A Data-Driven Approach for Predictive Maintenance of Impellers in Flexible Impeller Pumps Using Prophet

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Keywords: Predictive Maintenance, Flexible Impeller Pumps, Prophet Algorithm, Data-Driven Approach, Textile Industry, Fabric Dyeing Efficiency, Machine Learning.

Abstract: This article presents a data-driven approach aimed at improving the efficiency of fabric dyeing operations in the textile industry. It specifically focuses on the predictive maintenance of flexible impeller pumps (FIP) and the application of the Prophet algorithm. The study extensively explores the potential of machine learning and data analytics to increase operational efficiency and enable early failure detection. By using the Facebook Prophet model and time series data for early detection of wear and tear, it offers an approach to maintain pump efficiency without installing new hardware, relying solely on data.

1 INTRODUCTION

The textile industry is a broad sector encompassing complex physical and chemical processes involved in the production stages of textile products. At the heart of these processes is the fabric dyeing operation, where dyes and chemicals are applied to ensure color and durability. Fabric dyeing, as a batch process, is conducted in fabric dyeing machines and requires careful control of various variables such as temperature, chemical ratio, dye quantity, conductivity, pH, and duration. This control is a critical element determining the success of the dyeing process and the correct chemical application is a crucial step in achieving the fabric's color absorption capacity and desired color. (Sarkar et al., 2023).

In the textile dyeing process, liquid chemicals are weighed in order of the steps of the dyeing process and transferred to the chemical dosing tanks in real-time without human intervention. This process, enhancing the repeatability of the dyeing process, is carried out by mechatronic systems shown in Figure 1. These systems robotically weigh chemicals according to the given recipe and send them to the main tanks of the fabric dyeing machines for dosing. For instance, in a factory with 40 fabric dyeing machines, a liquid chemical weighing system performs about 1000 weighings daily for approximately 30 different chemicals.

Figure 1: Liquid Chemical Weighing and Dispensing System.

In the liquid chemical weighing process, chemicals taken from chemical silos are weighed using pumps and flow meters. The impeller in the FIP (Flexible Impeller Pump), a significant rotating mechanical part containing blades in the middle between two faces, is often referred to as a closed impeller. Due to mechanical wear, the impeller requires careful monitoring. This wear can lead to serious damage in the pump and significantly reduce both the life span of the pumps and overall efficiency. In weighing and dispensing systems using FIP, the wear of the impeller over time is inevitable. Predicting this wear is vital for ensuring accurate weighing within tolerance limits and the uninterrupted continuation of production. Recently, there has been an increase in the use

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Demir, E. and Sultanoğlu, S.
A Data-Driven Approach for Predictive Maintenance of Impellers in Flexible Impeller Pumps Using Prophet.
DOI: 10.5220/0012710100003756

In *Proceedings of the 13th International Conference on Data Science, Technology and Applications (DATA 2024)*, pages 245-252
ISBN: 978-989-758-707-8; ISSN: 2184-285X

of machine learning-based methods for anomaly and damage detection in textile dyeing processes (Görgül et al., 2023), (Wang and Li, 2022). Studies related to the detection of impeller wear in FIP have been conducted experimentally or using additional sensors (Qu et al., 2009), (Daraz et al., 2019). Our proposed approach focuses on effectively solving the impeller wear issue in FIP without additional hardware, using a data-driven approach and the Facebook Prophet method (Taylor and Letham, 2017). The necessary methodology for this approach has been determined and its effectiveness has been demonstrated through implementation. This study addresses the wear issue of FIP not merely as the deterioration of a machine part but also as a strategic matter in terms of the efficiency and sustainability of the entire production chain.

The rest of the paper is organized as follows. In Section 2, related works on predictive maintenance of pumps are given Section 3 defines the problem in detail. In Section 4, the proposed methodology is presented. Section 5 gives details of application in the pilot textile factory. Finally, concluding remarks are provided in Section 6.

2 RELATED WORKS

Recent studies in the literature mainly focus on predictive maintenance and performance prediction of FIP , with emphasis on various approaches including artificial intelligence models and real-time data analysis, especially in the textile industry. This area of research integrates various approaches, including advanced computational models and real-time data analysis, to improve the operational efficiency and reliability of FIP in industrial environments.

(Demirkiran et al., 2022) conducted a study on the application of the Prophet method for time series forecasting in AI models and the real-time data analysis of industrial equipment. This research highlights the effective utilization of the Prophet method with optimized parameters.

(Chhabria et al., 2022) focused on the development of a system architecture for the early detection of failures in industrial water pumps using machine learning techniques. Utilizing the Random Forest method, this approach enables the early detection of potential failures.

(Emir Žunić, 2020) presents a retail sales forecasting framework using Prophet algorithm, focusing on real-world data from a major retail company. It aims to enhance inventory and production planning through accurate forecasts and product classification.

(Khoie et al., 2015) developed a novel magnetic sensor to measure wear in centrifugal pumps. This sensor provides real-time measurements of wear, crucial for maintaining the efficiency of pumps and minimizing downtime.

(Sugiyama et al., 2009) examined the prediction of wear depth distribution caused by slurry in aluminum pump impellers. The study successfully predicts wear distribution, showcasing its usefulness in maintenance and material selection.

(Almazrouei et al., 2023) conducted a comprehensive review of AI models used in the predictive maintenance of water injection pumps. This review underscores the effectiveness and challenges of various AI techniques including machine learning and deep learning.

(Sanayha and Vateekul, 2017) developed a two-stage model for fault detection in circulating water pumps. The model focuses on forecasting sensor trends using the ARIMA method and classifying failure modes based on these predictions.

(Chen et al., 2022) designed an IoT system architecture with smart sensors for monitoring and predictive maintenance of centrifugal pumps. This design emphasizes the effectiveness of both wired and wireless sensors in real-time fault detection and diagnosis.

This research area integrates varied approaches, including advanced computational models and real-time data analysis, to enhance the operational efficiency and reliability of FIP in industrial environments.

3 PROBLEM DEFINITION

A FIP shown in Figure 2 is a pump style featuring a rubber impeller that is circular in shape, equipped with numerous pliable rubber vanes. This impeller is set within a housing or casing (Hooton, 2019).

The liquid chemical weighing and dispensing system shown in in Figure 3, significant wear and tear occur over time on the impeller within the FIP, as shown in Figure 4. These harsh working conditions can lead to incorrect amounts of liquid chemical weighing or

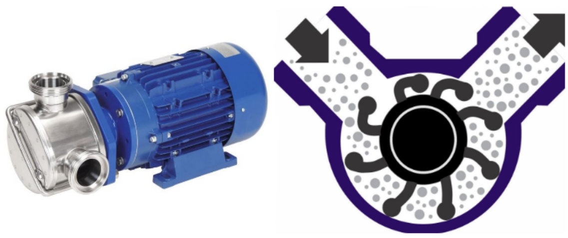

Figure 2: Flexible impeller pump and impeller.

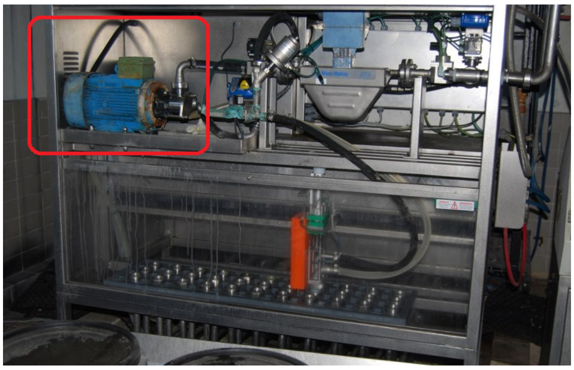

Figure 3: Pump position of liquid chemical weighting and dispensing system.

prolonged weighing durations. This may result in undesirable dyeing quality and can disrupt the dyeing process if the pump fails.

Figure 4: Impeller wear out.

FIP, particularly in precise operations like fabric dyeing, are critical for the accurate and timely transmission of fluids. As one of the most crucial components of these pumps, the impeller, being in constant motion, wears down depending on the physical and operational stress, the chemicals weighed, and the number of weightings. This wear jeopardizes the efficiency of the pumps over time and thus the integrity of the entire production process. Detailed observations and process analyses have revealed that these pumps typically show significant signs of wear after a usage period of 4 to 6 months. During this time, the wear of the impeller leads to a noticeable decrease in the amount of fluid pumped per unit time.This reduction is observed to adversely affect not just the efficiency of the operation.

However, the real magnitude of the problem manifests in the quality of the final product. Due to the wear of this critical component, the pump becomes dysfunctional, which may lead to the machine operating at reduced efficiency for weeks, thereby causing serious disruptions in production processes. These disruptions lead not only to financial losses but also to negative impacts on production continuity and customer satisfaction.

4 PROPOSED METHODOLOGY

4.1 Data Acquisition and Cleaning

In factories, impeller pumps used are prone to wear and tear and fragmentation depending on the intensity and conditions of use, leading to the halt of chemical weighing operations in the factory and disruptions in production.This study aims to detect the wear condition of the pump early by using data collected from the devices, and to provide a solution by informing the operation before a problem occurs. The analysis of the data obtained from the devices plays a critical role in determining the wear condition of the pump over time and making predictions for the pump's performance based on the amount of wear. This methodology aims to reduce the need for regular maintenance in businesses and prevent disruptions in production processes. The flowchart of the methodology is given in Figure 5.

Our database reflects daily data records showing the operational performance of the pump system. The data are obtained through daily ETL (Extract, Transform, Load) data collection cycles. Our ETL module deployed on a cloud server and connect the databases of dispensing systems through VPN. These records include process values such as Weighting time, Weighted amount (g), Weighting duration (s) and g/s. Our sample dataset can be examined in Table 1. Below are the descriptions of the dataset columns:

- **Name / Type:** Weighting time / Timestamp
  Description: The operation start time with precise timestamps.
- **Name / Type:** Weighted amount (g) / Float
  Description: The amount of substance used.
- **Name / Type:** Weighting duration (s) / Integer
  Description: The total operation duration in seconds.
- **Name / Type:** g/s / Float
  Description: The rate of substance pumped per second.

This dataset is not limited only to the compilation of process data but also includes these data in a simplified and transformed form.

During the data collection process, the accuracy of each weighing in liquid chemical weighing and distribution systems is of critical importance. Outlier detection identifies data points that deviate from the expected or indicate possible errors. For example, interruptions in the weighing process, deviations from expected values, or sensor errors, as well as

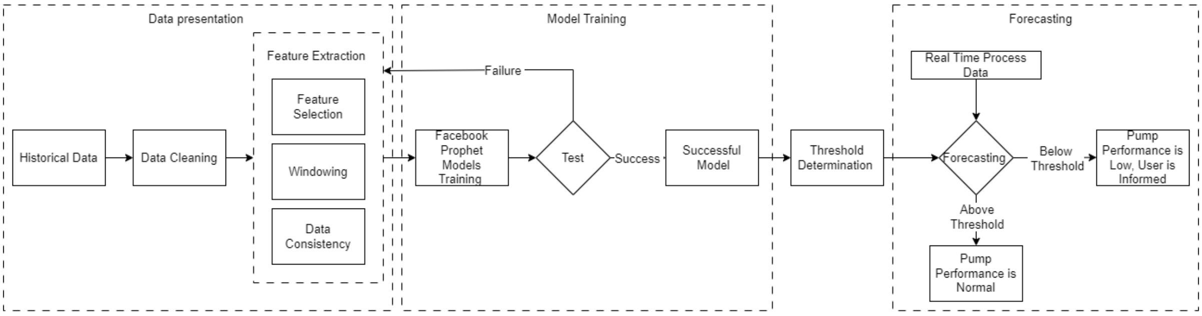

Figure 5: Flowchart of the methodology.

Table 1: Sample dataset.

#	Weighting time	Weighted amount (g)	Weighting duration (s)	g/s
1	2024-01-23 15:49:43.160	168.166	59	2.850
2	2024-01-23 15:48:38.152	497.0	5	99.4
3	2024-01-23 15:48:21.447	239.087	50	4.781
4	2024-01-23 15:47:41.000	4790.0	27	177.407
5	2024-01-23 15:47:40.263	144.0	3	48.0

certain inconsistencies in daily weighing speeds, can be observed. These inconsistencies may stem from the operational status of the business; for instance, days when the business is closed due to bans, reduced working hours, or holidays, can affect the integrity of our dataset. Such data are carefully filtered out from the dataset. In the data cleaning phase, canceled weightings, failed operations, and other anomalies are identified using statistical filters and algorithms. These data are labeled and stored in the database, so that when analysis queries are performed, work is carried out on a meaningful and clean dataset.

One of the biggest challenges encountered in the data analysis process is the accurate interpretation of the unique characteristics displayed in the weighing operations of each chemical. Especially frequently used chemicals like hydrogen peroxide, liquid caustic, and acetic acid, when examined individually, can give misleading results due to the complexity of the weighing process. This is because the weighing speed, amount of weight, type of chemical, environmental factors (such as seasonal temperature, humidity), and machine parameters depend on numerous variables.

Therefore, to analyze the daily operations of the business and enhance efficiency, it is need to examine the average values of all chemicals and weighings. This approach aids in understanding the relationship between the quantities of chemicals used daily and the overall performance of the business. For instance, it has been observed that there is a significant correlation between the daily usage amounts of frequently used chemicals ('SERAZ ZYME CKXE', 'LAUCOL SRD CONC', 'EXAPON BHL-PLUS') and the overall performance of the business. These correlations have been determined to be 89.87%, 84.77%, and 84.54% respectively, which has proven to be a meaningful method of measuring daily performance and consistency.

Figure 6 provides a detailed representation of the chemical weighings performed by the liquid chemical weighing and distribution system. Our graph shows the average flow rate in grams per second of different chemicals based on date. The axes represent time (Date) and flow rate (Average Grams/Second), with different chemicals distinguished by color codes. These data are collected for the purpose of continuous monitoring and improvement of our devices' performance.

In the outlier detection process, the quantile method, a statistical approach, has been used to identify outliers in the dataset. The primary purpose of this method is to determine values representing a certain percentage of the dataset. In this context, the 0.1 quantile value has been chosen to detect outliers. This choice implies that 10% of the observations in the dataset will be considered outliers. Determining this ratio is critical to measure and calibrate how well the algorithm can detect outliers.

To express this in formulaic terms, let Q(p) be a quantile function, then for p=0.1 the value Q(0,1) represents the top and bottom 10% of the observations in the data set, and all other than this value observations are considered anomalies. This outlier detection has been fine-tuned to discern real issues and significant patterns within the dataset.

4.2 Data Analysis and Machine Learning

After outlier detection and cleaning processes on the dataset, the data were prepared for machine learning and advanced analysis techniques. At this stage, various algorithms for time series analysis were examined and tested. The Prophet algorithm developed

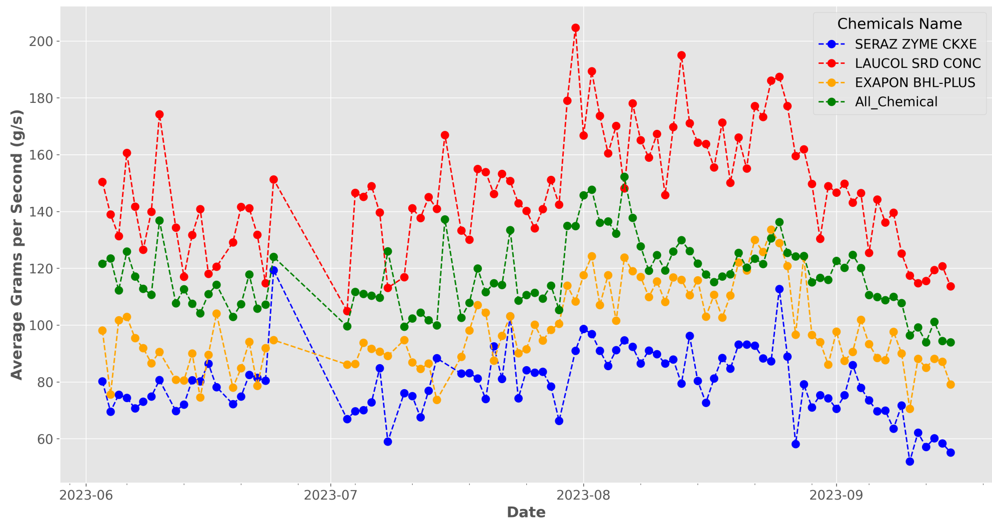

Figure 6: Daily average chemical usage of some chemicals.

by Facebook was selected for use. During time series analyses, it was observed that data points in the dataset that spanned periods longer than six months responded slowly to future predictions. Therefore, the necessity of using more dynamic and current data for analyses emerged. In order to capture trends and seasonal effects more quickly, it was decided to use data less than six months old in the analysis.

4.2.1 Enhancing Predictive Maintenance with the Prophet Algorithm

The Prophet algorithm offers unique advantages when working with datasets that include seasonal patterns, holidays, and other periodic effects in time series data. This algorithm contains flexible components designed to adapt to the characteristics of time series data. These components enable Prophet to explain complexities in the dataset and make accurate future predictions.

The prominent features of Prophet are:

- Adaptive Seasonality: It models complex seasonalities using Fourier series, adjusting to various frequencies and magnitudes.
- Holiday Effects: Prophet effectively captures holidays and events, a common shortcoming in traditional models.
- Robust Anomaly Detection: Prophet robustly manages outliers and missing data, reducing their adverse effects on prediction accuracy.
- Ease of Implementation and Adjustability: The model's hyperparameters are easily tunable, ensuring flexibility and ease of use across various datasets.

The basic mathematical model of Prophet is as follows:

$$y(t) = g(t) + s(t) + h(t) + \varepsilon_t \quad (1)$$

- y(t): Time-dependent target variable.
- g(t): The trend component is usually modeled with linear or logistic growth functions.
- s(t): The seasonal component is modeled using a Fourier series
- h(t): The holiday effects component represents the impacts of holidays or special days.
- ε_t : The error term represents random effects not explained by other factors.

The daily chemical weighing data obtained from the database are analyzed using this model, and the potential failure times of the impeller pump are predicted. Based on the learned data characteristics, our application of the Prophet algorithm can predict potential pump failures up to two weeks in advance and convey this information to businesses. This predictive capability provides a significant contribution to factories and businesses in maintaining uninterrupted production processes and allows for the implementation of an effective predictive maintenance program.

5 APPLICATION

This section details the pilot applications of the determined modeling and fault detection methodology in various textile factories.

5.1 Input and Data Collection

In the first step, historical data obtained from machines performing daily chemical weighing operations were collected to begin data preparation. The machines used for data selection are those employed as liquid chemical weighing and distribution systems in factories. In total, 5400 manipulated and 1048000 raw data points were used per machine.

5.2 Outlier Detection, Setting Threshold Values, Data Analysis, and Performance Evaluation

After the dataset was formatted appropriately, two new threshold values were calculated: Pump Maintanance Date (PMD), representing the average weighing amount at the last repair period of the pump, reflecting the machine's optimum performance; and Predictive Maintanence Alarm Limit (PMAL), a value used to detect the presence of any problem. When calculating PMAL, the average of the dataset from the last repair point PMD and the smallest value in the dataset are determined. Then, 5% of the average value is calculated. This step performs a type of fine-tuning by setting aside a 'safety margin' from the average value for determining the threshold value. The PMAL is calculated by subtracting 5% of the average from the obtained minimum value. This process not only ensures that the threshold value is more protective than just the minimum value but also takes into account the overall data distribution. Thus, it shifts the lower boundary of the dataset to a point that is lower than the lowest value. Such an adjustment helps prevent the model from overreacting while still offering a sensitive enough threshold to detect potential problems. Especially, it reduces the impact of anomalies such as noise or sudden changes in the dataset, ensuring that the model is more stable and reliable.

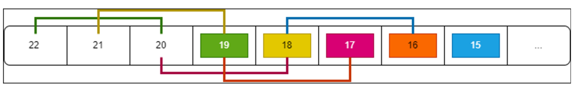

Figure 7: Three-day windows.

After the process, the dataset was reversed in time and divided into three-day windows, starting from the most recent date. The average weighing amounts and counts for the created three-day windows (for example Figure 7, January 22, 21, and 20) were found, summed up, and then divided by the number of days. Thus, the average weighing amount and count for each three-day window were calculated. Subsequently, for performance analysis, a comparison was made with the next day (in our example Figure 7, January 19), and two main control mechanisms were used to determine whether the pump performance was at an acceptable level:

1. **Fixed Threshold Value (Pump Maintenance Date Threshold):** As a predetermined fixed threshold value has been used a comparison point in evaluating whether the pump performance is sufficient. This threshold value represents the lower limit of performance that is considered normal for the pump.
2. **Data Set Time Range:** When conducting performance evaluations, it is important that the dataset covers a minimum period of 14 days. We estimate a 14-day period because studies conducted on datasets shorter than our estimated period may not yield accurate results.

When the established checks are met, the selected date (for our example Figure 7, January 19) is considered as the last repair date of the pump, and the average weighing from this date onwards is evaluated as an indicator of the pump's optimum performance. Since variables such as the environmental conditions of the machines in each factory, the usage styles of the operators, and their changing work habits over time are taken into account, the average weighing and quantity obtained since the last repair, rather than a general average, are used as a more meaningful performance indicator. This method has been found to provide a more consistent performance measurement by reducing the impact of daily and environmental variability.

5.3 Modeling and Forecasting

From the identified date, the dataset was reorganized, and training was conducted with customized hyperparameters for each machine using the Facebook Prophet algorithm. The used hyperparameters are as follows:

1. **Changepoint Range (changepoint_range):** This parameter specifies the portion of the dataset used to detect trend changes. A value between 0 and 1 is set, where 1 means using the entire dataset. For instance, a value of 0.95 indicates the model uses 95% of the data for detecting trend shifts, making it sensitive to even minor changes, essential in monitoring pump performance over time.
2. **Changepoint Prior (changepoint_prior_scale):** This controls how rapidly the model responds to trend changes. A higher value means quicker adaptation to trends, crucial for promptly identifying potential issues in the dataset.

3. **Seasonality Mode (seasonality_mode):** Prophet offers two modes: 'additive', where seasonal effects are a fixed amount added to the forecast, and 'multiplicative', where seasonal effects vary in proportion to the forecasted value. The 'multiplicative' mode is chosen when seasonal variations are proportional to the time series level, as seen in datasets where weighings increase on busy days.

4. **Additional Seasonalities (add_seasonality):** Besides standard annual, weekly, and daily seasonality, extra patterns like monthly or quarterly can be added. For instance, 'daily' seasonality is added with three sub-parameters:
   - Name: Specifies the seasonality type, e.g., 'daily'.
   - Period: Defines the duration of the seasonality, e.g., '1' for daily.
   - Fourier Order: Determines the complexity of the seasonal component, with higher values capturing more complex patterns.

Table 2: Comparison of Default and Optimized Parameters.

Default Parameter	Optimized Parameter
Changepoint Range = 0.8	Changepoint Range = 0.95,
SeasonalityMode= 'additive'	SeasonalityMode= 'Multiplicative',
Sparse Prior = 10.0,	Sparse Prior = 0.01,
Changepoint Prior = 0.05	Changepoint Prior = 0.1,
add_seasonality(name=annual, period=365, fourier_order=5)	add_seasonality(name='daily', period=1, fourier_order=15)

The model is prepared, trained, and tested in accordance with the specified parameters. If the accuracy rate of the model is found insufficient, this process is repeated until the model makes predictions under the desired conditions. When the model operates with the desired level of accuracy, it is ready to make performance predictions. Thus, the performance prediction of the machine for the next fourteen days has been made. If the predicted values fall below the 'PMAL' threshold, it is concluded that the pump performance is declining and needs to be replaced to prevent disruptions in the production process.

5.4 Reporting and Communication of Results

The examination of the prediction Figures 8, 9 and 10 generated by our model shows that the pump performance displays a decreasing trend over time. Initially, it appears that the pump functions with normal operating performance; however, as time progresses and issues related to the FIP arise, a decrease in performance is observed. These performance declines have been successfully predicted by our model, and these predictions indicate the need for early measures to prevent potential problems.

The analysis conducted on the performance decline has attempted to determine the underlying causes of the decrease in pump efficiency, considering various factors. The examination of the graph suggests that the observed fluctuations in performance during certain time intervals could be related to factors such as the pump's operating conditions, maintenance programs, usage intensity, and wear.

In detail, the time series data in Figures 8, 9 and 10 show the frequency and severity of performance declines on specific dates. The red line represents the observed actual performance, while the black line represents the predicted performance. The alignment between these two lines reflects the accuracy of the prediction model and its early warning capability against potential performance issues.

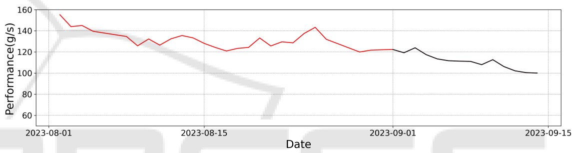

Figure 8: Model prediction graph start 01-08-2023 - prediction time 01-09-2023.

In Figure 8, the model covering the period from August 1st to September 1st does not forecast a significant decline in the pump's performance. The performance indicators show that the PMAL threshold is calculated as 111.40 and the estimated value of FIP is determined to be 113.32. Therefore, no warning or intervention is deemed necessary.

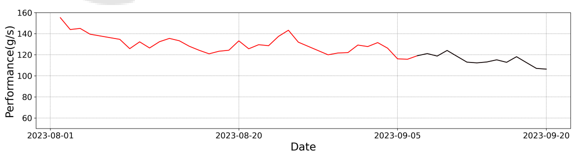

Figure 9: Model prediction graph start 01-08-2023 - prediction time 07-09-2023.

Figure 9 encompasses an extended version of the same date range for the pump's operation, showing no significant changes in its performance. PMAL threshold being set at 109.16, while the estimated value of the impeller in the FIP is at 115.15, indicates that no problematic issues have been detected, thus negating the need for any intervention.

However, there is a noticeable change in Figure 10. The model predicts a critical decrease in pump performance from September 7th onwards. Recent

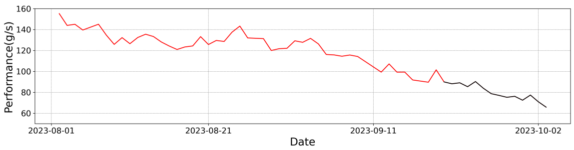

Figure 10: Model prediction graph start 01-08-2023 - prediction time 17-09-2023.

calculations have determined the threshold for Pump Maintenance Alert Level (PMAL) at 83.37. In light of these findings, the estimated value of the impeller in the FIP has been assessed at 80.02. This value, falling below the established PMAL threshold, indicates the necessity for maintenance intervention.

Consequently, our model's predictions enable maintenance and repair teams to plan effectively, thereby increasing the efficiency and reliability of the business. The identified situation is presented to the relevant departments with reports containing visual and statistical data from the trained model. This analysis process is conducted in accordance with a three-day windowing logic. This method allows adaptation to the dynamics of factory operations and enhances the ability to respond quickly to changes in machine performance.

6 CONCLUSIONS

In summary, we underscore the critical impact of impeller wear in FIP on the textile dyeing process and liquid chemical weighting systems through our study. We emphasize the necessity for regular monitoring and predictive maintenance of these pumps, especially considering the wear patterns typically observed within 4-6 months. Our use of the Facebook Prophet model and time series data for early detection of wear presents a proactive approach to maintaining pump efficiency without installing new hardware and high cost.

Our future research will involve applying the Prophet model to time-series data we have already collected from equipments in fabric dyeing machines to develop predictive maintenance solutions.

ACKNOWLEDGEMENTS

This work is supported by The Scientific and Technological Research Council of Turkey (TÜBİTAK) under the project number №3200916.

REFERENCES

Almazrouei, S. M., Dweiri, F., Aydin, R., and Alnaqbi, A. (2023). A review on the advancements and challenges of artificial intelligence based models for predictive maintenance of water injection pumps in the oil and gas industry. *SN Applied Sciences*.

Chen, L., Wei, L., Wang, Y., Wang, J., and Li, W. (2022). Monitoring and predictive maintenance of centrifugal pumps based on smart sensors. *Sensors*, 22:2106.

Chhabria, S., Ghata, R., Mehta, V., Ghosekar, A., Araspure, M., and Pakhide, N. (2022). Predictive maintenance using machine learning on industrial water pumps. *International Journal of Innovations in Engineering and Science*, 7(9):76–81.

Daraz, A., Alabied, S., Gu, F., and Ball, A. D. (2019). Modulation signal bispectrum analysis of acoustic signals for the impeller wear detection of centrifugal pumps. In *2019 25th International Conference on Automation and Computing (ICAC)*, pages 1–6.

Demirkiran, C. N., Üstün, E., and Urhan, O. (2022). Time series forecasting performance analysis of the prophet method for predictive maintenance applications. ELECO 2022 Electrical-Electronics and Biomedical Engineering Conference.

Emir Žunić, Kemal Korjenić, K. H., D. Đ. (2020). Application of facebook's probhet algorithm for successful sales forecasting based on real-world data. International Journal of Computer Science & Information Technology (IJCSIT) Vol 12, No 2.

Görgül, A., Çom, M., and Sultanoğlu, S. (2023). Kernel ridge regression based modelling and anomaly detection for temperature control in textile dyeing processes. In *27th International Conference on System Theory, Control and Computing*, pages 392–397.

Hooton, S. (2019). Flexible impeller pump guide. `https://www.northridgepumps.com/article-141\_flexible-impeller-pump-guide`.

Khoie, R., Gopaluni, B., Olson, J. A., and Stoeber, B. (2015). A magnetic sensor to measure wear in centrifugal pumps.

Qu, J., Miao, C., Hoseini, M., and Zuo, M. J. (2009). Wear degree prognostics for slurry pumps using support vector machines. In *2009 8th International Conference on Reliability, Maintainability and Safety*.

Sanayha, M. and Vateekul, P. (2017). Fault detection for circulating water pump using time series forecasting and outlier detection.

Sarkar, A., Johnson, I., and Cohen, A. (2023). Jj pizzuto's fabric science. `https://books.google.com.tr/books?id=5APXEAAAQBAJ`.

Sugiyama, K., Nagasaka, H., Enomoto, T., and Hattori, S. (2009). Prediction of wear depth distribution by slurry on a pump impeller. *International Journal of Fluid Machinery and Systems*, 2(1).

Taylor, S. J. and Letham, B. (2017). Forecasting at scale. *PeerJ Preprints*.

Wang, C.-C. and Li, Y.-H. (2022). Machine-learning-based system for the detection of entanglement in dyeing and finishing processes. Sustainability 2022.