which helps to plan maintenance in a timely manner and minimize the risk of unexpected equipment failures. These insights demonstrate the value of intelligent condition monitoring in driving more effective predictive maintenance, equipment reliability, and reducing maintenance costs and downtime. The proposed framework offers a holistic and structured strategy to assess the health of hydraulic systems using sensor-based analysis. Future research should be directed toward testing the framework under more operating conditions, including the use of real-time monitoring data, and studying new artificial intelligence methods in order to further enhance the diagnostic accuracy and use the framework for the building of intelligent maintenance system in industrial hydraulic applications.

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