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Optimizing Grinding Processes with Machine Learning: Predictive Models for Enhanced Precision

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Abstract
Fives machines are renowned for their high precision grinding capabilities, consistently delivering parts that meet stringent industrial standards. Despite this, a significant challenge remains in the underutilization of the extensive data generated during grinding operations. Currently, this valuable data is often archived, representing a missed opportunity for further process optimization. In this paper, these challenges are addressed by exploring the application of machine learning to leverage extensive time series data from the grinding process. It is demonstrated how this data can be used to train a machine learning model that predicts part diameter with high accuracy. This model facilitates dynamic optimization of the grinding process and predicts the final part diameter of a high alloy forged steel crankshaft produced in a high volume environment. The approach demonstrates how logged machine data can be repurposed into predictive models that directly support process optimization and adaptive control in precision grinding.

Keywords: adaptive machine control, machine learning in grinding

1. Introduction

High precision grinding applications demand micron level control of part geometry, where small deviations can lead to significant consequences. Fives machines have earned a reputation for delivering high-precision grinds that meet stringent industrial requirements. However, despite their advanced technology, these machines still rely on manual oversight. This dependence not only introduces variability into the process but also leaves vast amounts of valuable data unexamined, representing a missed opportunity for optimization.

Every grinding operation performed by a Fives machine generates large amounts of logged data, capturing detailed information about the process, the condition of the equipment, and the final product. The data is typically used during machine acceptance, fault finding or for process optimization. Yet, despite the enormous potential of this data, it is often discarded or left unexamined. The pre-existing approach to grinding relies on the operator's ability to manually adjust the machine, monitor the quality of the parts, and decide when maintenance is necessary. These decisions are typically based on experience and intuition rather than on a systematic analysis of the data generated during the grinding process. As a result, the final size and quality of the parts produced are relatively variable.

To address these challenges and unlock the potential of the data collected, this white paper will introduce a machine learning approach designed to enhance the precision and efficiency of the grinding process. The model utilizes time series data logged during grinding operations to predict part diameter with high accuracy. By analysing transducer-based post process measurements, the machine learning model can provide actionable insights and predictions that inform adjustments to the grinding process. Section 2 will detail the problem statement. Section 3 will describe the machine learning model and its implementation. Section 4 will present the results obtained from applying the model, and Section 5 will offer conclusions and recommendations for future improvements.

2. The problem statement

Figure 1 shows a high precision grinding machine used to grind parts for this study. Despite the high precision that Fives machines can achieve, the grinding process is currently hindered by several inefficiencies that stem from its reliance on manual oversight. This manual approach introduces several key challenges that affect the overall effectiveness and consistency of the grinding process.

Figure 1: a high precision grinding machine used to grind parts for this study

Firstly, the grinding process requires the machine to be manually serviced after every set number of parts. This maintenance routine is not dynamically controlled through a data-driven schedule. The decision about when to perform maintenance or replace the grinding wheel is based on subjective assessments of machine condition and performance. This reliance on operator intuition leads to inconsistencies in machine upkeep, resulting in variable part quality and performance.

Secondly, operators must continuously monitor the grinding process to ensure that parts remain within the desired tolerance. This real-time oversight involves making manual adjustments to the machine settings and inspecting parts for quality. Variations in operator skills, focus, and experience can introduce significant variability into the grinding results. For instance, less experienced operators may struggle to maintain the same level of precision as their more seasoned counterparts, leading to inconsistencies in part size and quality.

Thirdly, the enormous amounts of data generated by Fives machines during each grinding operation are typically discarded or left unanalysed. This data includes critical information about machine performance, wear and tear on components, and the quality of the parts produced. The final part diameter is linked to the machine's internal log file via a unique serial number, ensuring complete data traceability. By not systematically analysing this data, manufacturers miss out on valuable insights that could inform more precise adjustments and maintenance schedules. The lack of data-driven decision-making results in a process that relies heavily on trial and error, rather than informed, systematic improvements.

Previous attempts to optimize the grinding process have often relied on traditional methods such as trial-and-error. These methods have their limitations, as they are constrained by human judgment and the inconsistent application of best practices. This approach can lead to inefficiencies and reduced precision, as it fails to consistently capture and apply lessons learned from previous operations.

These challenges highlight the need for a more advanced approach to grinding that minimizes manual intervention and leverages the power of data. By adopting a machine learning-driven approach, it is possible to transform the grinding process. Machine learning algorithms can analyse the vast amounts of data generated during operations, identify patterns, and make real-time adjustments to the process. This data-driven method would enhance the precision, consistency, and efficiency of the grinding process.

Machine learning can provide a systematic, objective approach to optimizing the grinding process. By learning from transducer-based post process measurements, these algorithms can predict when maintenance is needed, identify optimal settings for the machine, and detect subtle signs of wear or deviations. This shift to AI-driven adaptive control will stabilize the grinding process, reduce human error, and improve overall product quality, paving the way for more efficient and reliable precision manufacturing. Adopting a machine learning approach can provide real-time, data-driven insights and adjustments, thereby enhancing the overall performance and consistency of the grinding process.

3. Mathematical model:

3.1: Signal representation and FFT

The discrete Fourier transform [1] of a time series $s[n]$ of length N is given by:

$$X[k] = \sum_{n=0}^{N-1} e^{-2\pi j \frac{kn}{N}} s[n],$$

where $X[k]$ are the FFT coefficients, $k = 0, 1, \ldots, N-1$ and i is the imaginary unit.

3.2: Multiple linear regression model

The target variable y is to be predicted using the FFT coefficients $X[k]$. The regression model may then be formulated as [2]:

$$y = \beta_0 + \beta_1 X[1] + \beta_2 X[2] + \cdots + \beta_m X[m] + \epsilon,$$

where β_0 is the intercept term, $\beta_1, \beta_2, \ldots, \beta_m$ are the regression coefficients, and ϵ is the error term.

3.3: Design matrix

Let $\boldsymbol{X}$ be the design matrix of FFT coefficients for p samples, where each row corresponds to a different sample. The design matrix is:

$$\boldsymbol{X} = \begin{pmatrix} 1 & X_1[1] & X_1[2] & \ldots & X_1[m] \\ 1 & X_2[1] & X_2[2] & \ldots & X_2[m] \\ \ldots & \ldots & \ldots & \ldots & \ldots \\ 1 & X_p[1] & X_p[2] & \ldots & X_p[m] \end{pmatrix}$$

The design matrix is orthogonalized using the PCA technique [3].

3.4: Regression coefficients

The coefficients β may be estimated using the least squares method, which minimizes the sum of squared residuals:

$$\widehat{\boldsymbol{\beta}} = (\boldsymbol{X}^T\boldsymbol{X})^{-1}\boldsymbol{X}^T\boldsymbol{y},$$

where $\boldsymbol{y}$ is the vector of observed values for the target variable.

In summary, m equations can be written in matrix form as:

$$\begin{pmatrix} y_1 \\ y_2 \\ \ldots \\ y_p \end{pmatrix} = \begin{pmatrix} 1 & X_1[1] & X_1[2] & \ldots & X_1[m] \\ 1 & X_2[1] & X_2[2] & \ldots & X_2[m] \\ \ldots & \ldots & \ldots & \ldots & \ldots \\ 1 & X_p[1] & X_p[2] & \ldots & X_p[m] \end{pmatrix} \begin{pmatrix} \beta_0 \\ \beta_1 \\ \ldots \\ \beta_m \end{pmatrix} + \begin{pmatrix} \epsilon_1 \\ \epsilon_2 \\ \ldots \\ \epsilon_p \end{pmatrix}$$

or

$$\boldsymbol{y} = \boldsymbol{X\beta} + \epsilon$$

4. Results:

In this section, it will be demonstrated that leveraging time series data from the grinding process enables us to predict the final part diameter with high accuracy. 62 signals were tested, each representing different operational parameters such as power, position, velocity, angular position, torque etc., logged throughout the grinding process and the best variable was chosen after an extensive study. Figure 2 provides a visual representation of the selected variable, showing five time-domain signals from five different parts ground by the machine.

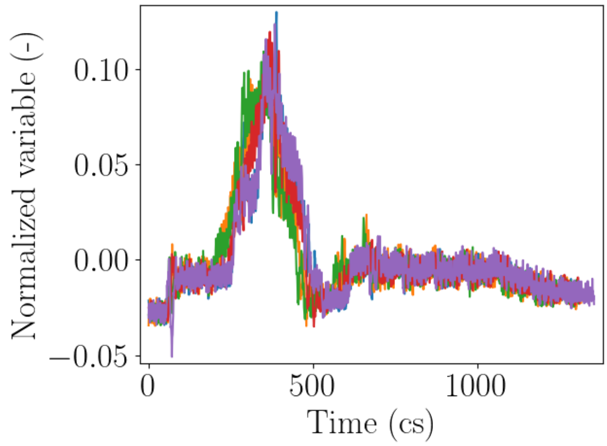

Figure 2: time domain signal from five parts ground by the machine

Figure 3 illustrates the transformation of the grinding signals, observed in figure 1, from the time domain to the frequency domain using Fast Fourier Transform (FFT) analysis.

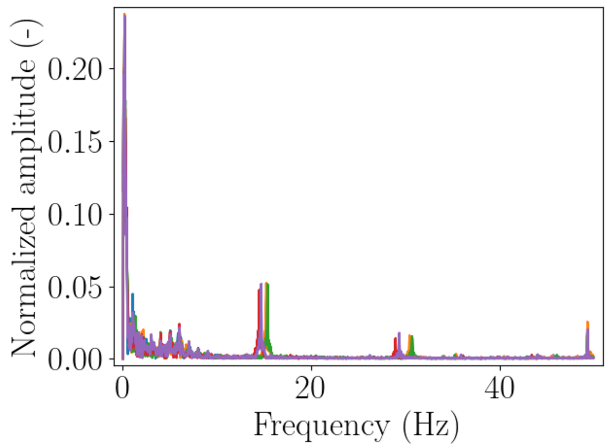

Figure 3: FFT transformation of the five grind signals of figure 2

This process of FFT transformation was repeated for 5,508 parts, and the resulting data was arranged in a design matrix $\boldsymbol{X}$ as illustrated in section 2. The design matrix was then orthogonalized using the PCA technique and the first and second principal components are shown in figure 4. About 96% of the data was retained in the orthogonalized PCA matrix neglecting the last 4% as noise.

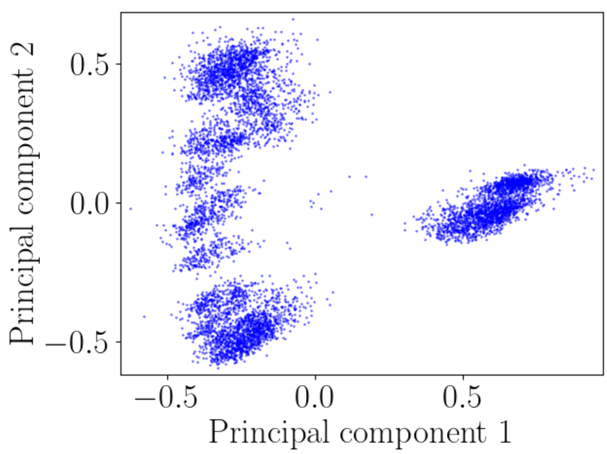

Figure 4: first and second principal components of the PCA of the design matrix

For the learning phase, 5,508 data points were utilized, spanning six months of grinding, and for the testing phase, 1,402 data points were employed, adhering to the standard 80:20 train-test split ratio. In this context, the target variable y is the final part diameter, which is aimed to be predicted. The design matrix $\boldsymbol{X}$ used in the model consists of the orthogonalized FFT matrix derived from time series data of multiple ground parts. The model was then trained on this data. Figure 5 displays a distribution plot of the 1,402 predictions generated by the model, which achieved an r^2 score of 0.79. Notably, this model also shows its versatility in predicting the bimodality of the ground parts. Figure 6 shows the scatter plot for the predicted as well as actual test data points. The model produces very accurate results.

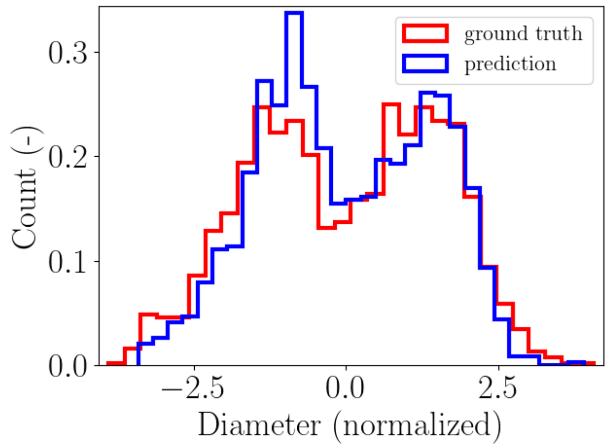

Figure 5: distribution plot for the predicted and actual diameters

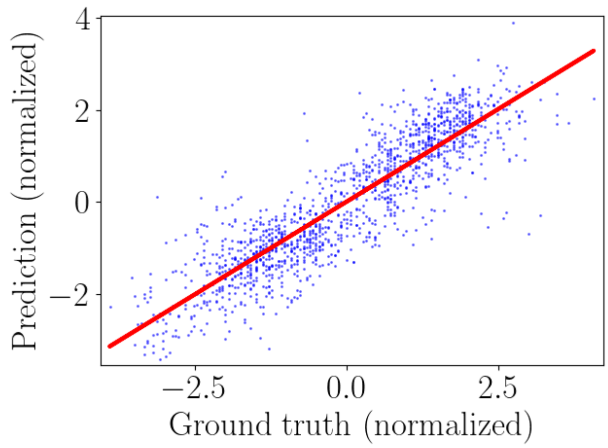

Figure 6: scatter plot for the actual vs predicted diameters

Another approach to tackling this problem involved recursively training the model using a sliding window technique. In this method, the model was trained on a dataset of 800 parts, capturing the time series data associated with each part's grinding history. This window size was about 4 times the dress frequency. Once this training phase was complete, the model was used to predict the diameter of the subsequent part, effectively applying its learned insights to real-time predictions. This process was repeated iteratively, with each new part serving as a test for the updated model.

Figure 7 illustrates the results of this recursive training approach. The graph compares the predicted diameters in blue against the actual diameters in red for the subsequent parts. The close alignment between the predicted and actual values demonstrates the model's effectiveness and reliability. This approach not only ensures that the model remains adaptable to new data but also confirms its ability to maintain high accuracy over time. By continuously refining predictions with each new part, the sliding window method enhances the model's performance and robustness, ensuring that it remains responsive to variations in the grinding process.

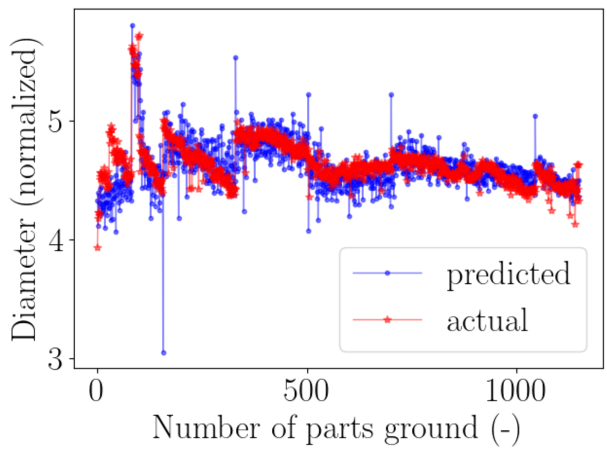

Figure 7: sliding window approach using 800 parts per window to predict the subsequent parts diameter

5. Conclusions and recommendations

5.1 Conclusion

The application of machine learning to time series data from Fives machines has yielded promising results, demonstrating high accuracy in predicting part diameter. The model's performance underscores its effectiveness in enhancing the precision of the grinding process. Additionally, the model is lightweight and can be trained recursively for each part, offering a scalable solution that adapts to varying operational conditions. This capability supports dynamic machine optimization and service, ultimately contributing to improved part quality and operational efficiency. By harnessing the predictive power of this model, informed adjustments can be made to maintain consistent part dimensions.

5.2 Future Recommendations

The current model, while highly effective, could be complemented by exploring more complex machine learning techniques in the future. The sliding window approach used for recursive training of the model with each new part proves beneficial, as it allows for dynamic adjustments and continuous learning. For this approach, a lightweight model, such as the one currently employed, is preferable to more complex non-linear models. The latter typically require significantly longer training times, which could impact operational efficiency. Although the existing model already delivers excellent results, maintaining its simplicity while incorporating advanced techniques as needed ensures that the system remains agile and responsive to evolving requirements. Future work will evaluate whether introducing more complex, nonlinear models offer measurable gains over the current regression approach, while maintaining the speed and adaptability needed for in process optimization.

6. Acknowledgements

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7. References:

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