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Citation for the original published paper (version of record):

Lang, X., Nilsson, H., Mao, W. (2024). A machine learning based analysis of bearing vibrations for predictive maintenance in a
hydropower plant. IOP Conference Series: Earth and Environmental Science, 1411.
http://dx.doi.org/10.1088/1755-1315/1411/1/012046

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IOP Conference Series:
Earth and
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To cite this article: Xiao Lang *et al* 2024 *IOP Conf. Ser.: Earth Environ. Sci.* **1411** 012046

A machine learning based analysis of bearing vibrations for predictive maintenance in a hydropower plant

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Abstract. This study employs machine learning techniques to model bearing vibrations for predictive maintenance within a hydropower plant, utilizing over three years of full-scale vibration measurement data. Operational parameters, including turbine speed, guide vane opening, and generator active power, serve as input features to predict vibrations in both upper guide and turbine guide bearings. The models, developed from datasets across different periods, aim to predict and analyze discrepancies in future monitoring data to evaluate potential performance degradation. When the statistical distribution of the future monitoring data closely aligns with the training data, the models demonstrate a capacity to predict gradual bearing performance degradation effectively. However, when future monitoring data diverge significantly from the training set, traditional machine learning models produce irrational predictions, leading to unreasonable trends. To overcome these challenges, the adoption of more sophisticated machine learning approaches is recommended to enhance the reliability of predictive maintenance in the face of unseen data scenarios.

1. Introduction

As renewable energy becomes increasingly recognized as an important component of global decarbonization, hydropower is entering a new golden age. It has several advantages over other renewable energy sources. For instance, the mechanical-to-electrical energy conversion process can achieve a combined efficiency exceeding 90% for large turbine-generator units [1]. Moreover, hydropower can provide a valuable source for electrical grid balancing, such as supporting the integration of wind and solar power [2,3]. However, factors such as frequent start-stop cycles, shifts between operational modes, and load rejections can accelerate the degradation of its power unit components [4]. Key failure modes associated with these unstable conditions in HPPs include cavitation, erosion, material defects, and fatigue [5]. It is crucial to understand and predict the degradation of HPP components before they reach critical failure thresholds. Moreover, it is equally essential to comprehend the relationship between system operations and the degradation processes to ensure timely maintenance and operation adjustments.

Traditionally, HPPs have predominantly relied on scheduled periodic maintenance as their principal maintenance strategy. Condition monitoring was typically limited to protective systems, triggering plant shutdowns whenever monitored signals, such as temperature and vibration in bearings, exceeded preset thresholds [6]. The rapid pace of technological advancements in hydropower operations and maintenance, coupled with enhanced capabilities to process and analyze large volumes of data, there has been a surge in research efforts dedicated to evaluating and forecasting performance degradation in such facilities over recent years [7]. These initiatives aim to refine predictive maintenance strategies by leveraging sophisticated data analytics and machine learning techniques. This focus on advanced technologies facilitates the early detection of potential equipment failures, optimizing maintenance timetables and minimizing operational interruptions. Among the earliest contributions to the predictive maintenance of HPPs, a notable early application involved using Artificial Neural Networks (ANNs) to monitor, identify, and diagnose the dynamic performance of HPP systems [8, 9]. Li et al. [10] proposed a transient model of an HPP system to evaluate performance and optimize setting parameters to diminish risks. Li and Korczynski [11] introduced a reliability-based approach for planning the maintenance of transmission systems in an HPP. Guedes et al. [12] developed a nonlinear model for cascaded hydropower generation, incorporating a preventive maintenance schedule to replenish thermal energy. Rodriguez et al. [13] proposed a mixed-integer programming model tailored to address the maintenance scheduling complexities in hydropower systems, which includes the specific timings and the nonlinear dynamics of the generators. Özcan et al. [14] tackled the multi-objective and multi-criteria aspects of maintenance planning in HPPs by integrating the Analytical Hierarchy Process (AHP) and TOPSIS methodologies, enhancing decision-making processes in maintenance management. Bulut and Özcan [15] used MCDM-based reliability analysis to determine the maintenance periods in the hydroelectric power plants for 16 different equipment groups. Li et al. [16] formulated the new maintenance interval and inspection times using a hidden Markov model with the monitoring data of hydro-turbine runner cracks from actual operations. Bulut and Özcan [17] applied fuzzy set theory to monitor a HPP degradation and predicting failures.

While bearings are essential components in the machinery of HPPs, their degradation often goes unnoticed during regular operations because inspections cannot be performed while the plant is active [18]. This invisibility means the degradation process unfolds covertly, without a direct observation method. To address this issue, vibration measurements are utilized as an indirect indicator of the bearings' health status. Operations in HPPs induce mechanical vibrations that increase shaft surface displacement and lead to bearing performance degradation and lubrication leaks [19]. These effects are compounded by the frequent start-stop cycles typical in HPP operations, which progressively deteriorate these critical components. Consequently, installing vibration monitoring systems in the bearings of power units is essential for effectively understanding and quantitatively assessing the degradation [20].

This study is based on three years of full-scale measurements from an HPP, focusing on developing machine learning models to analyze the vibrations of upper and turbine guide bearings. The objective is to utilize these models to identify potential performance degradation in the bearings. The remainder of this paper is organized as follows: Section 2 introduces the HPP case study and describes the data processing. Section 3 details the machine learning methodology used in the analysis. Section 4 presents the results from two distinct case studies. Finally, Section 5 draws the conclusions.

2. Case study and full-scale measurement

2.1. Data acquisition

This study's analysis of hydropower plant operations relies on measurement data collected from a hydropower plant in northern Sweden. The data was gathered from April 2020 to March 2023, with measurements recorded every 10 seconds (a sampling frequency of 0.1 Hz). The dataset includes variables such as turbine speed, guide vane opening, active power, and vibration for different bearings. In this study, the relevant data parameters are listed in Table 1, including their respective symbols and units. Turbine speed and guide vane openings are recorded as percentages of their design specifications for rotation speed and maximum opening. The active power is measured in megawatts (MW), although its unit is also shown as a percentage of the maximum designed power for confidentiality reasons.

The vibrations of the turbine guide bearing and the upper guide bearing were measured using an accelerometer responsive from 0 to 100 Hz. The root mean square (*RMS*) values, collected every 10 seconds, represent the total vibration energy. These *RMS* data are crucial for checking the plant's operational health. They reflect the combined effect of factors like parts not being aligned, parts being out of balance, and structural vibrations. Regular analysis of these *RMS* values helps in the early detection of wear or damage, allowing for timely maintenance. Monitoring and analyzing vibration data is vital in keeping the equipment in good working condition.

Table 1. Measurement signals and corresponding symbols and units used in this study.

Parameter	Symbol	Unit
Turbine speed	N	%
Guide vane opening	α	%
Generator active power	P	%
Upper guide bearing vibration *RMS*	V_{Upper}	mm/s²
Turbine guide bearing vibration *RMS*	V_{Tubine}	mm/s²

2.2. Data preprocessing

The HPP does not continuously generate electricity but alternates between working and non-working states. The first step in data processing involves extracting distinct and coherent working periods. Vibrations of bearings differ between steady operations and transients (start-up, shut-down, and adjustments to different settings). This study focuses on the vibrations of bearings during steady operation to monitor their performance. Therefore, an in-house code was employed to extract steady operations from each working condition. Figure 1 presents the upper guide bearing vibrations (V_{Upper}) and turbine guide bearing vibrations ($V_{Turbine}$) over three years of measurements. The blue dots represent the raw measurements during all working periods, while the black markers denote the mean values of each extracted steady operation.

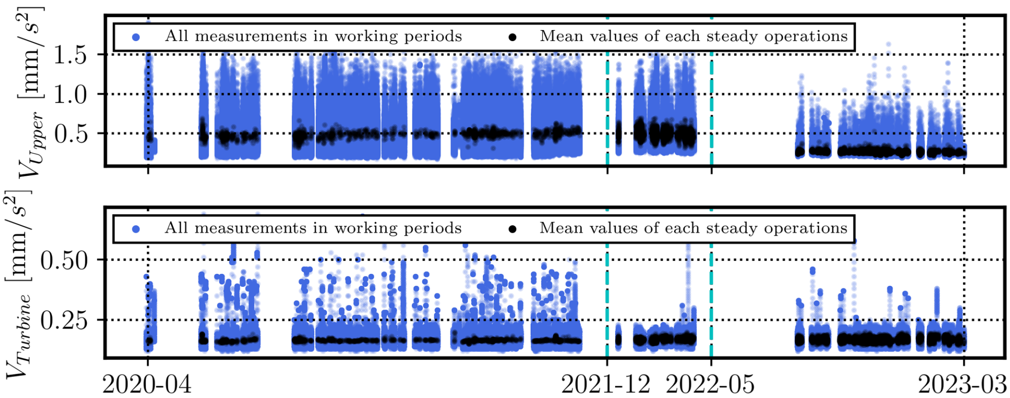

Figure 1. Raw vibrations, and vibrations in steady operations, of the upper guide bearing (V_{Upper}) and the turbine guide bearing ($V_{Turbine}$) over the three-year period of the case study HPP. The first vertical line marks the initiation of frequency regulation, while the second vertical line denotes planned maintenance timing.

As illustrated in figure 1, the raw measurements of bearing vibrations exhibit significant fluctuations, including pronounced peak values (both upper and lower). These large oscillations are primarily due to transient states. In contrast, the mean values of vibrations during steady operations, as depicted, do not span as broad a range as those during transients. They are more consistently confined within a narrower range, with relatively smaller extremes. The mean values of each steady operation, utilized in this study for analysis and machine learning modeling, provide a clearer representation of bearing behavior under normal operating conditions. For enhanced visualization, the extracted vibrations from steady operations, organized in a time sequence, are presented in figure 2.

As shown in figure 2, the scatter of vibrations increased for both bearings following the implementation of frequency regulation. Prior to December 2021, the operation of the HPP was characterized by long-duration constant settings for continuous power generation. After the adoption of frequency regulation in December 2021, the plant experienced frequent setting adjustments during each operating period to meet the requirements of the power grid. Specifically, the vibrations in the upper guide bearing significantly decreased following maintenance, indicating an effective improvement in its performance. In contrast, the vibrations in the turbine guide bearing became even more intense after maintenance. These observations will be further analyzed in conjunction with the operational settings of the HPP.

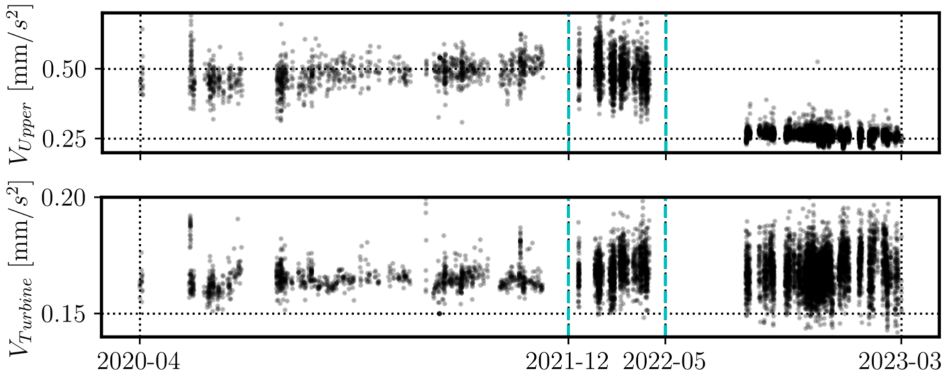

Figure 2. Vibrations of the upper guide bearing (V_{Upper}) and the turbine guide bearing ($V_{Turbine}$) during steady operation, over the three years period. The first vertical line marks the initiation of frequency regulation, while the second vertical line denotes planned maintenance timing.

2.3. Data analysis

In addition to the vibrations of the bearings, the turbine speed, the guide vane opening, and the generator active power during steady operation were extracted from the raw measurements for machine learning modeling. Figure 3 depicts these variables over the three-year period in a time sequence. It is evident from the data that prior to the implementation of frequency regulation, the settings for the guide vane opening were primarily between 60% to 75%. Following the introduction of frequency regulation, there was an increase in the guide vane opening, which consequently led to a significant rise in power generation after December 2021. This study focuses on data prior to maintenance, segmenting it into four batches as indicated in figure 2, labeled Periods 1 to 4. Each batch serves as a distinct dataset for developing machine learning models or as an evaluation set. The goal is to employ models trained on different temporal data to predict future vibrations of the bearings, thus enabling the identification of potential bearing degradation through discrepancies in predictions.

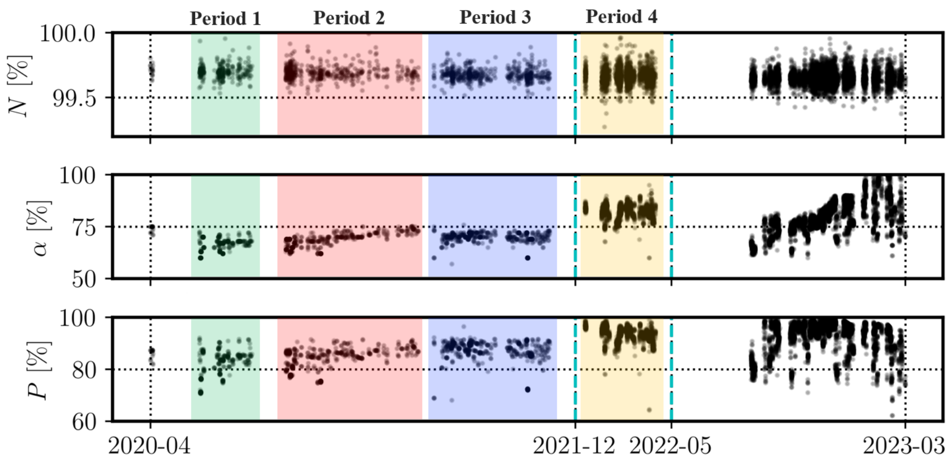

Figure 3. The mean values of turbine speed (N), guide vane opening (α), and generator active power (P) of each steady operations over the three years period. The first vertical line marks the initiation of frequency regulation, while the second vertical line denotes planned maintenance timing.

Subsequent analysis involved statistical examinations of the three variables across each period, as depicted in figure 4. The distribution of turbine speeds N remains fairly consistent across all four periods, operating near 100% during working states. In contrast, the distributions for guide vane opening α and power generation P show similar ranges in Periods 1 to 3, whereas Period 4 exhibits higher values, with guide vane opening mainly above 80% and power generation predominantly exceeding 90%. Therefore, data from Periods 1 to 3 are considered as seen data with respect to each other, while Period 4 represents unseen data relative to the earlier periods.

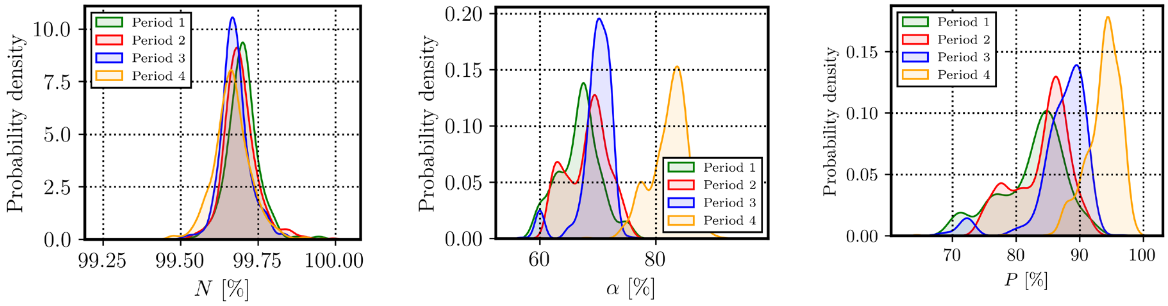

Figure 4. The turbine speed (N), guide vane opening (α), and generator active power (P) distribution of different period dataset.

3. Methodology

3.1. Artificial neural networks

To accurately predict the upper guide bearing vibration V_{Upper} and turbine guide bearing vibration $V_{Turbine}$, this study employs artificial neural networks (ANNs) regression model. The model's architecture, as illustrated in figure 5, consists of an input layer, multiple hidden layers, and an output layer, designed to handle the complexities of dynamic behavior in the HPP unit. The input feature includes the turbine speed N, guide vane opening α, and generated power P.

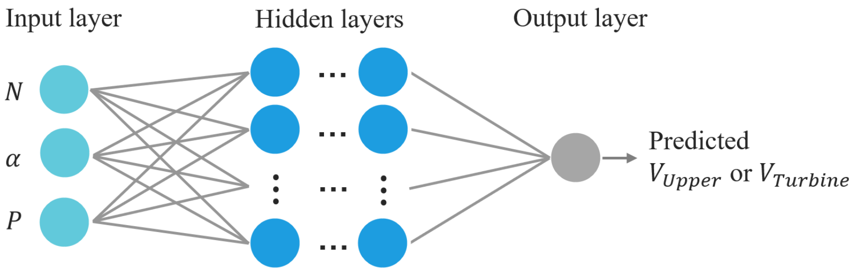

Figure 5. Schematic of the multi-layer neural network used for modeling the vibrations of bearings.

The neural network is structured to capture the non-linear relationships between the input variables and the target outputs. The hidden layers, composed of several neurons, use the Rectified Linear Unit (ReLU) activation function, which helps the network learn complex patterns efficiently. The ReLU function is preferred due to its ability to avoid the vanishing gradient problem, which is common in networks with deep architectures. Here, the model for the V_{Upper} prediction is used as an example. For a dataset with m samples, the expression for the ANNs model can be written as

$$\hat{V}_{Upper_{(i)}} = h\left(N_{(i)}, \alpha_{(i)}, P_{(i)}\right), i = 1,2, \dots, m, \tag{1}$$

where $\hat{V}_{Upper_{(i)}}$ is the predicted vibration of the upper guide bearing. The Square Error loss is introduced as the regression objective function, with a L_2 regularization term $\gamma\|\boldsymbol{\omega}\|^2$ as

$$Obj = \frac{1}{2}\sum_{i=1}^{m}(V_{Upper_{(i)}} - \hat{V}_{Upper_{(i)}})^2 + \frac{\gamma}{2}\|\boldsymbol{\omega}\|^2. \tag{2}$$

The stochastic gradient-based optimizer Adam is applied to update the weights $\boldsymbol{\omega}$ and minimize the loss.

3.2. Model establishment

This study primarily examines how models, built using data from different periods, perform in predicting future datasets and identify potential performance degradation over time. Two case studies are applied in this study as shown in figure 6. The first case study utilizes data from Period 1 and Period 2 to develop Models P1 and P2, respectively, which are then used to predict bearing vibrations for Period 3. This scenario presumes an abundance of historical data, such that the distribution of future data has already been seen within the training sets, resulting in high accuracy of the data-driven models. However, a more common scenario arises when limited historical data are available, necessitating the monitoring of bearing performance as future datasets inevitably include unseen data, potentially leading to significant prediction errors by machine learning models. Consequently, the second case study builds Models P1 through P3 using data from Periods 1 to 3, to predict and analyze the data of Period 4 with distinctly different distributions, as figure 4 shows.

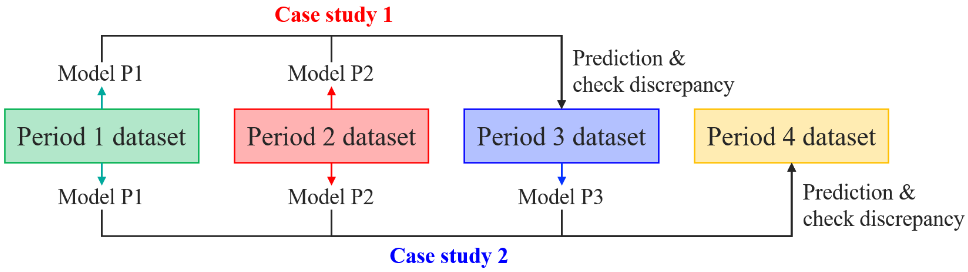

Figure 6. The two case studies analyzed in this study. Case Study 1 explores a scenario with abundant historical data, while Case Study 2 addresses a scenario with limited historical data and future datasets that include unseen data.

There are some hyperparameters in the ANNs, and the change in hyperparameter values can affect the performance of the constructed model. Since the hyperparameters interact, the optimum combination cannot be obtained by adjusting a specific hyperparameter individually. In this study, Bayesian optimization is employed to identify the optimal hyperparameters, i.e. the number of layers, the number of neurons in each layer, learning rate and epochs for ANNs. This method leverages the Bayesian theorem to adaptively generate hyperparameter data and utilizes surrogate models to ascertain their most effective values. Distinct from traditional grid and random search methods, Bayesian optimization integrates results from previous iterations, facilitating a more focused search around promising solutions and efficiently balancing exploration and exploitation to prevent local optima. To mitigate model overfitting and verify the appropriateness of the hyperparameter settings, a 10-fold cross-validation strategy is implemented. The training set is sequentially divided into ten parts without shuffling to preserve temporal relationships. Nine of these parts are used for training, with the tenth reserved for testing, ensuring robust model evaluation. Performance across these folds is averaged, employing the root mean square error (*RMSE*) as the primary metric for assessing cross-validation accuracy.

4. Results and discussion

4.1. Case study 1

In the first case study, Models P1 and P2, developed from data in Periods 1 and 2 respectively, are employed to predict vibrations for Period 3. The focus is on assessing the discrepancies, denoted as ΔV_{Upper} ($V_{Upper} - \hat{V}_{Upper}$) and $\Delta V_{Turbine}$ ($V_{Turbine} - \hat{V}_{Turbine}$), which represent the deviations between predicted and actual vibration measurements. This analysis examines both the scatter of these discrepancies over time and their distribution throughout the entire Period 3.

Figure 7 illustrates the scatter of ΔV_{Upper}, based on Models P1 and P2, over the five-month span (June to November 2021) of Period 3, each accompanied by its respective linear regression line. The predictions from both models underestimate the actual measurements from Period 3, resulting in scatters of ΔV_{Upper} consistently above zero. However, the discrepancies are larger in Model P1. Analysis based on linear regression reveals a gradual widening of ΔV_{Upper} over time for both models, with the

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regression line for Model P1 noticeably higher than that for Model P2. This pattern is attributed to a greater performance difference in bearings' data between Period 1 and the later Period 3, compared to Period 2.

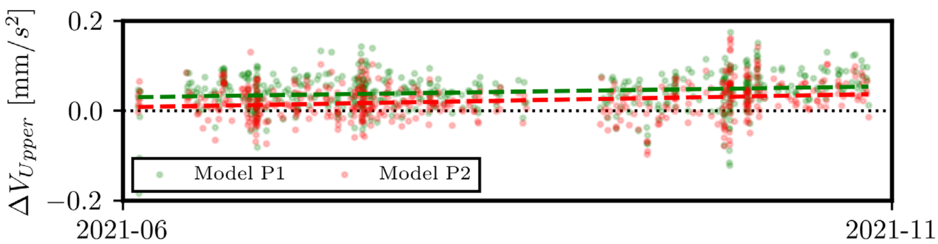

Figure 7. Scatter plot of ΔV_{Upper} for Period 3 (June to November 2021), based on predictions from Models P1 and P2, each accompanied by its respective linear regression line.

Figure 8 presents the probability density distribution of ΔV_{Upper} for Period 3, based on predictions from Models P1 and P2. Consistent with observations from figure 7, predictions from Model P2, which is based on data from Period 2, are closer to the actual measurements from Period 3, with a mean value of ΔV_{Upper} (indicated by the red vertical line) at 0.0222. Conversely, the distribution of ΔV_{Upper} from Model P1 shifts towards positive values, with its mean value (indicated by the green vertical line) at 0.0419, approximately double that of Model P2. This analysis suggests that models built on data from time periods more closely resembling the operational input data distribution tend to predict future data with smaller discrepancies. Over time, the discrepancy gradually increases, potentially indicating a degradation in upper bearing performance.

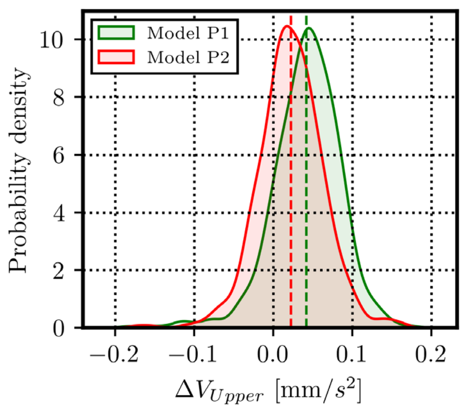

Figure 8. Probability density distribution of ΔV_{Upper} for Period 3, based on predictions from Models P1 and P2. Each model's mean value is indicated by a vertical line.

Similar results for the turbine guide bearing are presented in figures 9 and 10. Figure 9 displays the scatter of ΔV_{Upper} for Period 3 (June to November 2021), based on predictions from Models P1 and P2. Although the prediction discrepancies ΔV_{Upper} from both models exhibit fluctuations between positive and negative values, those from Model P1 are consistently higher than those from Model P2, similar to the results for the upper guide bearing. Furthermore, the linear regression analysis reveals a general trend of increasing discrepancy over time, with Model P1's regression line situated higher, indicating greater underestimation.

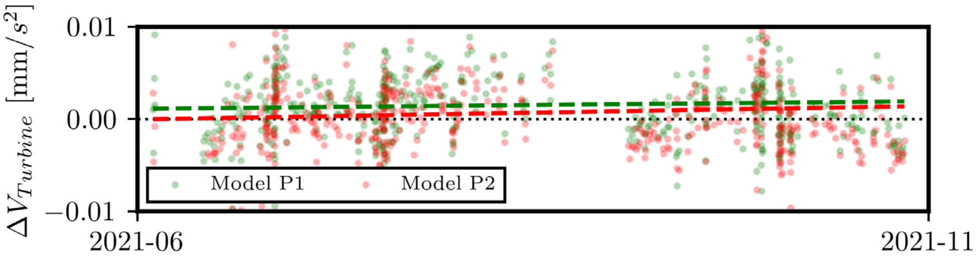

Figure 9. Scatter plot of $\Delta V_{Turbine}$ for Period 3 (June to November 2021), based on predictions from Models P1 and P2, each accompanied by its respective linear regression line.

Figure 10 displays the probability density distribution of $\Delta V_{Turbine}$ for Period 3, based on predictions from Models P1 and P2. The mean value of $\Delta V_{Turbine}$ from Model P2, indicated by a red vertical line, is 0.0007, while the mean value from Model P1, shown with a green vertical line, is approximately 0.0015. This is consistent with the results for the upper guide bearing, showing a relative increase of about 100%. Similarly, a potential increase in performance degradation over time has also been observed in the turbine guide bearing.

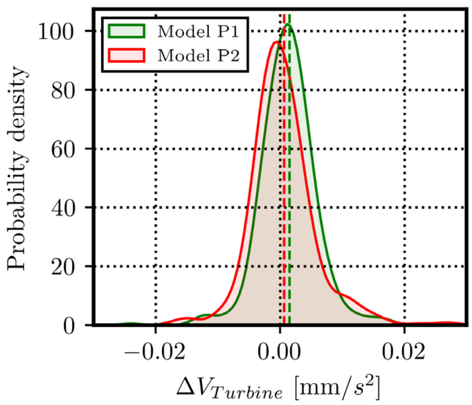

Figure 10. Probability density distribution of $\Delta V_{Turbine}$ for Period 3, based on predictions from Models P1 and P2. Each model's mean value is indicated by a vertical line.

4.2. Case study 2

For the more challenging Case 2, Period 4 data are unseen relative to Periods 1 to 3, and purely data-driven machine learning models typically exhibit weaker extrapolation capabilities, often resulting in unreasonable results. Figures 11 and 12 present the scatter of ΔV_{Upper} and $\Delta V_{Turbine}$ for Period 4 (January to April 2022), based on predictions from Models P1, P2, and P3.

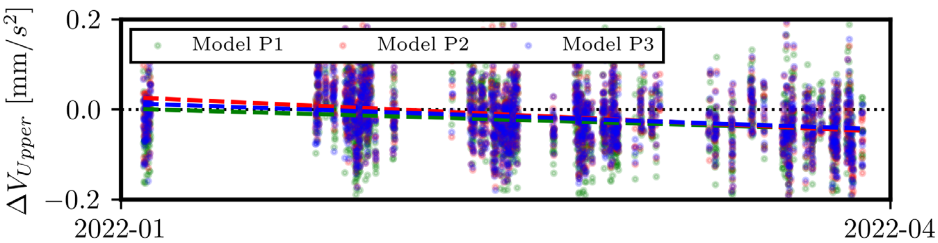

Figure 11. Scatter plot of ΔV_{Upper} for Period 4 (January to April 2022), based on predictions from Models P1, P2 and P3, each accompanied by its respective linear regression line.

As depicted in figure 11, the predictions of ΔV_{Upper} from Models P1 to P3 are very close, almost overlapping. The linear regression lines for these models also overlap. The predictions for the upper guide bearing vibrations in Period 4 are remarkably similar across all models, indicating significant prediction errors due to the models' exposure to the previously unseen data of Period 4. Unlike in Case 1, the linear regression fittings do not show a gradual increase over time. Instead, there is a noticeable trend of overestimation in the latter half of Period 4.
As illustrated in figure 12, all models, Models P1 to P3, exhibit significant overestimation when predicting the vibrations of the turbine guide bearing, resulting in most discrepancies ($\Delta V_{Turbine}$) below zero. Although the predictions from these three models do not overlap as closely as those for the upper guide bearing, they nonetheless yield illogical outcomes. Model P3, which was trained on data most closely resembling that of Period 4, shows the greatest level of overestimation. Conversely, Model P2, which utilized data from Period 2, produced predictions closest to the actual measurements in Period 4.

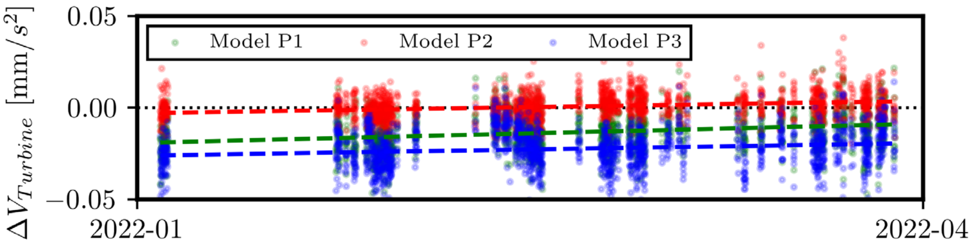

Figure 12. Scatter plot of $\Delta V_{Turbine}$ for Period 4 (January to April 2022), based on predictions from Models P1, P2 and P3, each accompanied by its respective linear regression line.

Based on the results and analysis from case study 2, traditional machine learning methods face significant limitations when tasked with monitoring unseen operational data for predictive maintenance, especially with smaller datasets typical of HPP. These traditional models often lack sufficient extrapolation capabilities and interpretability, leading to unreliable monitoring predictions that fail to forecast potential performance degradation in HPP bearings accurately. To overcome the challenges posed by diverse data distributions, it is crucial to adopt and rigorously test more advanced machine learning algorithms designed to handle such complexities.

5. Conclusion

This study conducted a comprehensive analysis of an HPP over three years, employing artificial neural networks to model the vibrations of two types of bearings, namely, the upper guide bearing and turbine guide bearing. Models were developed using datasets from different periods to predict and evaluate the discrepancy in future monitoring data, thereby assessing potential performance degradation. The main conclusions are as follows:

- In Case 1, where the statistical distribution of future monitoring data closely matches the training data, models built from different time periods may successfully predict a gradual degradation in the performance of both bearings.
- In Case 2, where the distribution of future monitoring data diverged from the training data, the machine learning models yielded irrational predictions, resulting in unreasonable observed trends.

For future work, more advanced machine learning approaches, will be tested to address the challenges posed by unseen data scenarios. Additionally, more precise quantification of bearing performance is necessary.

Acknowledgments
The research presented in this paper was financially supported by Chalmers Area of Advance Energy. It was carried out as a part of the “Swedish Centre for Sustainable Hydropower – SVC”. SVC has been established by the Swedish Energy Agency, Energiforsk and Svenska kraftnät together with Luleå University of Technology, Uppsala University, KTH Royal Institute of Technology, Chalmers

University of Technology, Karlstad University, Umeå University and Lund University. The authors also acknowledge Skellefteå Kraft for providing the full-scale measurements.

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