Data-driven material removal rate estimation in bonnet polishing process

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Abstract: Bonnet polishing is an ultra-precision polishing technique used for manufacturing components utilized in optics, electronics, and scientific instrumentation, where sub-nanometer accuracy is required. However, the process is not fully deterministic and requires multiple process-metrology iterations. In modern computer numerically controlled (CNC) machines, polishing is performed by moderating the bonnet tool dwell time at each location based on the input parameters and material removal rate (MRR). While the MRR is typically treated as constant once established, it continuously evolves due to the process's dynamic nature and changing conditions. This variability in MRR impacts the convergence of the polishing process, necessitating repeated surface processing and resulting in increased manufacturing time and cost. In this work, we present a data-driven approach to estimate the amount of material removed during the pre-polishing routine in bonnet polishing. The estimations are based on the force exerted by the bonnet tool on a polished surface along the three dimensions. Measurements were obtained using a bespoke force table with load sensors across three axes, mounted on the Zeeko IRP600 machine table. The results demonstrate the effectiveness of this data-driven approach for estimating MRR, achieving a mean absolute error of 0.0541 µm and a mean absolute percentage error of 5.89% across the test set.

Keywords: Bonnet polishing, machine learning, material removal rate.

1. INTRODUCTION

Bonnet polishing is a critical surface-finishing process used for components utilized in fields such as electronics, optics, astronomy, or Science Base instrumentation where sub-nanometer texture and form accuracy are of utmost importance. To achieve the desired surface finish, a CNC machine needs to estimate material removal rate (MMR) to remove a precise amount of material from the workpiece. However, accurate estimation of MRR is challenging due to the complexity of the polishing process, poor understanding of the underlying physics, and continuous evolution of process parameters.

MRR in bonnet polishing follows the empirical, physics-based Preston equation (Preston, 1927) which states that the amount of material removed is proportional to the applied pressure, the relative speed between the surface and rotating bonnet tool and a constant called Preston's coefficient. A number of the techniques aimed at improving MRR estimation have relied on the Preston equation as the starting point and extended the formula to consider factors such as slurry particle size or bonnet pressure (Zeng and Blunt, 2014). However, closed-form analytical solutions derived from empirical models might be limited by certain distributions and assumptions incorporated while developing the model (Li et al., 2019; Rao et al., 2015).

Moreover, traditional techniques for estimating MRR do not consider the dynamic nature of the process and lack the flexibility to account for changes in process conditions. Once MRR is established, it is typically considered constant throughout the polishing routine even though MRR fluctuates continuously due to the fundamental complexity of polishing at molecular scale (Walker et al., 2019). These fluctuations introduce variability and unpredictability into the process significantly impacting both the quality of the polished surface and overall component lead time.

Data-driven techniques, such as machine learning and statistical modelling, offer promising alternatives by incorporating multiple machine and process parameters to dynamically predict MRR during the actual polishing procedure. Unlike traditional model-based methods, these approaches can capture complex non-linear relationships between variables directly from the data, without prior assumptions or knowledge about the underlying physical interactions.

Since surface measurement during a polishing run is impossible due to the polishing slurry covering the surface, several process parameters can be monitored online during the polishing procedure, such as polishing slurry characteristics, CNC machine parameters, and forces exerted on the workpiece. Among these, only forces can be measured in real time with negligible delay and can provide feedback on surface geometry. Furthermore, force is one of the variables described in Preston's equation, highlighting its importance on the final surface quality.

The goal of this study is to investigate the correlation between forces exerted on the workpiece during a polishing routine and MRR as well as develop a data-driven model that predicts MMR based on the force distribution data. Accurate MRR prediction has the potential to reduce the number of time-intensive workpiece measurements that are carried out in between the iterative measurement-polishing process chain. A reduced number of measurements lowers the risk associated with transporting the part from the polishing machine to the metrology instruments and reduces the time between polishing runs, thus increasing machine throughput.

The remainder of this paper is organized as follows: Section 2 reviews related work and data-driven techniques developed in chemical-mechanical planarization and robot polishing. Section 3 describes machine setup as well as data processing steps. Section 4 presents the modelling results. Finally, section 5 concludes the paper with key findings, recommended improvements to the system, and suggestions for future research.

2. RELATED WORKS

Material removal rate is a critical aspect of many types of polishing processes, including bonnet polishing, chemical mechanical planarization (CMP) or magnetorheological polishing. Accurate MRR is necessary to achieve the desired surface quality and reduce the number of required process-metrology iterations. The literature addressing MRR estimation can be broadly classified into physics-based methods, with the Preston equation as a focal point, and more recent data-driven approaches that focus on statistical modelling and machine learning techniques.

2.1 Preston Equation-based Models

Traditionally, MRR models were derived from the empirical Preston equation,

$$MRR = k_p \cdot P \cdot V \tag{1}$$

which states that the amount of material removed is proportional to applied pressure P, the relative speed between the tool and the workpiece V, and a constant k known as Preston's coefficient Preston (1927). The Preston equation is widely adopted in many types of polishing processes, (Deja, 2023; Kakinuma et al., 2022; Chen et al., 2024), including bonnet polishing, to provide a basic estimate of MRR. However, this model has limitations due to its assumption of uniform tool pressure and velocity and a lack of adaptability to variations in process conditions that occur during the polishing process. Additionally, the model relies on the Preston coefficient, which must be experimentally determined for each specific tool and workpiece material combination (Lin et al., 2018) and does not consider process-specific parameters of particular polishing mode e.g. precess angle in bonnet polishing.

Several modifications to the traditional Preston removal rate model have been proposed to improve the accuracy and account for more process parameters. Zeng and Blunt (Zeng and Blunt, 2014) investigated the effect of process parameters on the influence function in bonnet polishing and reported a modified Preston equation model that included process parameters to allow prediction of MRR during polishing of chrome alloy. Shi et al. (2018) established an improved model that incorporates the effect of cumulative pad wear over the polishing time. Pan et al. (2018) proposed a modified model that incorporates interfacial friction coefficient between the tool and workpiece. In subsequent research, the model was modified to take the influence of polishing slurry into consideration (Pan et al., 2022). Despite these modifications, the first principle models, like Preston equation derivatives, are not suited to estimate MRR under evolving process conditions.

2.2 Data driven techniques

Machine learning has enabled the development of data-driven models that can estimate MRR without establishing the significance of specific variables in advance. Data-driven approaches can overcome the limitations of traditional physics-based approaches and model non-linear relationships between multiple variables, capture complex interactions, account for process dynamics, and remove reliance on empirical coefficients.

There exists a host of literature focusing on the estimation of MRR using machine learning in chemical-mechanical planarization (CMP), a process widely used in semiconductor manufacturing. Wang et al. (2017) applied a deep belief network (DBN), demonstrating the effectiveness of deep learning in capturing nonlinear relationships between MRR in wafer polishing and process parameters such as pressure and rotational speeds of the wafer and pad. Yu et al. (2019) introduced a physics-informed machine learning approach that combined a physics-based model with a data-driven model. Hsu and Lu (2023) proposed a hybrid virtual metrology framework using a one-dimensional convolutional neural network and bidirectional LSTM with attention mechanisms to track the health condition of components in CMP.

Data-driven approaches have also been applied to MRR prediction in robot polishing. Yi et al. (2019) proposed a material removal model for robot polishing based on feature selecting deep residual neural network, which outperformed the Preston baseline model by combining experimental data with simulations from Preston's equation. Schneckenburger et al. (2022) presented an artificial neural network (ANN) model to predict MRR in robotic glass polishing that included multiple machine and process parameters as well as sensor readings from a bespoke polishing head.

However, the application of data-driven techniques specifically to bonnet polishing remains under-explored. While the CMP process has been the subject of significant research efforts due to higher economic value, public dataset

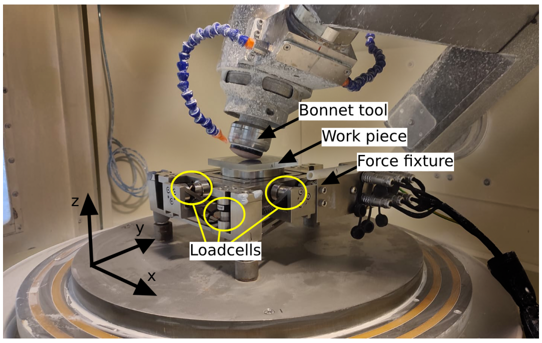

Fig. 1. Force fixture fitted in Zeeko IRP600 (Darowski et al., 2023)

availability, and a larger research community, few studies have focused on MRR prediction in bonnet polishing,

3. METHODOLOGY

3.1 Experimental Setup

Polishing experiments were carried out using a 7-axis CNC Zeeko Intelligent Robot Polisher IRP600 located at the Laboratory for Ultra Precision Surfaces at the University of Huddersfield. The machine used a recirculated slurry based on Super Cerox 1663 cerium oxide polishing powder. The IRP600 was fitted with an inflatable R40 bonnet covered with polyurethane cloth and a metal plate base to interface with a bespoke force table.

The force table included six compression load cell sensors installed along the X, Y, and Z-axes, with full-scale output accuracy of ±1% and a hysteresis error of ±0.8%. One sensor was installed along the horizontal x-axis, two along the horizontal y-axis, and three along the vertical z-axis. The load cells were connected through the I-Net card cage system and the iNet-240 cable to a computer with LabVIEW data acquisition software. A detailed description of the data acquisition system can be found in one of our earlier works (Darowski et al., 2023).

The polishing process involved a pre-polishing routine using a raster tool-path. The objective of the pre-polishing routine is to ensure a uniform removal of material across the entire surface. The experimental workpiece was a 100 mm square piece made of Fused Silica by Corning, restricted to the central 70 mm zone of the surface to mitigate the edge effect, which occurs when the bonnet tool slides off the edge of the workpiece. This 70 mm zone was further divided into two regions, designated as Y- and Y+. This segmentation allowed for successive polishing runs on each region without the need to transfer the workpiece to the metrology station after each run, thus saving time on the otherwise time-consuming metrology procedures. Figure 2 illustrates a workpiece with Y- and Y+ regions marked in green and blue, respectively. The black lines at the top of each region illustrate a tool-path shape, and red lines indicate profiles that were taken across the tool-path tracks.

A Tylor Hobson Form Talysurf Series 2, with a measurement resolution of 0.8 nm, was used to capture 2D profile surface measurements before and after each polishing run. Before the first polishing run, a narrow trench was etched

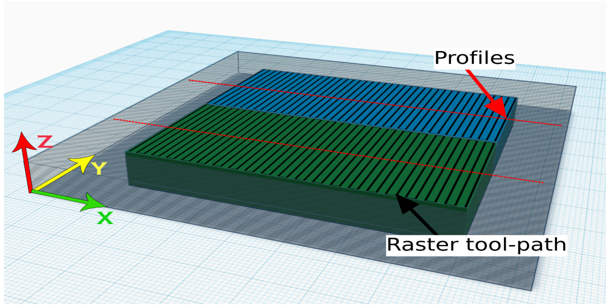

Fig. 2. Illustration of the workpiece with raster tool path and profile

into the surface to serve as a reference point to align the profiles. Measurements were taken in the middle of each polishing region along the x-axis and perpendicular to the raster tool-path tracks. Since the pre-polishing routine was combined with the raster tool-path, it was assumed that the material removal, and thus the profiles, would be consistent across the entire length of any given track.

In total 34 polishing runs were carried out with varying polishing times. The polishing time was varied by adjusting the surface feed rates to 1000, 500 and 250 mm/min corresponding to 5, 10 and 20-minute polishing runs.

3.2 Profiles data preprocessing

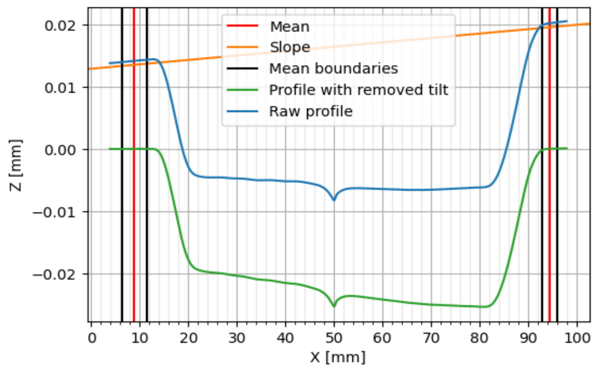

Fig. 3. Example of a profile before and after tilt removal

As mentioned above, a trench was etched in the workpiece prior to the first polishing run. As the first step in data preprocessing, the profiles were aligned so that the lowest point of the trench was at the centre.

Next, tilt was calculated and removed by determining the intercept and slope of a line that was fit between the unpolished regions of the workpiece. The unpolished regions are defined as arbitrary 5 mm wide sections at the beginning and end of the profile, where the surface remains unaffected by polishing. Within these regions, the mean Z-value was computed as the average height (Z) across the 5 mm section, while the mean boundaries represent the start and end limits of these regions in the X-direction (e.g., 0–5 mm and 95–100 mm). To avoid systematic errors introduced by the profilometer at the edges of the measurement, the first and last 2.5 mm of the profile were omitted during calculations. This ensures an objective determination of the tilt, as opposed to manual

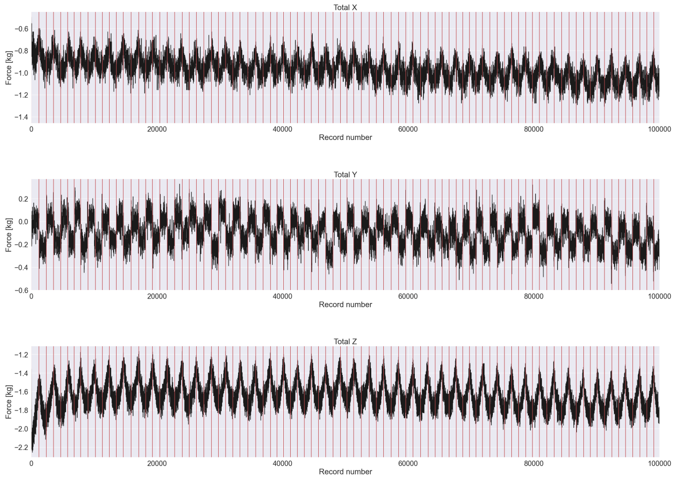

Fig. 4. Excerpt of a force signal with segment boundaries in red

methods that rely on the judgment of the operator. The results of this procedure are illustrated in Figure 3.

Finally, profile pairs from corresponding polishing runs were subtracted from each other to calculate the Material Removal Rate (MMR) by depth. The MMR by depth was then divided into 141 segments and integrated to calculate the total material removed for a segment. The 141 segments correspond to the number of raster tracks in the tool-path used during the polishing trials. Finally, the values were scaled by a factor of 10^6 to avoid operations on extremely small numbers and mitigate floating-point precision errors.

3.3 Forces data preprocessing

Polishing forces were recorded as a time series with a sampling rate of 500 Hz. To reduce the signal noise that was in the range of ± 0.5 kg we applied an arbitrary 20-point moving average filter. The standard deviation of a signal was reduced from 0.23, 0.26 and 0.15 down to 0.05, 0.06 and 0.03 kg for the x, y, and z axis, respectively. In the initial step of force data processing, an offset was calculated and subtracted from each channel to ensure that the recordings started from a relative zero signal. The sensors corresponding to each axis were then summed together and manually trimmed to align with the start and end of the polishing process. Manual operation was necessary because data acquisition was manually triggered before initiating the CNC machine run, thus recording data before and after polishing.

As in the case of the profile data, the forces were divided into 141 segments, corresponding to the number of raster tracks, and integrated to calculate the total force applied over each segment length. It should be noted that the forces had to be manually synchronised with the raster tracks, as simply dividing the time series into 141 equal parts was not effective. This issue can be attributed to the fact that the data acquisition software utilised software-timed acquisition and that the IRP600 modulates feed rates when the bonnet tool approaches the turning points of the tool-path.

3.4 Machine Learning Models

Estimating MRR is a regression type of problem, where the objective is to estimate continuous values of the target variable, MRR, based on the predictor variables - total forces along the X, Y and Z axes. Four models were developed and evaluated: random forest (RF), XGBoost (XGB), linear regression (LR) and multilayer perceptron (MLP) artificial neural network. The models were chosen to represent a range of simple, easy-to-implement techniques with different learning approaches including linear, non-linear and ensemble methods.

The dataset was split into training (60%), validation (20%) and test (20%) sets, to evaluate model performance on the previously unseen data. Both test and validation datasets included 5, 10 and 20-minute-long polishing profiles. The models were tuned using the validation set, and the following hyperparameters were found optimal:

- Random Forest: 200 estimators and maximum feature selection of 2
- XGBoost: Squared loss objective
- Linear Regression: Used as a baseline with no hyperparameters
- Multilayer Perceptron: Comprised of three hidden layers (10, 60 and 10 neurones) with ReLU activation and L2 regularisation. The model used Adam optimiser and learning rate reduction on a plateau.

4. RESULTS AND DISCUSSION

4.1 Model Performance

Four machine learning models - RF, XGB, LR and ANN - were evaluated on the test dataset. The models were evaluated on the basis of mean absolute error (MAE) and mean absolute percentage error (MAPE). The formulas for each metric are defined as follows:

- Mean Absolute Error (MAE):

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{y}_i| \tag{2}$$

- Mean Absolute Percentage Error (MAPE):

$$\mathrm{MAPE} = \frac{1}{n}\sum_{i=1}^{n} \left| \frac{y_i - \hat{y}_i}{y_i} \right| \times 100\% \tag{3}$$

where y_i is the actual value, $\hat{y}_i$ is the predicted value, and n is the number of observations in the test dataset.

Table 1 summarizes the performance of each model based on these metrics.

Table 1. Summary of the performance metrics for RF, XGB, LR, and ANN

Model	**MAE (µm)**	**MAPE (%)**
RF	0.1115	13.61
XGB	0.1394	14.83
LR	0.0716	10.72
ANN	0.0713	10.03

The ANN model achieved the lowest MAE of 0.0713 µm and MAPE of 10.03%, demonstrating the best overall

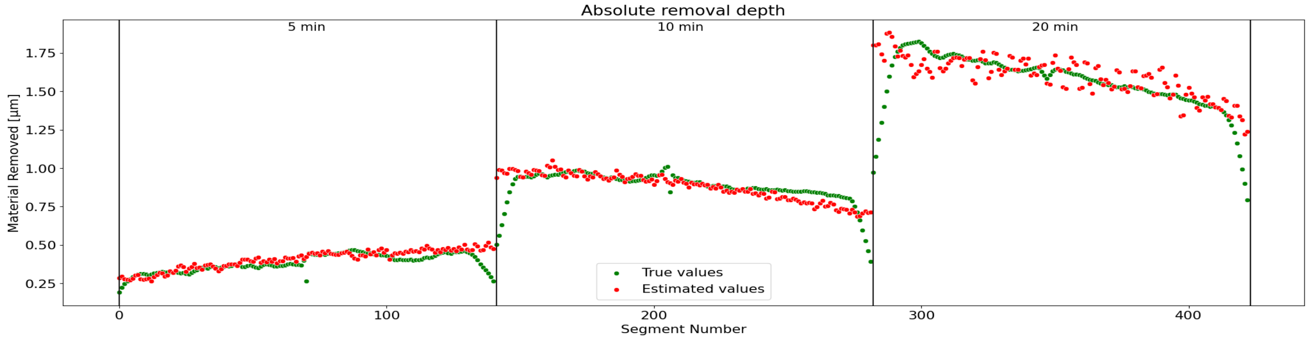

Fig. 5. Absolute removal rate by depth per raster track

performance in predicting MRR. The LR model performed similarly, with only a slight increase in error metrics. This comparable performance between LR and ANN could be attributed to insufficient data or a lack of complex non-linear relationships within the data that typically provide ANN models an advantage over other techniques. In contrast, the RF and XGB models showed higher error metrics, with RF having an MAE of 0.1115 µm and MAPE of 13.61%, and XGB slightly higher with an MAE of 0.1394 µm and MAPE of 14.83%.

Table 2. Summary of performance metrics for the ANN model

Polishing time	MAE (µm)	MAPE (%)
5 min	0.0539	11.91
10 min	0.0572	10.16
20 min	0.1027	8.01
Average	**0.0713**	**10.03**

In table 2 detailed performance metrics for the ANN model are presented at 5 min, 10 min, and 20 min polishing runs. At 5 and 10 minutes polishing time, the model achieved relatively low error metrics with a slight increase for 10-minute long runs. However, for 20-minute experiments, performance significantly deteriorates with a noticeable increase in MAE while MAPE decreases. It indicates that there are more fluctuations closer to the actual values.

4.2 Visual Comparison of Predicted and Actual MRR

Figure 5 presents a plot of predicted versus true MRR values for the best-performing ANN model. The majority of the predicted points closely align with the actual values, indicating a strong correlation, however, some noticeable deviations are most pronounced in the beginning, centre and at the end of the profiles. Poor estimation performance in the terminal regions is related to only partial coverage of the bonnet tool at the very edge of the polishing area, leading to a reduced amount of removed material with the same amount of applied force. We can also observe some fluctuations in predicted values, which can be associated with relative fluctuations of force readings that are caused by the miscalibrated load cells' gain. A mismatch in the centre of each of the profiles is caused by periodic etching of the alignment trench on the workpiece surface, which gives a false perception of elevated or lowered amounts of material removed.

To mitigate the impact of edge zones on the overall model performance, we trained an additional ANN model excluding a 12.71 mm region from the edge zones. This 12.71 mm corresponds to the spot size of the R41 bonnet tool contact area with the workpiece at a 0.5 mm tool offset. Furthermore, we removed 2mm from the centre of the profile to exclude the artificially generated trench. The re-trained model achieved an MAE of 0.0471 µm and a MAPE of 5.43%, representing improvements of 34% and 46%, respectively, relative to the initial error metrics. The results are presented in Table 3.

Table 3. Summary of performance metrics for the ANN model

Polishing time	MAE (µm)	MAPE (%)
5 min	0.0379	7.16
10 min	0.0403	5.64
20 min	0.0631	3.47
Average	**0.0471**	**5.43**

5. CONCLUSION

In this paper, we developed a data-driven approach to predict the material removal rate (MRR) by depth in the pre-polishing routine for bonnet polishing. Using machine learning techniques, this approach demonstrated promising accuracy in estimating the MRR based on the forces exerted by the polishing bonnet along three axes. Among the models evaluated, the artificial neural network model (ANN) performed the best and, with improved data processing, achieved 0.0541 µm MAE or 5.89% MAPE. Accurately estimating the amount of material removed enables improved process control and, even with imperfect convergence and determinism, reduces the need for metrology checks after each polishing run, thereby improving factory throughput. By providing precise estimates of MRR, this approach can help in reducing costs and lead times for ultra-precision components.

While the ANN model effectively estimated MRR, some limitations were observed. Model performance decreased with longer polishing durations, indicating that temporal factors, such as changes in particle size distribution, tool wear, pH, or temperature, may need to be considered for improved accuracy. Moreover, the raster tool-path track limits our ability to synchronise force data with the exact position on the workpiece due to the older CNC control system on the IRP machine used in these experiments. In addition, this study focused on a specific type of machine, tool, slurry, and material; therefore, the results may vary under different conditions. Finally, both data collection and preprocessing were extremely time consuming

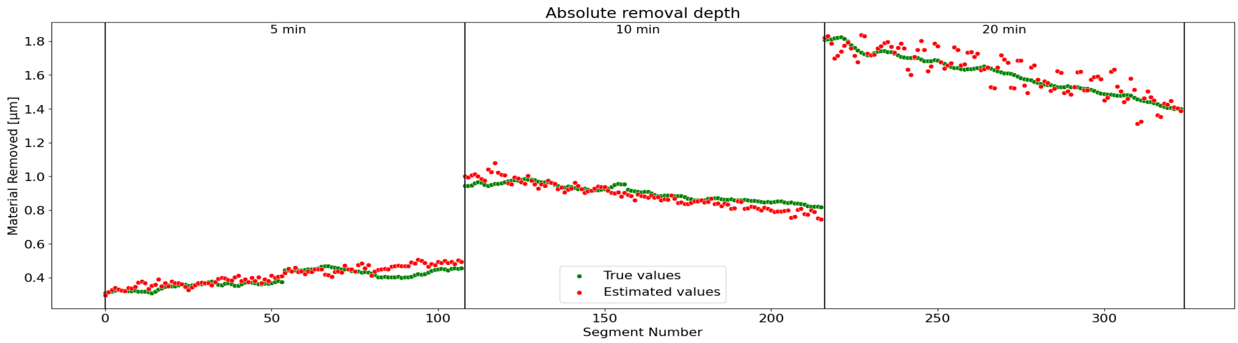

Fig. 6. Absolute removal depth rate by depth excluding the edge zones and trench area

and required substantial manual intervention. A potential method to automate and standardise the data acquisition process is to trigger measurement and polishing processes simultaneously or at known intervals. This approach would establish a predetermined and consistent section before the start of usable data in the recorded files, thereby eliminating the need for manual selection of the starting point.

Future research could explore the integration of additional process parameters, such as the particle size distribution of the slurry, pH, and the tool wear, to improve the precision and robustness of the model. Moreover, hybrid modelling techniques such as physics-informed learning could be considered to include known mechanics of material removal. Furthermore, it is essential to evaluate how this approach performs beyond the pre-polishing routine, particularly during corrective polishing where feed rates are modulated to achieve varying material removal. However, this requires precise knowledge of the tool's position at any given time, synchronised with the force readings.

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