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Degradation Prediction for Hydraulic Piston Pump Based on Physics-informed Recurrent Gaussian Process

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Accurately degradation analysis and prediction for hydraulic piston pump is crucial to ensure hydraulic system reliability, reduce unexpected downtime, and optimize maintenance schedules. The hydraulic piston pump's degradation from wear is typical gradual failure mode. Traditional methods for degradation modelling often rely on physics of failure models or machine learning models. However, physics of failure models may not fully capture the degradation process of the hydraulic piston pump with multiple randomness and uncertainties. Machine learning models generally needs massive degradation data to learn black-box models to reach high accuracy prediction. In order to incorporate the benefits of both methods, a novel physics-informed recurrent Gaussian process model is developed to describe degradation process of hydraulic piston pump and predict remaining useful life. Firstly, the wear process model of three friction pairs including swash plate/slipper, valve plate/cylinder block, and piston/cylinder bore for a type of hydraulic piston pump is investigated. Secondly, the degradation process of hydraulic piston pump is constructed by physics informed recurrent Gaussian process (PI-RGP) model. Comparing with Gaussian process model, recurrent Gaussian process model can reflect time accumulative effect. The mean function of the model is generated by deriving equations from physics of failure model to guide the forecasting process, so that the degradation model is more in line with the actual wear process. In addition, the model can also initiate small data training, and then update and extrapolation the model with new measurements. Finally, the experimental results indicate that the proposed PI-RGP model has foresight of the degradation process and can further improve the degradation prediction accuracy of hydraulic piston pump.

Keywords: Recurrent Gaussian process, Physics-informed, Hydraulic piston pump, Degradation.

1. Introduction

As the core element of the hydraulic system, the pump provides essential power, and its degradation directly influences the system's performance and efficiency. Moreover, the reliability and stability of the overall equipment operation are closely tied to the condition of the hydraulic system. Therefore, accurately assessing and prediction degradation of the hydraulic pump is of significant practical importance for developing effective maintenance strategies and ensuring the smooth operation of aircraft systems (Ș Ţălu, 2024; Chen et al. 2024).

Recent studies on degradation process of hydraulic piston pump can be classified into two methods: physics of failure (PoF) methods and data-driven method (Yang et al., 2022) As for PoF methods, we can find that recent studies conduct the failure mechanism analysis for hydraulic pump by numerical models, and they are validated by typical commercial software (Wang et al., 2021; Novak et al. 2023). However, due to harsh working conditions and coupling failure mechanisms of aviation hydraulic pumps, the lubrication films in three friction pairs are also in the changeable state. Too many assumptions are also made, which might not be reasonable in real case. Besides, it will lead to too much computation burden no matter numerical models or commercial software. They cannot obtain immediate response to monitor real degradation state under dynamic working operations (Wang et al., 2016)

Data driven method has been widely used to describe the degradation process for the mechanical or hydraulic components like hydraulic pump. Ma et al. (2019) proposed an engineering-driven performance degradation analysis method based on inverse Gaussian process model considering the nature of mechanical wear of hydraulic piston pumps. Wang et al. (2016) used Wiener process to predict the remaining useful life of the pump, and the unknown parameter was estimated by maximum likelihood estimation and expectation maximization algorithm. Yu et al. (2021) constructed conditional factor variational auto-encoder model to assess performance degradation of hydraulic pumps. Li et al. (2020) constructed the abrasive debris generation model with rough sliding under mixed lubrication, and a partition-integration remaining useful life prediction framework was also proposed. From the discussions above, we can find massive degradation data should be used to obtain high accuracy degradation or remaining useful life prediction for data-driven method. However, it is difficult to obtain enough degradation data for high-reliability and long-life hydraulic component like hydraulic pump. In addition, there are lacks of interpretability for pure data-driven method, which leads to low model robustness and generalization.

Physics-informed data driven method takes the advantages of PoF method and data-driven method, which has been used in degradation analysis for hydraulic or mechanical component (Yu et al., 2023; Xu et al., 2024). The challenge of this method is to establish an accurate physical model with an appropriate number of parameters and select the corresponding data-driven method to avoid excessive computation and overfitting while ensuring accuracy. Physics-informed data driven models include physics-informed neural network models (PINN) (Raissi et al., 2019), physics-informed long short-term memory (LSTM) (Liu et al., 2023), physics-informed deep learning (Shen et al., 2021) and physics-informed Gaussian process (PIGP), etc. Among of them, PIGP can not only capture the degradation process of component, but also handle the uncertainties (Shu et al., 2024; Zhang et al. 2022). However, at present, there are many theoretical foundations for Gaussian process based on physical information fusion, but most of them use classical degenerative models (such as Arrhenius models or low-order polynomial empirical functions) as mean functions to solve practical problems, and fit them in a data-driven way. To the best of authors' knowledge, few studies focus on the real degradation process while considering the dependency between current and formal degradation state. In summary, the main contributions of this paper rest on constructing a physics-informed recurrent Gaussian process model for hydraulic piston pump degradation analysis combing the wear degradation analysis.

The rest of paper is organized as follows. Section 2 presents the wear degradation process of hydraulic piston pump. Section 3 constructs the physics-informed recurrent Gaussian process model for degradation analysis. Section 4 uses a real case to verify the model we proposed. Section 5 concludes the whole paper.

2. Wear Degradation Process for Hydraulic Piston Pump

The typical structure of a hydraulic piston pump is illustrated in Fig. 1. When driven by the engine, the pump operates with the valve plate and swash plate remaining stationary while the cylinder block rotates. Inside the cylinder block, pistons reciprocate within their respective chambers. During operation, as a piston chamber aligns with the suction port, the piston retracts from the cylinder block's bottom, drawing low-pressure fluid into the chamber via the suction slot. Conversely, when the piston chamber aligns with the discharge port, the piston advances toward the bottom of the cylinder block, expelling high-pressure fluid through the discharge slot. This cyclical motion occurs for each piston as the cylinder block completes a single rotation, facilitating the conversion of mechanical energy into hydraulic energy.

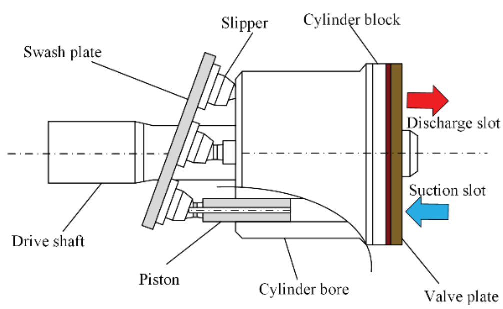

Fig. 1. The typical structure of hydraulic piston pump.

Previous research has identified three primary failure mechanisms in hydraulic piston pumps, with the most significant being wear in the three friction pairs: swash plate/slipper, valve plate/cylinder block, and piston/cylinder.

Progressive wear in these areas leads to pump failure, primarily due to internal leakage.

The wear process is influenced by multiple factors, including friction speed, applied pressure, surface roughness, material characteristics, wear mechanisms, lubrication conditions, surface coatings, and the design of the friction pair. It is inherently a function of the tribological system. Wear progresses in distinct phases, with a predictable pattern emerging during the stable wear stage following initial material degradation. Generally, the basic process of wear can be divided into three stages: running stage, stable wear stage and failure stage, as shown in Fig. 2 (Liu et al.,2022, Ma et al., 2019).

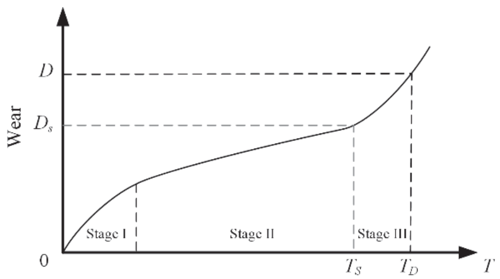

Fig. 2. Hydraulic pump wear process.

Under a specific stress load with constant pressure and angular speed of pump, the amount of degradation affected by the introduction of different stages can be expressed as (Ma et al., 2019):

$$W = \frac{c_1 P^{g_1} n^{g_2}}{c_2 P + c_3 n} \exp\{c_2 P + c_3 n\} \tag{1}$$

where W is the amount of wear, P is the pressure, n is the rotation speed, c_1, c_2, c_3 and g_1, g_2 are the constant values. From Eq. (1), we can find that the degradation follows an exponential trend.

Considering the wear process and the function form of Eq. (1), the degradation function under a specific stress load can be expressed as:

$$W(t) = \alpha \exp\left(\beta\left(\frac{t}{\alpha}\right) - \gamma\left(\frac{t}{\alpha}\right)^{-1}\right) \tag{2}$$

where α denotes the shape parameter, β and γ are the scale parameters. In the absence of sufficient lifetime data, a reliable degradation model is required to characterize the hydraulic piston pump degradation process.

3. Physics-informed Recurrent Gaussian Process

3.1. *Gaussian process degradation model*

Gaussian process regression is a non-parametric model that provides both the estimated value and the associated uncertainty for a prediction point, enhancing the reliability of the estimation. Assuming that the input matrix of Gaussian process can be defined as $X \in R^{d\times N}$, and the output vector is defined as $Y \in R^{N\times 1}$. The relationship between the output vector and the input matrix can be expressed as:

$$y = f(x) + \varepsilon \tag{3}$$

where ε is a random variable representing independent, identically distributed Gaussian noise with variance.

The Gaussian process degradation model can be constructed by its mean function $m(x)$ and covariance function $k(x,x')$, and it can be expressed as:

$$f(x) \sim \mathrm{GP}\left[m(x), k(x,x')\right] \tag{4}$$

where

$$m(x) = \mathrm{E}\left[f(x)\right] \tag{5}$$

$$k(x,x') = \mathrm{E}\left[\left(f(x) - m(x)\right)\cdot\left(f(x') - m(x')\right)\right] \tag{6}$$

The mean function $m(x)$ indicates the expected value of $f(x)$ at the input point x, while the covariance function $k(x,x')$ quantifies the confidence level of $m(x)$.

According to the definition of Gaussian process, the observed value and function value of the new test point follow the joint Gaussian prior distribution, which can be expressed as:

$$\begin{bmatrix} y \\ f' \end{bmatrix} \sim \mathrm{N}\left(\begin{matrix} m(x) \\ m(x') \end{matrix}, \begin{bmatrix} K(x,x)+\sigma_n I & K(x,x') \\ K(x',x) & K(x',x') \end{bmatrix} \right) \tag{7}$$

where $K(x,x)$, $K(x',x')$, and $K(x,x')=K(x',x)^T$ are the covariance matrices between merely training inputs, merely testing inputs, as well as training and testing inputs respectively. σ_n is the noise observation.

3.2. *Physics-informed Recurrent Gaussian Process*

From the discussion of the degradation process of hydraulic piston pump has the time accumulative effect. Associating pump degradation data from consecutive time points is an effective approach to limit the pump degradation process. Comparing with the classical Gaussian process, we propose physics-informed recurrent Gaussian process (PI-RGP) degradation model, as shown in Fig. 3. The PI-RGP model is reconstructed from two aspects:

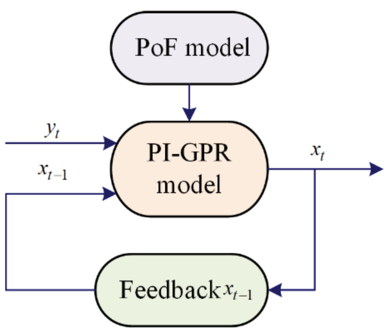

Fig. 3. The structure of PI-RGP

(i) Recurrent mechanism

The PI-RGP model can accurately capture the distinct wear degradation mechanism, integrating working condition information into the model input. In addition, the time-dependent cumulative effect is represented in a closed-loop structure through a feedback mechanism. Specifically, along with the monitoring degradation data , the predicted x_{t-1} from the previous step is fed back into the input vector to estimate the current x_t .

(ii) Physical-informed mechanism

The mean function in Gaussian process represents the expected value of the sample function at each input point. The RGP model's predicted value is closely linked to this mean function, as well as the deviation from the observed value. To enhance interpretability and prediction accuracy, the wear process model is used as the mean function in the RGP, that means:

$$m(x)=W(t) \tag{8}$$

In generality, the covariance function is chosen as the Gaussian kernel function. Once the mean function and covariance function are determined, the unknown parameters need to be estimated by Bayesian MCMC method (Ma et al., 2019). The marginal likelihood of PI-RGP obtained by using Bayesian rules.

4. Case Study

In this section, we present a case study on the degradation of hydraulic piston pump. The datasets are obtained from Ma et al. (2019). In a 750-hour endurance test of a hydraulic piston pump, pressure and flow were applied as the primary accelerating stresses. The return oil of the hydraulic pump is measured every hour. The smoothed data is selected for every 10 hours. After smoothing the original data, the smoothed values were selected at 10-hour intervals. Fig. 4 shows the degradation path of the return oil. From Fig. 4, we can find that the degradation trend has the characteristic of typical wear process. During the first 80 hours, the return oil flow increased rapidly. After 200 hours of operation, the oil return volume stabilized around 2.0 L/min and then gradually increased.

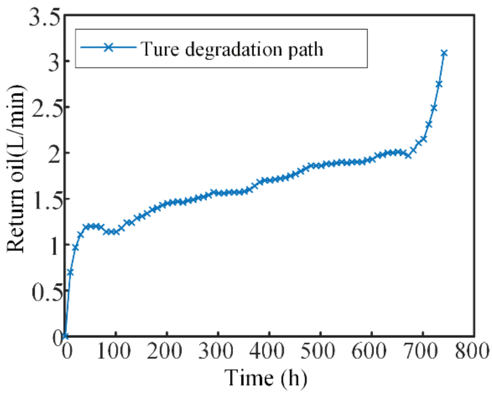

Fig. 4. Return oil flow degradation path (Ma et al., 2019)

We use PI-RGP model to describe the degradation process of return oil. The soft failure threshold is defined as 2.15 L/min. The oil-return flow data prior to reaching the soft failure threshold was used to estimate parameters for the first part, while the remaining data was used for parameter estimation of the second part. The failure threshold of this type of pump is 5.1 L/min.

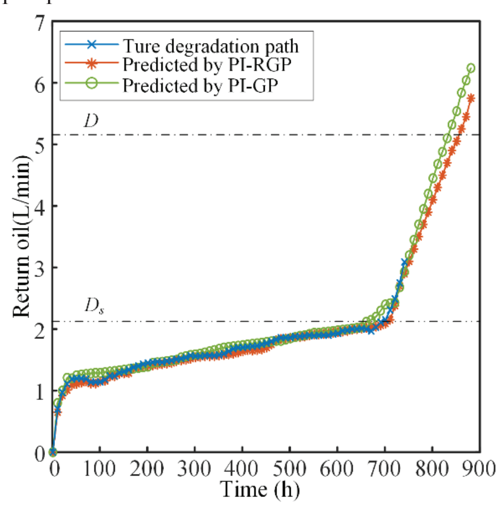

Fig. 5. The degradation prediction results of return oil.

We use root mean square error (MSE) to measure the stability and accuracy of the PI-RGP model. Assuming that model 1 denotes the PI-RGP model, and model 2 denotes the PI-GP model. Fig. 5 shows the degradation prediction results of these two candidate models. We can find that PI-RGP model closely match with actual degradation values. The sum of MSE for model 1 is 0.3864, and the sum of MSE for model 2 is 0.6329. Therefore, the PI-RGP model is consistent with the actual degradation process. We also conduct statistical significance testing, and it shows that the p-value is less than 0.05. It is suitable to combine PoF model to construct a more accurate degradation prediction model for degradation analysis. In addition, it is necessary to construct degradation model for hydraulic piston pump, considering the dependent degradation value.

5. Conclusion

In this paper, we construct a novel degradation analysis model, namely as PI-PGR, for hydraulic piston pump. The study firstly focuses on measuring the wear of a specific type of hydraulic piston pump, which is identified as a primary contributor to major failure modes. Then, PI-RGP model is constructed by combing the wear degradation process model and formal degradation value. A real case study on degradation of hydraulic piston pump is used to verify the model we proposed. The results show that PI-RGP not only provides a reliable framework for predicting the degradation of hydraulic piston pumps but also aids in the design and optimization of aircraft components.

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