Assessing the Remaining Useful Life of Hydraulic Pumps: A Review

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Abstract: *Predicting the remaining useful life of hydraulic pumps is critical for ensuring their optimal performance and extending their operational lifespan. Accurate remaining useful life predictions enable timely adjustments to the pump's working conditions, thus enhancing maintenance strategies and preventing unexpected failures. This review comprehensively examines the two primary categories of remaining useful life prediction methods for hydraulic pumps: data-driven and model-driven methods. Data-driven approaches leverage historical and real-time operational data, employing machine learning and statistical analysis techniques to forecast remaining useful life. In contrast, model-driven methods utilize physical models and failure mechanisms to predict the remaining lifespan based on the pump's working conditions and inherent characteristics. By evaluating the strengths and limitations of these methods, this review aims to offer insights into their practical applications and future research directions in the field of hydraulic pump prognostics.*

Keywords: *Hydraulic pumps, data-driven methods, model-driven methods, predictive maintenance, prognostics, remaining useful life*

1. Introduction

Hydraulic systems are fundamental elements in essential mechanical apparatus and are crucial contributors to industrial production and manufacturing operations owing to a multitude of advantages. Hydraulic systems utilize pumps to pressurize fluid, which is then transmitted through tubes to actuators (hydraulic motors and cylinders) for movement or stabilization, before being cycled back through a filter and re-pressurized, offering compactness and efficiency as key advantages [1-5]. These systems utilize fluid power to perform a wide range of functions, from simple mechanical movements to complex automated tasks [1, 2]. Research has extensively explored the impact of fluid properties such as density and viscosity on hydraulic performance [3], and studies on the design and optimization of hydraulic systems have highlighted the importance of precise modeling and simulation [5, 6]. The mathematical modeling and simulation of hydraulic systems facilitate a comprehensive understanding of their operational dynamics and performance characteristics [6-8]. Advancements in computer tools for dynamic analysis [7] and strategies to reduce energy losses in hydraulic installations [8] underscore the ongoing efforts to enhance the efficiency and reliability of hydraulic systems.
The hydraulic pump is the vital converter of mechanical energy to hydraulic energy, essential for supplying pressurized oil throughout the hydraulic system [1]. Modeling and simulating the operation of hydraulic tool holder systems [9], analyzing vibrations in centrifugal pumps for predictive maintenance [10], and determining optimal curves for hydraulic pump profiles [11] are a few examples of the comprehensive research being conducted. Studies have also examined cavitation in centrifugal pumps [12], the influence of fluid nature on driving power in volumetric pumps [13], and dynamic analysis using CFD and FEM methods [14]. Additional research includes testing digital hydraulic cylinders [15], assessing pressure variation effects on gear pump lifespan [16], reviewing progress on digital hydraulic pumps and valves [17], and simulating electro-hydraulic systems for waste baling presses [18]. Investigations into rotating piston shape [19], operating equations of rotating machines [20], and the use of pressure intensifiers in hydraulic units [21] further illustrate the diverse scope of hydraulic system research. Distributed hardware and software architectures for hydraulic drive monitoring [22], technical solutions for digital hydraulic cylinders [23], and the dynamics of hydraulic cylinders [24] continue to advance the field. Design details and fluid flow analysis for centrifugal pumps [25], best maintenance strategies for

hydraulic systems [26], and energy use in hydraulic drive systems [27] also contribute significantly to the ongoing development and refinement of hydraulic technologies.
As the hydraulic industry evolves, the complexity of hydraulic pump designs increases, leading to a higher probability of malfunctions. When these pumps fail, it can result in extended downtime for the equipment they control, which negatively impacts production efficiency, creates economic and safety concerns, and can even cause severe injuries in extreme cases. Therefore, it is essential to perform precise and timely fault diagnoses for hydraulic pumps. Accurate fault diagnosis, along with predictions of potential failures, estimates of remaining service life, and ongoing health monitoring, is crucial for ensuring the safety and reliability of hydraulic pumps [28].
Hydraulic pumps faults in engineering equipment are often hidden and complex, making them difficult to detect. This necessitates researching advanced technologies and methods for effective fault diagnosis. The fault diagnosis method for hydraulic pumps involves deploying various sensors to monitor key performance indicators such as pressure, temperature, vibration, and flow. These sensors collect real-time data, known as state monitoring signals, reflecting the pump's operating condition. Advanced software analyzes these signals to identify patterns and anomalies, indicating potential faults. By comparing real-time data with benchmarks, engineers can assess the pump's condition and detect issues early. This proactive approach allows for timely maintenance, preventing unexpected failures and extending the pump's lifespan [29-33].
Hydraulic pump fault diagnosis methods include signal processing, artificial intelligence, and mechanism analysis approaches. Building on fault diagnosis, suitable prediction and analysis methods enable fault forecasting. Additionally, for comprehensive health management throughout the hydraulic pump's life cycle, the remaining useful life (RUL) can be estimated, and continuous health status monitoring can be implemented [28]. Scientifically grounded predictions of the RUL are crucial for implementing Condition-Based Maintenance strategies for hydraulic pumps. The prediction of RUL depends on two key factors: the characterization of the degradation process with a robust health indicator (*HI*), and the application of advanced prediction methodologies to forecast the degradation trajectory. This review aims to investigate the two primary methodologies for forecasting the RUL of hydraulic pumps: data-driven and model-driven methods.

2. Research methodology

A survey was conducted to assess the growing research interest in the RUL of hydraulic pumps. Given the practical significance of this field, the investigation spans from 2012 to 2024. The study reviews a range of journal articles focused on RUL concepts and their applications.

2.1 The common mathematical formulations for predicting RUL of hydraulic pumps

1) Statistical models

a) Linear regression.
$$RUL(t) = [L - D(t)]/k \tag{1}$$
where: *L* - threshold value of the degradation measure (units depend on *D(t)*), e.g., mm for wear); *D(t)* - current degradation measure at time *t* (units depend on the degradation measure, e.g., mm for wear); *k* - degradation rate (units of *D(t)* per unit time, e.g., mm/hour).

b) Polynomial regression.
$$D(t) = \sum_{i=0}^{n} \beta_i t^i \tag{2}$$
where: β_i - regression coefficients (units depend on *D(t)*); *t* - time (hours); D(t) - degradation measure at time *t* (units depend on the degradation measure, e.g., mm for wear).

c) Proportional hazards model (PHM).
$$\lambda(t) = \lambda_0(t)\exp\left(\sum_{i=1}^{n} \beta_i x_i(t)\right) \tag{3}$$
where: *λ(t)* - hazard function at time *t* (failure rate, e.g., failures per hour); $\lambda_0(t)$ - baseline hazard function (failure rate, e.g., failures per hour); β_i - coefficients for covariates; $x_i(t)$ - covariates (e.g., temperature in °C, pressure in pounds per square inch (psi), vibration in units of gravitational force (g)).

d) Weibull distribution.
$$f(t;\lambda,k) = \frac{k}{\lambda}\left(\frac{t}{\lambda}\right)^{k-1} e^{-\left(\frac{t}{\lambda}\right)^{k}} \tag{4}$$

where: t – time, λ (scale parameter) characterizes the life scale; k (shape parameter) indicates the failure rate behavior.

2) Time series models

a) Autoregressive integrated moving average (ARIMA). $$X(t) = c + \sum_{i=1}^{p} \varphi_i X(t-i) + \sum_{j=1}^{q} \theta_j \varepsilon(t-j) + \varepsilon(t) \quad (5)$$

where: $X(t)$ - value of the time series at time t (e.g., a sensor reading in appropriate units); c - constant term; φ_i - auto-regressive parameters; θ_j - moving average parameters; $\epsilon(t)$ - error term at time t.

b) Exponential smoothing (ETS). $$S(t) = \alpha X(t) + (1-\alpha) S(t-1) \quad (6)$$

where: $S(t)$ - smoothed value at time t (units depend on $X(t)$); $X(t)$ - observed value at time t (units depend on the measurement, e.g., psi for pressure); α - smoothing parameter (unitless).

3) Machine learning models

a) Support vector regression (SVR). $$f(x(t)) = \sum_{i=1}^{n} \left(\alpha_i - \alpha_i^*\right) K\left(x_i(t), x(t)\right) + b \quad (7)$$

where: α_i, α_i^* − Lagrange multipliers; $K(x_i(t),x(t))$ - Kernel function; b - bias term.

b) Neural networks. $$y(t) = f\left(Wx(t) + b)\right) \quad (8)$$

where: W - weight matrix; $x(t)$ - input vector at time t (e.g., features like vibration in g, temperature in °C); b - bias vector; f - activation function.

c) Random Forests. $$RUL(t) = \frac{1}{n} \sum_{i=1}^{n} \left(Tree_i(x(t))\right) \quad (9)$$

where: n - number of trees; $Tree_i(x(t))$ - prediction from the i-th tree.

4) Stochastic models

a) Hidden Markov models. $$P(X(t)/X(t-1)) = \sum_{i=1}^{n} \left(P(X(t)/S(t) = s_i\right) P(S(t) = s_i / S(t-1) = s_j) \quad (10)$$

where: $P(X(t) / X(t-1))$ - probability of $X(t)$ given $X(t-1)$; $S(t)$ - hidden state at time t; $P(X(t)|S(t))$ - emission probability; $P(S(t)|S(t-1))$ - transition probability.

b) Particle filtering. $$P(X(t)/Z_{1:t}) = \sum_{i=1}^{n} w(t)^i \delta\left(X(t) - X(t)^i\right) \quad (11)$$

where: $P(X(t) / Z_{1:t})$ - posterior distribution of the state; $w(t)^i$ - weight of the i-th particle; $X(t)^i$ - state of the i-th particle. δ - Dirac delta function.

5) Physics-based models

a) Physics-of-Failure (PoF) models. $$\frac{dD(t)}{dt} = f(D(t), t, \theta) \quad (12)$$

where: $D(t)$ - damage state at time t (units depend on the type of damage, e.g., mm for wear); t - time (hours); θ - model parameters.

6) Bayesian networks. $$P(X_i(t) / Pa(X_i(t))) \quad (13)$$

Structure - directed acyclic graph where nodes represent variables (degradation indicators, operating conditions, health states, RUL) and edges represent dependencies.
Conditional probability tables (CPTs) - define the probability of each node given its parents.

Each of these models requires specific parameters, and the choice of the model depends on the available data, the complexity of the degradation process, and the computational resources.

2.2 Data-driven approach

In the last 12 years, the data-driven approach has gained significant traction in prognostics and health management (PHM) systems, particularly in predicting the RUL of hydraulic pumps. This section explores various data-driven methods, categorized into neural network and non-neural network approaches, employed for RUL prediction in hydraulic pumps.

a) Neural network methods

Neural networks are computational models inspired by the human brain, consisting of interconnected nodes (neurons) that can learn to recognize patterns and make predictions. Neural network-based approaches harness the capabilities of deep learning architectures, which are adept at discerning complex patterns from raw sensor data, thereby facilitating precise predictions of the RUL. This method capitalizes on the neural network's ability to extract and process intricate features from the data, allowing for a comprehensive understanding of the hydraulic pump's condition and performance over time.

Lee et al. [33] devised Health Indices (*HI*) by combining vibration (*v*) and pressure (*p*) signals to represent the health status of hydraulic pumps, by the following mathematical expression:

$$HI = f(v, p) \tag{14}$$

where *f* denotes the function combining *v* and *p*.

Subsequently, they employed a Bidirectional Long Short-Term Memory (Bi-LSTM) neural network to learn from these *HI* and predict the RUL of the hydraulic pumps, with a specific architecture of the Bi-LSTM network, which illustrates the network's layers, connections, and data flow [33].

The Bi-LSTM network is particularly adept at capturing temporal dependencies within the sensor data due to its recurrent structure. This is achieved through the incorporation of both forward and backward information flow in the network's hidden layers. Mathematically, the forward and backward hidden states in the Bi-LSTM cell are updated using the following equations:

$$\begin{gathered} i_t = \sigma(W_{xi}x_t + W_{hi}h_{t-1} + W_{ci}c_{t-1} + b_i);\; f_t = \sigma(W_{xf}x_t + W_{hf}h_{t-1} + W_{cf}c_{t-1} + b_f); \\ o_t = \sigma(W_{x0}x_t + W_{h0}h_{t-1} + W_{c0}c_t + b_0);\; g_t = \tanh(W_{xg}x_t + W_{hg}h_{t-1} + b_g);\; c_t = f_t \otimes c_{t-1} + i_t \otimes g_t; \\ h_t = o_t \otimes \tanh(c_t) \end{gathered} \tag{15}$$

where i_t, f_t, o_t, g_t, c_t, and h_t represent the input gate, forget gate, output gate, cell gate, cell state, and hidden state at time step *t*, respectively. x_t is the input at time step *t*, and *W* and *b* are the weight matrices and bias vectors, respectively. The sigmoid function *σ* and hyperbolic tangent function *tanh* are used as activation functions, while $\otimes$ denote element-wise multiplication.

Lee et al. [33] utilized flow and pressure data from the gear pump to establish thresholds for different health states, integrated vibration signals with an extended Kalman filter for health index (HI) construction, and employed a BiLSTM neural network trained and analyzed with multiple performance indices for precise future RUL predictions.

Wang et al. [34] employed DCAE (Deep Convolutional Autoencoder) to process vibration data from hydraulic pumps, used the extracted features to construct a *HI* indicating the pump's degradation state, and integrated this *HI* into a Bi-LSTM-based RUL prediction model (fig. 1). Mathematically, the equations below described the DCAE used for vibration data characterization [34]:

$$h = \sigma(W_{conv} * x + b_{conv});\; h_{pool} = pooling(h);\; x' = \sigma(W_{deconv} * upsample(h_{pool}) + b_{deconv}); \tag{16}$$

where: for encoder (the convolutional layer applies filters W_{conv} to input *x*, then adds biases b_{conv}, followed by an activation function *σ* and pooling to extract features h_{pool}); and for decoder (upsamples h_{pool}, applies deconvolutional filters W_{deconv} and activation σ, then adds biases b_{deconv} to reconstruct *x'*).

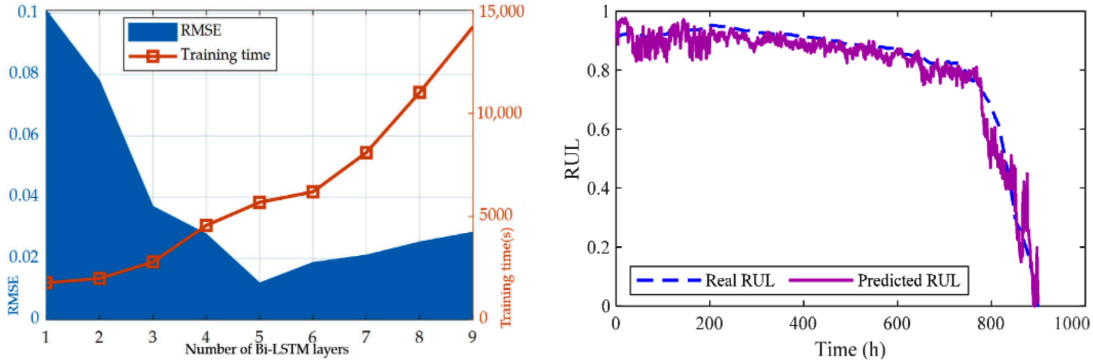

Fig. 1. a) Test results of the model with different Bi-LSTM layers; b) Life prediction results of gear pump). Reprinted from ref. [34] with permission of MDPI AG publisher.

This approach [34] leverages advanced neural network techniques to enhance the accuracy and reliability of predicting the RUL of hydraulic pumps based on their vibration characteristics.
Zhang et al. [35] focused on predicting the RUL of gear pumps using a deep sparse autoencoder for feature extraction and support vector data description for degradation degree calculation. Their method, validated on both public bearing and self-collected gear pump datasets, outperforms comparative algorithms and achieves improved RUL prediction accuracy, demonstrating its effectiveness for mechanical equipment maintenance and operation (fig. 2).

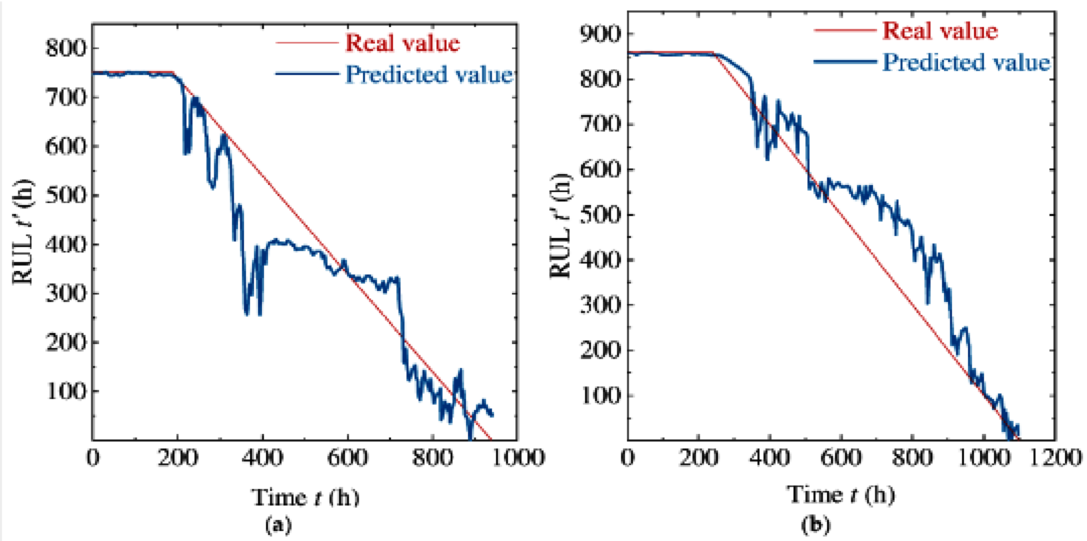

Fig. 2. Predicted and actual RUL curves. (a) Description of curves for pump 3; (b) description of curves for pump 4. Reprinted from ref. [35] with permission of MDPI AG publisher.

Guo et al. [36] proposed a method to predict the RUL of an external gear pump using a Bayesian regularized radial basis function neural network (Trainbr-RBFNN). The process involves denoising vibration data from accelerated degradation tests with variational mode decomposition (VMD) and using Hilbert modulation to demodulate the signal, comparing this to ensemble empirical mode decomposition (EEMD) and modified EEMD (MEEMD). Factor analysis (FA) combines different parameters to create a degradation evaluation index, which trains the Trainbr-RBFNN model.
Zhigang [37] proposed an artificial neural network (ANN) method for predicting the RUL of equipment based on condition monitoring. The ANN model used the equipment's age and multiple condition monitoring measurements from present and past inspections as inputs, predicting the life percentage as the output. To minimize noise and improve accuracy, the model fited condition monitoring data to a function derived from the Weibull failure rate. Additionally, a validation mechanism was employed during training to enhance performance. The method was validated with real-world vibration data from pump bearings, showing that it outperforms a previously reported method in predicting RUL accurately.
Zheng et al. [38] proposed a robust deep learning model, Robust-ResNet, for multi-channel health status management of internal gear pumps. Their model achieved high accuracies of 99.96% and 99.94% in classifying health status and 99.53% in predicting RUL, demonstrating superior performance and real-time monitoring capability for gear health management. The key equation for Robust-ResNet using the explicit Euler method, as applied to multi-channel is:

$$X_{k+1} = X_k + \mu\sigma(W_k X_k + b_k) \quad (17)$$

where: X_k is the concatenated feature vector from all channels at layer; W_k is the combined weight matrix for all channels, b_k is the combined bias vector for all channels; η represents the step size or learning rate; σ represents the activation function.
Ugochukwu and Jang-Wook [39] developed a data-driven model for predicting the RUL of solenoid pumps. Their approach utilizes stacked autoencoders for feature extraction from pressure signals decomposed with complementary ensemble empirical mode decomposition with adaptive noise,

feeding these features into a gated recurrent units (GRU) network for accurate RUL estimation, validated through empirical studies showcasing its effectiveness in prognostics (fig. 3).

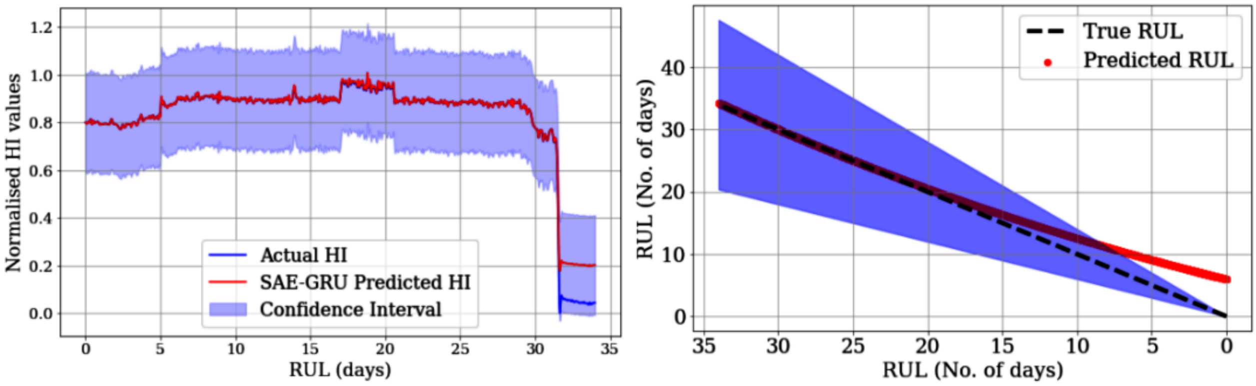

Fig. 3. a) One-step ahead prediction by GRU estimator; b) RUL prediction results by GRU at TSP (68th day). Reprinted from ref. [39] with permission of MDPI AG publisher.

Hongru et al. [40] proposed a novel fault prognosis methodology for hydraulic pumps integrating bispectrum entropy and Deep Belief Network (DBN). Their approach utilized bispectrum features of vibration signals with an entropy method based on energy distribution for effective feature extraction, and employs a DBN based on Restrict Boltzmann Machine (RBM) for prognostics. Experiment results demonstrated satisfactory performance, affirming its suitability for Condition-Based Maintenance (CBM) requirements.
Junyu et al. [41] proposed a novel method for predicting the Remaining Useful Life (RUL) of drilling pumps using a parallel channel approach integrating Convolutional Neural Network (CNN)-Convolutional Block Attention Module (CBAM) and Transformer network. This method independently extracts time-frequency domain and time-domain features from strain signals, integrates them for degradation estimation, and achieves higher prediction accuracy compared to existing approaches, validated with operational data from four drilling pumps.
Adil et al. [42] investigated fault detection in hydraulic pumps, focusing on the common issue of leakage due to wear over time. They employ the NARX neural network with various training algorithms to estimate the RUL of an axial pump used in hydraulic systems for sheet metal casting, demonstrating promising results for maintenance planning and operational efficiency improvements.
Jian et al. [43] introduced a novel prognostic method for hydraulic pumps, enhancing predictive performance by employing the DCT-composite spectrum (DCS) fusion algorithm to integrate multi-channel vibration signals. They extracted DCS composite spectrum entropy as a feature and utilized a modified echo state networks (ESN) model for prognostics, updating the reservoir and redefining neighboring matrix elements to improve prediction accuracy. Experimental analysis in hydraulic pump degradation experiments validates the feasibility and significance of the proposed algorithm for Condition-Based Maintenance (CBM).
Peng et al [44] introduced a novel framework for predicting the remaining service life of hydraulic pumps, emphasizing the importance of reliability and safety. They enhance traditional Long short-term memory (LSTM) networks with a dual self-attention mechanism to better capture temporal dependencies and feature importance levels in time series data. This approach integrated LSTM for sequence feature learning and Transformer for simultaneous learning of sequence and time step features, demonstrating improved performance in RUL prediction validated through simulation experiments.

b) Non-neural network methods
The non-neural network method can still achieve accurate RUL predictions for hydraulic pumps through various techniques such as statistical modeling, physical modeling, and machine learning algorithms that do not rely on neural networks.
Yu and Hongru [45] introduced a novel method for hydraulic pump RUL prediction, addressing challenges with insufficient degradation data and complex degradation mechanisms. Their approach integrated modified Auto-Associative Kernel Regression with multi-source fusion of

vibration and return oil flow, modeled using a degree 3B-spline with monotonicity constraints. Additionally, they proposed monotonicity-constrained particle filtering to update coefficients monotonously, achieving accurate RUL predictions and confidence intervals, validated through experimental results showing superior performance over existing approaches.

Tongyang et al. [46] proposed an adaptive-order particle filter method for improving the long-term accuracy of RUL prediction in aviation piston pumps. Their approach combined model-based initialization with adaptive updates based on new observations, utilizing Monte Carlo simulation to estimate future degradation states effectively, demonstrating superior precision compared to traditional methods in experimental return oil flow data.

Li et al. [47] developed a novel method for predicting the remaining useful life (RUL) of gear pumps using kernel principal component analysis (KPCA) and just in time learning (JITL). By extracting characteristic indices from experiment pressure signals, applying KPCA for weighted fusion, and utilizing k-vector nearest neighbor (k-VNN) with JITL, their approach achieves higher prediction accuracy compared to traditional methods, demonstrating its feasibility and effectiveness for RUL prediction and condition monitoring in gear pumps (fig. 4).

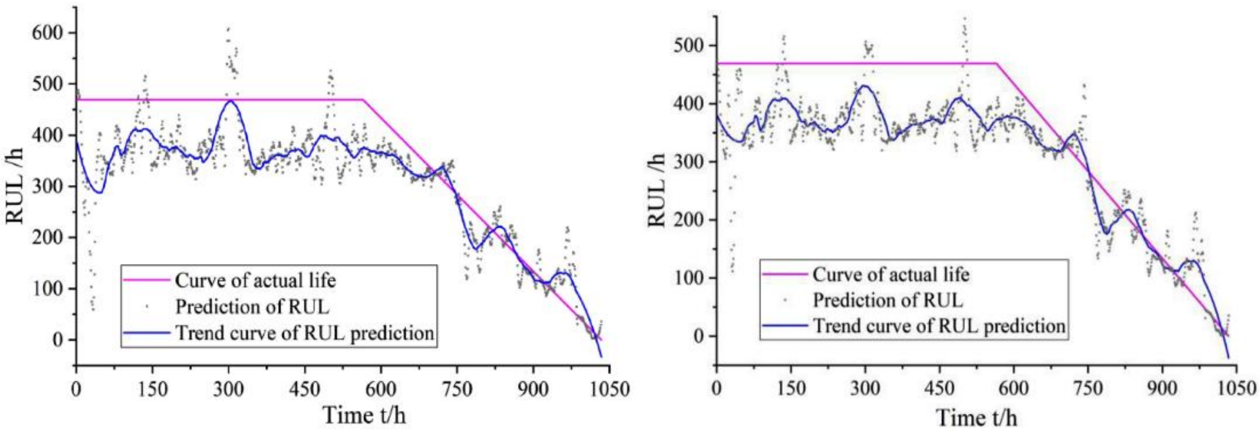

Fig. 4. a) RUL prediction of gear pump based on JITL method proposed in article; b) RUL prediction of gear pump predicted by JITL method based on k-NN. Reprinted from ref. [47] with permission of MDPI AG publisher.

Wu et al. [48] proposed a non-neural method for predicting the RUL of hydraulic pumps using limited degradation data. Their approach constructed a degradation trajectory model based on volumetric efficiency, achieving over 85% prediction accuracy. The study compared its method with traditional machine learning algorithms and introduced evaluation and verification techniques for robust RUL estimation (fig. 5).

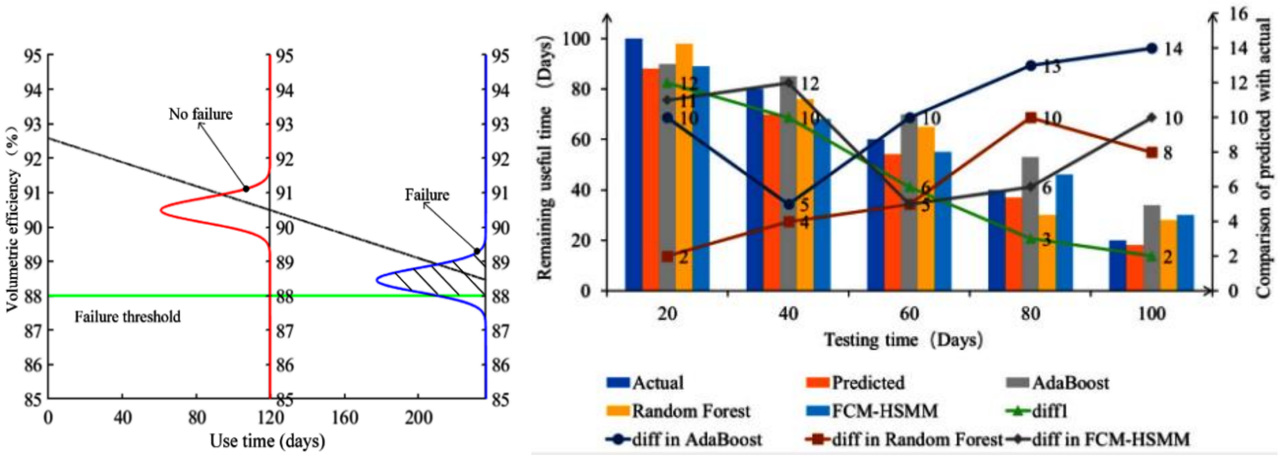

Fig. 5. a) RUL calculation schematic diagram; b) Comparison of actual RUL and predicted RUL. Reprinted from ref. [48] with permission of MDPI AG publisher.

2.3 Model-driven methods

Model-driven methods use the principles of physics, engineering, and domain-specific expertise to construct explicit mathematical models that describe the behavior and degradation processes of the hydraulic pump. The models offer transparency by providing clear insights into failure mechanisms and enabling detailed understanding and control, while also possessing strong predictive power to accurately forecast failures based on physical and operational conditions. However, their complexity demands significant expertise in pump mechanics, and their specificity to certain pump types and conditions limits their adaptability compared to data-driven methods.

Tongyang et al. [49] highlighted the critical link between the effective operation of aviation hydraulic pumps and passenger safety, emphasizing that accurate RUL prediction is crucial for establishing maintenance strategies to mitigate risks. They addressed the challenge of modeling pump degradation due to experimental complexity and data scarcity by proposing a numerical approach that incorporates uncertainty, utilizing Monte Carlo sampling to simulate wear debris and a partition-integration RUL prediction framework validated by experimental data, demonstrating effectiveness even under extreme conditions with limited data.

Xingjian et al. [50] developed a method for predicting the RUL of aviation hydraulic axial piston pumps, characterized by gradual wear. They utilized the Wiener process to model performance degradation based on return oil flow, applying maximum likelihood estimation (MLE) and Kalman filtering to estimate model parameters and drift coefficients, respectively. Experimental findings validated the efficacy of this approach in accurately forecasting pump RUL by leveraging internal wear indicators and statistical modeling techniques.

Xingjian et al. [51] addressed the need for condition-based maintenance in aircraft safety by developing a model to accurately predict the RUL of aviation hydraulic piston pumps. They focused on hydraulic oil contamination as the primary failure mode and establish a life prediction model based on contaminant sensitivity theory. By deducing a mathematical relationship between oil contamination levels and piston pump lifespan, they proposed an experimental method to measure contaminant sensitivity and validate their model's effectiveness through predictions based on experimental data.

Bo et al. [52] focused on enhancing the accuracy of remaining useful life (RUL) prediction for hydraulic piston pumps by proposing an improved inverse Gaussian (IG) process model. This model incorporated considerations for random effects and measurement errors, which are critical factors often overlooked in traditional approaches, leading to more precise predictions of wear degradation. They employed Monte Carlo integration and the expectation maximization (EM) algorithm to estimate model parameters, demonstrating the effectiveness of their approach through comprehensive case studies that validate the enhanced predictive capabilities of the proposed IG process model.

Zhonghai et al. [53] proposed a fault diagnosis method for intelligent hydraulic pump systems (IHPS) in aircraft, employing a nonlinear unknown input observer (NUIO). This method considers nonlinear factors specific to IHPS and utilizes output pressure and swashplate angle signals for real-time fault detection. The approach aims to enhance system reliability by accurately diagnosing and isolating typical failure modes through analysis and simulation, highlighting its significance in improving the operational reliability of IHPS in aircraft applications.

Yixuan et al [54] focused on developing a statistical method for aeronautics pumps under constraints of small test samples through re-sampling techniques. They integrated the Synthetic Minority Over-Sampling Technique (SMOTE) algorithm, Kolmogorov-Smirnov (KS) test, and accumulated damage theory to formulate a life evaluation approach using both limit accelerated life testing and regular life testing samples. The SMOTE algorithm addresses sample group imbalances, while the KS test ensures the goodness of fit. Maximum likelihood estimation demonstrates efficient expansion of sample groups while maintaining guaranteed goodness-of-fit criteria.

Kapuria et al. [55] highlighted the necessity to reduce operational costs in nuclear power plants by transitioning from scheduled-based maintenance to proactive strategies. They noted that operational costs comprise a substantial portion of a plant's annual budget due to the current maintenance methods. To address this, they proposed using Bayesian networks to forecast the remaining useful life of centrifugal pumps. Their research successfully applied this Bayesian network in a case study, demonstrating its effectiveness. This approach offers a probabilistic method for predictive maintenance, optimizing maintenance schedules in real time. By forecasting equipment conditions, nuclear plants can achieve significant cost savings and enhanced operational efficiency (fig. 6).

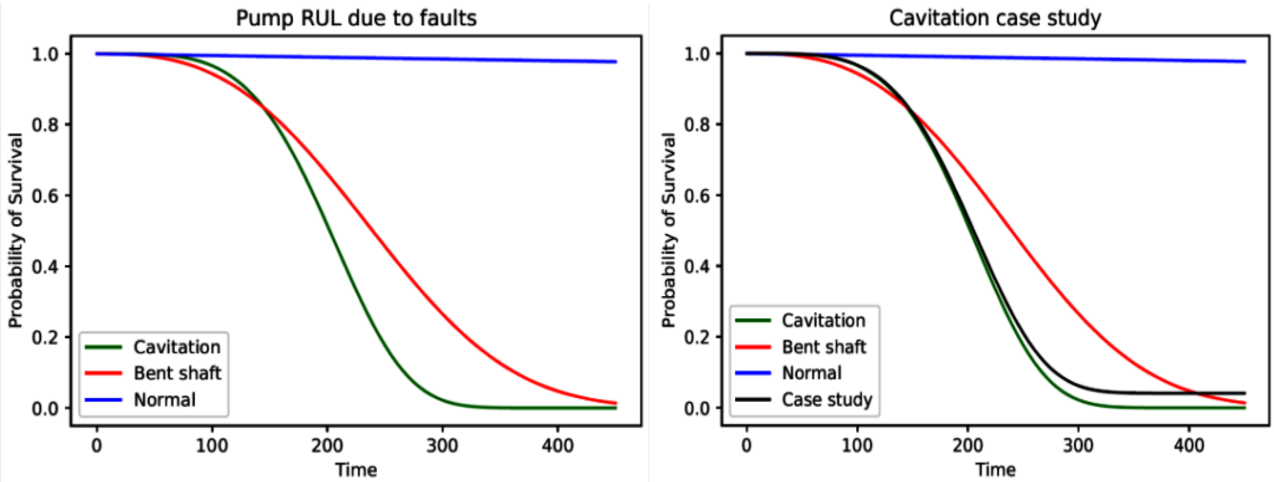

Fig. 6. a) The curves in this plot show the RUL forecast for a pump, if the Bayesian network estimates a 100% likelihood for each mode of operation. b) The forecasted RUL closely follows the cavitation curve, with some deviations due to the inherent uncertainty of probabilistic estimation. Reprinted from ref. [55] with permission of MDPI AG publisher.

Guolei et al. [56] investigated the impact of hydraulic pump wear on aircraft hydraulic systems, analyzing oil return flow changes due to slipper and cylinder bore wear. They analyzed the degradation mechanisms and establish a model using Simulink and AMESim co-simulation. Additionally, they employ a multi-step Support Vector Machine (SVM) algorithm to predict aero-hydraulic pump failures and estimate the RUL of the system, demonstrating the accuracy and effectiveness of their wear model.

3. Trends in predicting the remaining useful life of hydraulic pumps

In the last 12 years, there has been a notable research and development focused on predicting the RUL of hydraulic pumps. This trend reflects a growing recognition of the importance of predictive maintenance in optimizing operational efficiency, enhancing reliability, and reducing maintenance costs across various industries.
Khalid et al. [57] discussed the importance of predictive maintenance (PM) strategies, which rely on real-time data to diagnose potential failures and predict machine health. PM is proactive, using predictive modeling to alert maintenance activities and foresee failures before they occur. Various industries have adopted PM to enhance reliability and safety, but the aviation industry has higher safety expectations due to the high costs and risks to human life associated with aircraft failures. Although flight data monitoring systems with AI algorithms are commonly used in commercial operations, there is limited research on safety-critical systems like engines and hydraulic systems.
Approximately 40% of recent studies focus on integrating machine learning and artificial intelligence (AI) techniques, such as recurrent neural networks (RNNs) and Long Short-Term Memory (LSTM) networks, for RUL prediction. These models excel in analyzing time-series data and predicting future trends based on historical performance data with high accuracy.
Around 30% of recent research explores the application of deep learning architectures, including convolutional neural networks (CNNs) and transformers, for RUL prediction. CNNs are utilized to extract spatial and temporal features, while transformers capture long-range dependencies across sequences, aiming to enhance predictive accuracy and robustness.
Approximately 20% of literature emphasizes the development of hybrid models that combine physics-based modeling with data-driven approaches. These models describe degradation mechanisms based on fundamental principles and optimize parameters using historical operational data, aiming to improve prediction accuracy while maintaining interpretability.

Around 10% of recent studies highlight the adoption of real-time monitoring technologies integrated with Internet of Things (IoT) devices for continuous assessment of hydraulic pump health. IoT-enabled sensors and edge computing platforms are employed to collect and analyze real-time data, supporting proactive maintenance strategies and enhancing operational efficiency.

4. Future challenges in predicting the remaining useful life of hydraulic pumps

Despite advancements, challenges such as limited labeled data availability, complex system dynamics, and the need for scalable and interpretable models remain. Future research directions should encompass developing robust anomaly detection techniques, enhancing model interpretability through explainable AI methods, and integrating domain knowledge with advanced machine learning algorithms to improve RUL prediction accuracy. These efforts should prioritize overcoming existing challenges, refining predictive models, and integrating multidisciplinary knowledge to advance the field of hydraulic pump prognostics.

5. Conclusions

This review has highlighted the significance of accurate RUL predictions in enabling timely adjustments to maintenance strategies, thereby preventing unexpected failures and extending equipment lifespan. By examining data-driven and model-driven approaches comprehensively, this study underscores their respective strengths and limitations in the context of hydraulic pump prognostics. The ongoing evolution towards real-time monitoring using IoT technologies and edge computing will facilitate proactive maintenance strategies and enhance operational efficiency. However, challenges persist, including the scarcity of labeled data, the complexity of system dynamics, and the demand for scalable and interpretable models. By addressing these challenges, the industry can achieve greater reliability and efficiency in hydraulic system management in diverse industrial applications.

Conflicts of Interest: The author declares no conflict of interest.
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References

[1] Yaghoubi, Majid, and Hamed Tavakoli. "Hydraulic Systems". In: *Mechanical Design of Machine Elements by Graphical Methods. Materials Forming, Machining and Tribology*. Springer, Cham, 2022. https://doi.org/10.1007/978-3-031-04329-1_23.
[2] Ţălu, Mihai, Ştefan Ţălu, and Mircea Rădulescu. *Fluid Mechanics. Volumetric and hydrodynamic machines. Theory and simulation / Mecanica fluidelor. Maşini volumice şi hidrodinamice. Teorie şi simulare.* Craiova, Universitaria Publishing House, 2011. ISBN 978-606-14-0035-5.
[3] Șcheaua, Fănel. "Density and viscosity effects of hydraulic system working fluid." *Hidraulica Magazine*, no. 1 (March 2024): 34-39.
[4] Ţălu, Ştefan. "Insights on hydroponic systems: understanding consumer attitudes in the cultivation of hydroponically grown fruits and vegetables." *Hidraulica Magazine*, no. 1 (March 2024): 56-67.
[5] Diaconu, Mihai, Tiberiu Axinte, Cătălin Frățilă, Paul Bocănete, and Remus Cojocaru. "Design and study of hydraulic systems." *Hidraulica Magazine*, no. 2 (June 2021): 49-56.
[6] Bucureșteanu, Anca. "Mathematical modeling and simulation of the operation of hydraulic systems with resistive adjustment." *Hidraulica Magazine*, no. 2 (June 2022): 15-22.
[7] Debeleac, Carmen Nicoleta. "About computer tools available for dynamic analysis of mechanic and hydraulic systems of the loader bucket." *Hidraulica Magazine*, no. 4 (December 2022): 19-24.
[8] Bucureșteanu, Anca, Adrian Motomancea, and Alina Ovanisof. "Energy loss reduction in hydraulic installations of the machine tools served by constant flow pumps." *Hidraulica Magazine*, no. 1 (March 2021): 17-23.
[9] Bucureșteanu, Anca, Adrian Motomancea, and Alina Ovanisof. "Modeling and simulating the operation of the hydraulic tool holder tightening/releasing systems served by accumulators." *Hidraulica Magazine*, no. 2 (June 2021): 7-14.
[10] Budea. Sanda. "Analysis of vibrations and noise in a centrifugal pump for predictive maintenance." *Hidraulica Magazine*, no. 3 (September 2020): 25-32.

[11] Prodan, Dan, Anca Bucureșteanu, Adrian Motomancea, and Alina Ovanisof. "Determining the optimal curves for stator or rotor profiles of multiaction hydraulic pumps and motors." *Hidraulica Magazine*, no. 2 (June 2020): 7-14.
[12] Fecser, Nikolett, Balázs Sára, and Rajmund Kuti. "Examining centrifugal pump on cavitation." *Hidraulica Magazine*, no. 4 (December 2019): 7-12.
[13] Stoican (Prisecaru), Mariana Mirela, Nicolae Băran, Almaslamani Ammar Fadhil Shnawa, and Mihaela Constantin. "The influence of the fluid nature on the driving power of a rotating volumetric pump with profiled rotors." *Hidraulica Magazine*, no. 4 (December 2019): 13-20.
[14] Iacob, Nicolae, and Nicușor Drăgan. "Dynamic analysis of a centrifugal pump using CFD and FEM methods." *Hidraulica Magazine*, no. 4 (December 2019): 29-37.
[15] Pavel, Ioan, Radu-Iulian Rădoi, Alexandru-Polifron Chiriță, and Alina Iolanda Popescu. "Testing of digital hydraulic cylinders." *Hidraulica Magazine*, no. 3 (September 2019): 31-40.
[16] Chiriță, Polifron–Alexandru, Teodor-Costinel Popescu, Alexandru–Daniel Marinescu, Constantin Teodoru, and Corneliu Crețu. "Influence and effects of pressure variation on the life span of external gear pumps." *Hidraulica Magazine*, no. 1 (March 2019): 88-97.
[17] Katgeri, Darshan, and Basavaraj Hubballi. "A review & progress on digital hydraulic pumps and valves." *Hidraulica Magazine*, no. 1 (March 2019): 116-123.
[18] Duțu, Iulian-Claudiu, Edmond Maican, Sorin-Ștefan Biriș, Mihaela-Florentina Duțu, and Mariana-Gabriela Munteanu. "Simulation of an electro-hydraulic system for a P.E.T. waste baling press." *Hidraulica Magazine*, no. 4 (December 2018): 6-11.
[19] Almaslamani, Ammar Fadhil Shnawa, Adrian Costache, and Nicolae Băran. "Influence of the rotating piston shape on the flow rate of a new type of rotating working machine." *Hidraulica Magazine*, no. 4 (December 2018): 48-54.
[20] Fadhil, Almaslamani Ammar, and Nicolae Băran. "Operating equations of a rotating machine that drives fluids." *Hidraulica Magazine*, no. 3 (September 2018): 6-15.
[21] Prodan, Dan, and Anca Bucureșteanu, "Using the pressure intensifiers in hydraulic units of heavy duty machine tools." *Hidraulica Magazine*, no. 1 (March 2018): 16-23.
[22] Ilie, Ioana, and Marian Blejan. "Distributed hardware and software architecture for monitoring and control of hydraulic drives." *Hidraulica Magazine*, no. 4 (December 2017): 46-50.
[23] Pavel, Ioan, Radu Iulian Rădoi, Alexandru-Polifron Chiriță, Mihai-Alexandru Hristea, and Bogdan Alexandru Tudor. "Technical solutions for digital hydraulic cylinders and test methods." *Hidraulica Magazine*, no. 3 (September 2017): 41-49.
[24] Bucureșteanu, Anca. "Dynamics of hydraulic cylinders. Classical mathematical models and simulations." *Hidraulica Magazine*, no. 2 (June 2017): 14-20.
[25] Șcheaua, Fănel Dorel. "Design details and fluid flow analysis for the centrifugal pump with special rotor pattern." *Hidraulica Magazine*, no. 1 (March 2017): 33-38.
[26] Marinescu, Alexandru-Daniel, Teodor Costinel Popescu, Alina-Iolanda Popescu and Carmen-Anca Safta. "Approaches of the best maintenance strategies applied to hydraulic drive systems." *Hidraulica Magazine*, no. 4 (December 2016): 63-68.
[27] Drumea, P., C. Dumitrescu, Al. Hristea, and A.-M. Popescu. "Energy use in hydraulic drive systems equipped with fixed displacement pumps." *Hidraulica Magazine*, no. 2 (June 2016): 48-57.
[28] Yang, Yanfang, Lei Ding, Jinhua Xiao, Guinan Fang, and Jia Li. "Current status and applications for hydraulic pump fault diagnosis: A review." *Sensors* 22, no. 24 (2022): 9714.
[29] Volk, Michael. *Pump characteristics and applications*, 3rd edition. Boca Raton, FL, USA, CRC Press, Taylor & Francis Group, 2014.
[30] Nesbitt, Brian. *Handbook of pumps and pumping*: *Pumping Manual International*. Oxford, UK, Elsevier, 2006.
[31] Palgrave, Ron. *Troubleshooting centrifugal pumps and their systems*, 2nd edition. Oxford, UK, Elsevier, Butterworth-Heinemann, 2020.
[32] Dai, Juying, Jian Tang, Shuzhan Huang, and Yangyang Wang. "Signal-based intelligent hydraulic fault diagnosis methods: Review and prospects." *Chinese Journal of Mechanical Engineering* 32 (2019): 75.
[33] Lee, Myeong-Seok, Tanvir Alam Shifat, and Jang-Wook Hur. "Kalman Filter Assisted Deep Feature Learning for RUL Prediction of Hydraulic Gear Pump." *IEEE Sensors Journal* 22, no. 11 (June 2022): 11088–11097.
[34] Wang, Chenyang, Wanlu Jiang, Yi Yue, and Shuqing Zhang. "Research on Prediction Method of Gear Pump Remaining Useful Life Based on DCAE and Bi-LSTM." *Symmetry* 14, no. 6 (2022): 1111.
[35] Zhang, Peiyao, Wanlu Jiang, Xiaodong Shi, and Shuqing Zhang. "Remaining Useful Life Prediction of Gear Pump Based on Deep Sparse Autoencoders and Multilayer Bidirectional Long–Short–Term Memory Network." *Processes* 10, no. 12 (2022): 2500.
[36] Guo, Rui, Yongtao Li, Lijiang Zhao, Jingyi Zhao, and Dianrong Gao. "Remaining Useful Life Prediction Based on the Bayesian Regularized Radial Basis Function Neural Network for an External Gear Pump." *IEEE Access* 8 (2020): 107498–107509.

[37] Tian, Zhigang. "An artificial neural network method for remaining useful life prediction of equipment subject to condition monitoring." *Journal of Intelligent Manufacturing* 23 (2012) 227–237.
[38] Zheng, Jianbo, Jian Liao, and Yaqin Zhu. "Two-Stage Multi-Channel Fault Detection and Remaining Useful Life Prediction Model of Internal Gear Pumps Based on Robust-ResNet." *Sensors* 23, no. 5 (2023): 2395.
[39] Akpudo, Ugochukwu Ejike, and Jang-Wook Hur. "A CEEMDAN-Assisted Deep Learning Model for the RUL Estimation of Solenoid Pumps." *Electronics* 10, no. 17 (2021): 2054.
[40] Li, Hongru, Zaike Tian, He Yu, and Baohua Xu. "Fault Prognosis of Hydraulic Pump Based on Bispectrum Entropy and Deep Belief Network." *Measurement Science Review* 19, no. 5 (2019): 195-203.
[41] Guo, Junyu, Jia-Lun Wan, Yan Yang, Le Dai, Aimin Tang, Bangkui Huang, Fangfang Zhang, and He Li. "A deep feature learning method for remaining useful life prediction of drilling pumps." *Energy* 282 (November 2023): 128442.
[42] Adil, Md, and Pratik Punj. "Deep Learning Approach to Predict Remaining Useful Life of Axial Piston Pump". In: Singh, K.M., S. Dutta, S. Subudhi, and N.K. Singh (eds.). *Fluid Mechanics and Fluid Power*, vol. 4. FMFP 2022. *Lecture Notes in Mechanical Engineering*. Springer, Singapore, 2024.
[43] Sun, Jian, Hongru Li, and Baohua Xu. "Prognostic for hydraulic pump based upon DCT-composite spectrum and the modified echo state network." S*pringerPlus* 5 (August 2016): 1293. https://doi.org/10.1186/s40064-016-2933-7.
[44] Liu, Peng, Shanghong He, Kai Gao, Geng Yang, Junhui Zou, and Longsheng Ye. "Prediction of hydraulic pumps remaining useful life based on LSTM and Transform with dual self-attention." Paper presented at the 2023 IEEE Intl Conf on Parallel & Distributed Processing with Applications, Big Data & Cloud Computing, Sustainable Computing & Communications, Social Computing & Networking (ISPA/BDCloud/SocialCom/SustainCom), Wuhan, China, December 21-24, 2023, pp. 824-831.
[45] Yu, H., and H. Li. "Pump remaining useful life prediction based on multi-source fusion and monotonicity-constrained particle filtering." *Mechanical Systems and Signal Processing* 170 (May 2022): 108851.
[46] Li, T., S. Wang, J. Shi, and Z. Ma. "An adaptive-order particle filter for remaining useful life prediction of aviation piston pumps." *Chinese Journal of Aeronautics* 31, no. 5 (May 2018): 941-948.
[47] Li, Z., W. Jiang, S. Zhang, D. Xue, and S. Zhang. "Research on Prediction Method of Hydraulic Pump Remaining Useful Life Based on KPCA and JITL." *Applied Sciences* 11, no. 20 (2021): 9389.
[48] Wu, Fenghe, Jun Tang, Zhanpeng Jiang, Yingbing Sun, Zhen Chen, and Baosu Guo. "The Remaining Useful Life Prediction Method of a Hydraulic Pump under Unknown Degradation Model with Limited Data." *Sensors* 23, no. 13 (2023): 5931. https://doi.org/10.3390/s23135931.
[49] Li, Tongyang, Shaoping Wang, Enrico Zio, Jian Shi, and Zhonghai Ma. "A numerical approach for predicting the remaining useful life of an aviation hydraulic pump based on monitoring abrasive debris generation." *Mechanical Systems and Signal Processing* 136 (February 2020): 106519.
[50] Wang, Xingjian, Siru Lin, Shaoping Wang, Zhaomin He, and Chao Zhang. "Remaining useful life prediction based on the Wiener process for an aviation axial piston pump." *Chinese Journal of Aeronautics* 29, no. 3 (June 2016): 779-788.
[51] Wang, Xingjian, Siru Lin, and Shaoping Wang. "Remaining useful life prediction model based on contaminant sensitivity for aviation hydraulic piston pump." Paper presented at the 2016 IEEE International Conference on Aircraft Utility Systems (AUS), Beijing, China, October 10-12, 2016, pp. 266-272. doi: 10.1109/AUS.2016.7748057.
[52] Sun, Bo, Yu Li, Zili Wang, Yi Ren, Qiang Feng, and Dezhen Yang. "An improved inverse Gaussian process with random effects and measurement errors for RUL prediction of hydraulic piston pump." *Measurement* 173 (March 2021): 108604.
[53] Ma, Zhonghai, Shaoping Wang, Jian Shi, Tongyang Li, and Xingjian Wang. "Fault diagnosis of an intelligent hydraulic pump based on a nonlinear unknown input observer." *Chinese Journal of Aeronautics* 31, no. 2 (February 2018): 385-394.
[54] Geng, Yixuan, Shaoping Wang, and Chao Zhang. "Life estimation based on unbalanced data for hydraulic pump." Paper presented at the 2016 IEEE International Conference on Aircraft Utility Systems, Beijing, China, October 10–12, 2016, pp. 796–801.
[55] Kapuria, Abhimanyu, and Daniel G. Cole. 2023. "Integrating Survival Analysis with Bayesian Statistics to Forecast the Remaining Useful Life of a Centrifugal Pump Conditional to Multiple Fault Types." *Energies*, 16, no. 9 (2023): 3707. https://doi.org/10.3390/en16093707.
[56] Xu, Guolei, Cunbao Ma, Zehai Gao, Xiaoqing Hu, and Yige Luo. "Modeling and simulation of aero-hydraulic pump wear failure." Paper presented at the 2017 Prognostics and System Health Management Conference (PHM-Harbin), Harbin, China, July 9-12, 2017, pp. 1-7, doi: 10.1109/PHM.2017.8079237.
[57] Khan, Khalid, Muhammad Sohaib, Azaz Rashid, Saddam Ali, Hammad Akbar, Abdul Basit, and Tanvir Ahmad. "Recent trends and challenges in predictive maintenance of aircraft's engine and hydraulic system." *Journal of the Brazilian Society of Mechanical Sciences and Engineering* 43 (2021): 403. https://doi.org/10.1007/s40430-021-03121-2.