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Machine Learning Based Calibration of Force Sensors for Bonnet Polishing Process

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Abstract:
Bonnet polishing is a process that can achieve surface finishes down to sub-nanometer texture and form accuracies down to 5-10nm RMS, usually limited by metrology. While the polishing is conducted by computer numerical control (CNC) machines, the process remains imperfectly deterministic, requiring multiple iterations to converge on the desired surface quality. Key parameters are the axial force exerted by the bonnet tool on the workpiece, and the lateral components of frictional coupling. As direct real-time measurement of material removal is impractical, a force table equipped with loadcells has been used to estimate the forces at the tool-surface interface. In this work, a bespoke 3-axis force-table using six loadcells has been built and deployed on the horizontal work-piece table of a Zeeko IRP600 CNC polishing machine. Machine learning was then used to calibrate the force table and to account for any biases or cross-talk between axes.

Keywords: Bonnet polishing, machine learning, sensor calibration, force table, material removal rate.

1. INTRODUCTION

Ultra-precision polishing is a highly chemical-mechanical complex process capable of achieving surface accuracies at the nanometer scale. Ultra-precise optical components find applications in diverse sectors, including military, medical, photo-lithography, communications, and Science Base instrumentation, where exacting standards are imperative (Brinksmeier et al., 2010). There are several ultra-precision polishing techniques available, each with its own set of advantages and disadvantages. Bonnet polishing, also known as *Precessions*™ polishing, is one of such ultra-precision polishing techniques, developed by Walker et al. (2006). A 7-axis CNC machine is used, which may be equipped not only with the standard precessed, inflated bonnet tools but with a wide variety of alternatives for special purposes.

Moves to automate ultra-precision polishing are an inevitable consequence of the well-established global growth in demand, and the shortage of skilled craftspeople to make them. Polishing entails removing layers of material from the workpiece surface, by virtue of the force exerted by the tool in the presence of an abrasive, slurry, and the resulting frictional coupling. Preston's empirical Law is a widely adopted relationship for estimating material removal rate (MRR, cubic mm/minute), for a given tool-force and surface speed. Therefore, measuring tool force in real-time can be considered the first step towards the ultimate goal of closing the process-metrology loop automatically. With this in view, a separate measurement system called a 'force table' has been developed using six loadcell sensors, as previously reported in Walker et al. (2023) and Darowski et al. (2023).

Load cells are based on flexural units with strain gauges attached, and convert force into a mechanical deflection, and thence into an analogue signal that can be digitised. Price and complexity depend on various factors, including the ingress protection rating (IP), sensitivity, temperature coefficient, lifespan, resolution and absolute accuracy. Load cell measurement systems, like other sensors, are prone to signal interference, limited frequency response, parameter drift, or cross-talk (Piskorowski and Barcinski, 2008). Thus the calibration of load cell systems is required to facilitate monitoring of variables of interest.

When considering the importance of calibration, it is essential to consider the substantial human resources required for the calibration process. Users are often faced with the dilemma of choosing between purchasing an expensive, highly accurate sensor or investing time and resources in calibrating cheaper sensors. Moreover, even expensive sensors may not fully address inherent issues that can affect all sensors due to the system design in which they are installed, such as hysteresis or cross-talk. These system-level factors can impact the performance and accuracy of sensors, regardless of their cost or quality.

In the context of Bonnet Polishing, accurate force measurements are important in order that they can be correlated with the amount of removed material at any given position on the workpiece surface. Furthermore, these forces can be meaningfully linked to the wear of the polishing tool and the condition of the abrasive slurry (typically a suspension of abrasive particles such as cerium oxide in water).

Machine learning (ML) and deep learning, with their ability to automatically model non-linear relationships within data, have emerged as promising candidates for sensor calibration. Oh et al. (2018) and Wang et al. (2020) used a deep neural network to calibrate multi-axial force-torque sensors, whereas Tran et al. (2018) applied maximum likelihood estimation (MLE). Al-Mai and Ahmadi (2022) proposed a novel SSGPR model - state space (SS) model with Gaussian Process Regression (GPR) for calibration of multiaxis, fiber-optic-based force-torque sensors. An artificial neural network was used as well for calibrating a warm-up shift (Tseng et al., 2021). ML and deep learning models have the potential to reduce costs, enhance accuracy, and automate the calibration process.

This paper investigates the feasibility and performance of an ML approach for system calibration of a load-cell based force table, and cross-talk reduction. The performance of deep neural network calibration is evaluated and compared against linear transformation and manual calibration procedures. The data utilized in this study is obtained from a force table constructed by the Laboratory for Ultra Precision Surfaces, operated by the University of Huddersfield at SciTech Daresbury. By utilizing real-world data from the force table, the practical applicability of ML techniques in sensor calibration and cross-talk reduction has been evaluated.

The remainder of this paper is structured as follows: Section 2 provides the background of the ongoing research into material removal rate estimation, involving the force table and highlighting the need for accurate calibration of the sensors. Section 3 describes the experimental setup, including the system design and data collection process. Section 4 presents the data pre-processing stage and Section 5 describes the optimization of a deep learning network (DNN) and its performance compared against a linear regression model and manual calibration results. Finally, Section 6 summarizes the key findings and recommends improvements to the force table.

2. FORCES IN ULTRA-PRECISION BONNET POLISHING

Ultra-precision bonnet polishing and allied processes can achieve nanometer-level accuracy. Whilst CNC machines have released much of the hands-on burden from manufacturing technicians, the process lacks perfect determinism, requiring multiple iterations to achieve the desired surface quality (Walker et al., 2019). With demand growth for optics and scarcity of technicians, the case for automation is well-established but requires a deeper understanding of variables that affect MRR in real-time.

To gain this deeper understanding and develop an accurate model capable of predicting the resulting surface *in real-time*, monitoring of slurry pH, temperature, and particle size distribution is part of the solution, as is monitoring of the CNC machine to give tool positions, rotation, and surface-speed. The axial and lateral components of forces at the tool-workpiece interface present the next logical stage of process monitoring with the aim of establishing a comprehensive model that can predict and optimize the process in real-time (Darowski et al., 2023).

To facilitate this, the bespoke 3-axis force table was mounted on the CNC machine table as shown in Figure 1. The table served as a support for the workpiece during the polishing process. The force table is equipped with six load-cell sensors along the machine x, y, and z axes and this gives sufficient information to compute process torques about x, y, z.

Approaches using force sensors incorporated in polishing using robots have been proposed by (Schneckenburger et al., 2022), but this approach requires interference with the manufacturer's design of the bonnet head structure, hence without proper experience and knowledge might be difficult to achieve. Online measurements of the forces were also used in experimental research on influence functions in (Pan et al., 2019). However, the device measured only the DC component of the force i.e. they are not able to capture dynamic changes in forces in-process.

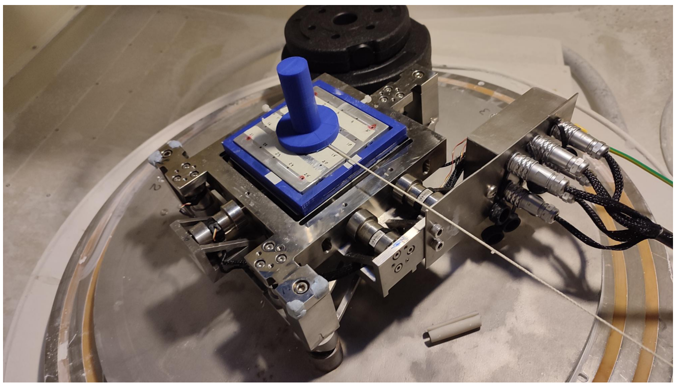

Fig. 1. Experimental setup for force table calibration

3. EXPERIMENTAL SETUP

3.1 Force table

The force table was developed as part of the international collaboration at the University of Huddersfield, UK with the following key design requirements (Walker et al., 2023):

(1) Three orthogonal axes of force measurement.
(2) Forces along any axis must not damage another axis.
(3) Capability of measuring torques and forces.
(4) Long-term drifts and rapid changes are to be measured.
(5) Mechanical overload protection is to be provided.

(6) The first resonant frequency is sufficient to resolve the effects of imperfect sphericity ("tramping") of a rotating polishing bonnet, with a target of four measurements per revolution at 3000 rpm (200 Hz), requiring a first resonant mode of>400 Hz.

The table incorporates one sensor along the horizontal x-axis, two sensors along the horizontal y-axis, and three sensors for the vertical z-axis. Table 1 presents the sensors' maximum compression rating mounted on each axis.

Table 1. Maximum compression rating of the load cells

Axis	No. of Load Cells	Max Compression [lbs]
X	1	25
Y	2	10
Z	3	25

The 6 load cells were connected through the I-Net card cage system and iNet-240 cable to a computer. Labview software was developed to analyze and capture the data from the system. During the initial test, it was established that the force table is extremely prone to line noise (50Hz interference) so a good ground connection is necessary as some 50Hz components were present in the signal under frequency analysis.

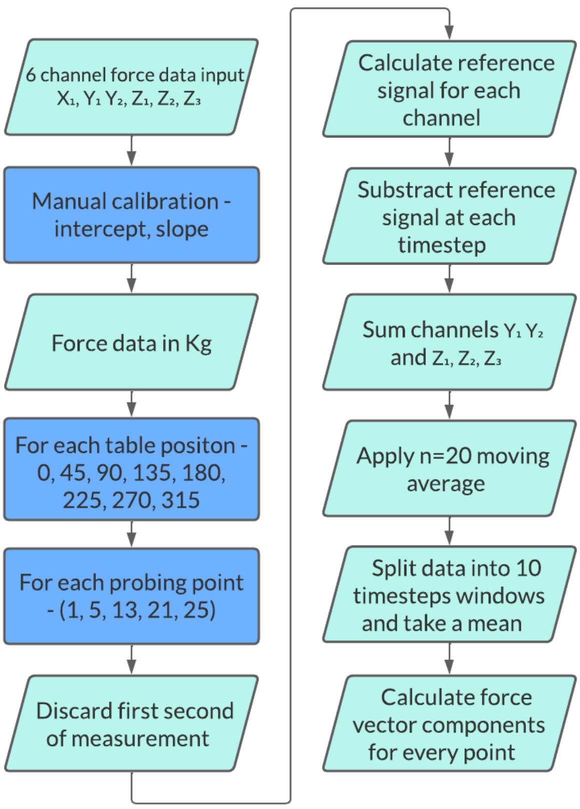

Fig. 2. Data processing steps

3.2 Manual Calibration

A manual calibration was performed as a first step using a pulley and rope system. Each of the six sensors was subject to several load tests in order to calculate the slope

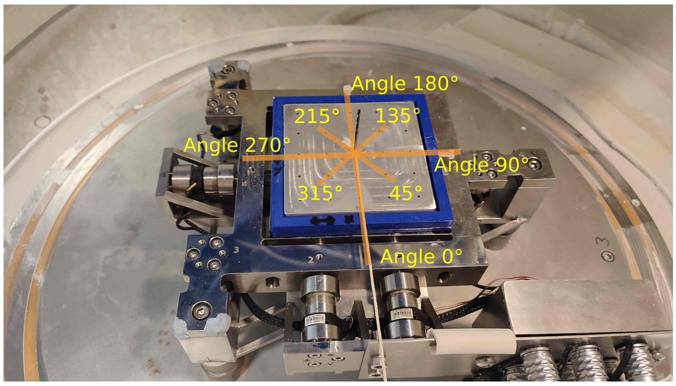

Fig. 3. Sampling angles relative to the table position

and offset coefficients to convert voltage into kilograms of force. The coefficients were implemented directly into the LabVIEW software. Moreover, as a part of the procedure, a midpoint in the sensing range was established. This way the system could determine both the magnitude and direction of the force from a relative change in the reading.

3.3 Data collection

The data collection process involved the use of a pin with a 3D-printed weight-holder. The pin was inserted into a square aluminum plate that contained a grid of uniformly distributed pin holes. To exert controlled forces on the Z axis, weight plates were loaded onto the pin. To apply lateral forces acting on the X, and Y axes, a string was attached at the bottom of the pin, which was then threaded through a pulley. Weights were attached to the string to provide the desired force as illustrated in Figure 1. By adjusting the weights and measuring the corresponding forces on the pin, we were able to collect data on the forces exerted in different directions. Figure 2 illustrates the data collection and processing stages.

Due to the limited clearance of the doors of the CNC doors, the whole table had to be rotated to enable the collection of the forces reading in all directions. However, this presented an additional challenge. The force table design included a cable connecting the table with the data collection system, which exerted a parasitic force on the plate to which it was fixed. This resulted in shifting the baseline signal levels each time the table was rotated. To address this issue, after each position change, we took a new reference signal that was specific to that particular angle position. By doing so, we were able to mitigate the impact of the cable-induced force on the baseline signal levels.

The data were collected at eight unique angles, as illustrated in Figure 3, and five cardinal positions at the aluminum plate across the diagonal axis - four corners and the center. The angles were relative to the starting position and served as a reference for calculating the vector force distributions based on the known distance between the pulley system and the central pinhole as explained in section 4.1.

In order to train an effective model that can closely represent non-linear relationships within the data, the maximum practical coverage of the sampling space was used. In total, 458 unique load-position-angle combinations were recorded, as part of the data collection stage, resulting in 221 unique XYZ load combinations. Figure 4 illustrates the sampling space, where positive and negative values indicate whether the loadcell was 'pulled' or 'pushed'. Each data entry was recorded as a five-second long six channel time-series. This setup allowed us to simulate and measure the forces experienced during the bonnet polishing process.

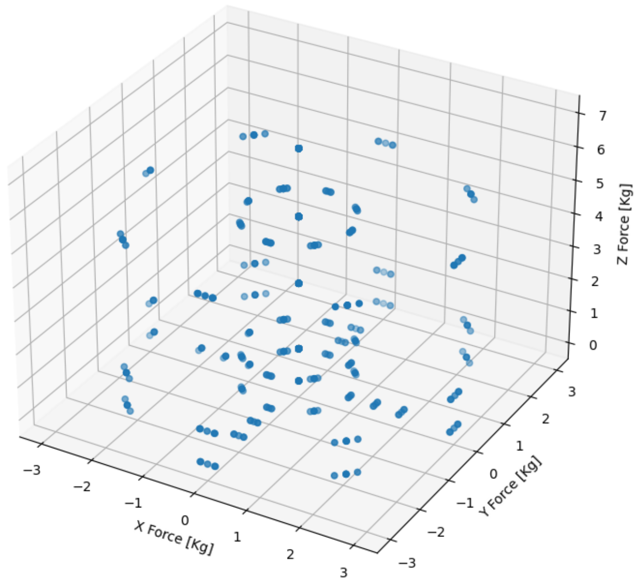

Fig. 4. Sampling space

4. DATA PREPARATION

4.1 Vector force components

As mentioned in section 3.3, each measurement was carried out at a specific load-position-angle combination. The relative angles of the CNC machine table rotation were taken with respect to the center point of the square plate. Loads were exerted on the force table vertically - by loading a weight plate directly onto the pin on the and horizontally on XY axes combined. The weight that was applied horizontally was effectively the resultant force vector of X and Y components. As each axis had to be calibrated separately, X and Y vector components were calculated for each measurement to serve as a ground truth for the model training.

First, the law of cosines was applied to find the angle γ that the resultant force vector made with respect to a given axis.

$$\gamma = \arccos(\frac{a^2 + b^2 + c^2}{2ab}) \quad (1)$$

Next, the angle γ was used to calculate the magnitude of the X and Y force components with respect to a chosen axis.

$$Fx = F * \sin(\gamma) \quad (2)$$

$$Fy = F * \cos(\gamma) \quad (3)$$

Where F is the weight applied through the pulley system. The final results were manually multiplied by ± 1 according to the direction in which the force was applied along the axis.

4.2 Data pre-processing

As described in section 3.3 data was collected as a 5-second long time-series reading from six-channel input. The first half a second of each measurement was discarded due to a systematic error at the start of the measurement resulting in a voltage spike. Each channel was offset by the relative zero-level reading (baseline), where the baseline was calculated by taking an average value of each channel without any load. Subsequently, the channels from the same axis were summed together.

The sensors exhibited a significant amount of noise within a range of 1 kilogram. To mitigate this noise, we applied a 20-point moving average filter with the aim of smoothing the signal. Subsequently, the signal was divided into non-overlapping windows of 10 timesteps, and the average of each window was calculated and assigned a ground truth weight calculated during vector force components.

As a last step the data set was resampled by applying a random undersampler from Imbalanced-learn python toolkit (Lemaître et al., 2017) to ensure equal representation of each of 221 load combinations. This technique involves removing instances of the majority class from the data set to obtain a more balanced distribution.

5. OPTIMIZATION AND EVALUATION

5.1 Architecture and hyper-parameter tuning

Hyper-parameters have a significant impact on training effectiveness in machine learning models (Yu and Zhu, 2020). As there are no hard-written rules regarding the network architecture or selection of hyper-parameters of DNN, usually those decisions are made by testing several combinations. There are several automated search techniques such as grid search, random search, or Bayesian optimization. In this paper, we used a random search with Weights and Biases platform (Biewald, 2020) to optimize five hyper-parameters as presented in table 2. Figure 5 visualizes hyper-parameter values and their respective validation loss score for 100 iterations over the search space. The ten best-performing combinations (models with minimum validation loss) are highlighted in purple.

Optimizer and activation function were selected from a discrete set of specified values whereas batch size and layer size values were drawn from a continuous uniform distribution. The batch size range was selected between 1% to 20% of the training data and layer size between input size (3) and input size to the power of 4 (81).

The lowest validation losses were achieved by the networks that used a hyperbolic tangent function and layer size between 45 and 80 neurons. We did not observe any significant impact on network performance when adjusting batch size, dropout rate, or optimizer.

5.2 Evaluation

Once the optimal combination of the hyper-parameters was identified the network performance was evaluated using k-fold cross-validation with k=5. K-fold validation involves splitting the data set into k equal parts where

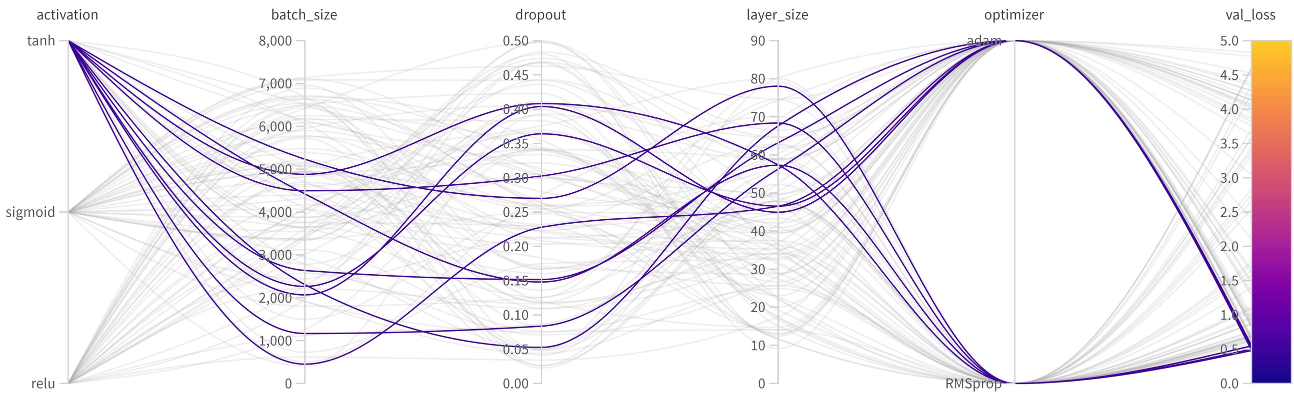

Fig. 5. Visualizing hyperparameter combinations and their validation loss scores (top 10 highlighted)

Table 2. Slurry density and flow rate in a given polishing trial

Hyper-parameter name	Values
Activation	Tanh, Sigmoid, Relu
Batch size	360 - 7200
Layer Size	3 - 81
Optimizer	Adam, RMSprop

one is used for validation and the rest for training. The evaluation was done by computing a mean absolute error (MAE) of the regression out on the previously unseen by the model test data. The results are shown in the table 4.

Table 3. Parameters used in final network training

Parameter	Value
No. hidden layers	2
Layer size	78
Activation	Tanh
Batch size	1024
Dropout	0.2
Optimizer	RMSprop
Epochs	35

The network performance was compared against a linear regression model and manual calibration baseline. The MAE was reduced by 3.4 and 5.4 times for PLSR and ANN respectively. The MAE score of 0.178 is close to the standard deviation (SD) of static signal noise calculated at 0.16.

Table 4. Mean absolute error with 5-fold cross validation

	Mean	SD
Baseline	0.967	0.115
PLSR	0.281	0.013
ANN	0.178	0.012

In the next step, we visually evaluated the model performance by creating an artificial signal, composed of eight concatenated signals (one for each angle) from the test data set given by black curve in Figure 6. Noticeable noise was observed on the X-axis because, unlike the Y and Z axes, only a single sensor is installed along X on the force table. The Y-axis suffered from incorrectly calibrated gain. As ANNs can model nonlinear relationships in the data, they learned to adjust the gain correctly. Z axis exhibited a significant amount of cross-coupling during the initial investigation. The results show that the model is able to improve over the baseline, however, the cross-coupling was not completely eradicated.

6. CONCLUSIONS

In this paper, a machine-learning approach for calibrating load cells mounted on a custom force table has been presented. Moreover, the performance of an artificial neural network, linear regression (partial least squares regression), and manual calibration baseline are compared.

The following recommendations are made for future iterations of the system:

- Improved quality of the load cells: The primary goal of including higher-quality load cells is to reduce the noise that currently hinders the system from detecting small changes in load. Since the typical forces associated with bonnet polishing range from zero to four kilograms, and the noise exhibited in the system is in the range of ± 0.5kg, fine modelling of the surface forces might not be possible.
- Redesigned connector plate: The force table is highly sensitive to any external force. Even a slight change in the load cell cable position can result in a shift in the reference signal. Therefore, an improved placement of the sensor connectors or a wireless data transmission option would significantly improve the reliability of the system.
- Automation of data collection: The manual data collection step is extremely time-consuming due. Exerting the force with the robotic arm or bonnet tool would significantly speed up the process.
- Integration of machine learning: Instead of collecting raw data and subjecting it to multiple preprocessing steps before feeding it through a machine learning model to obtain adjusted force readings, the data pipeline could be significantly simplified by modifying the data acquisition software and deploying a machine learning system online. This approach would allow for almost instantaneous availability of adjusted force measurements following the completion of the procedure.

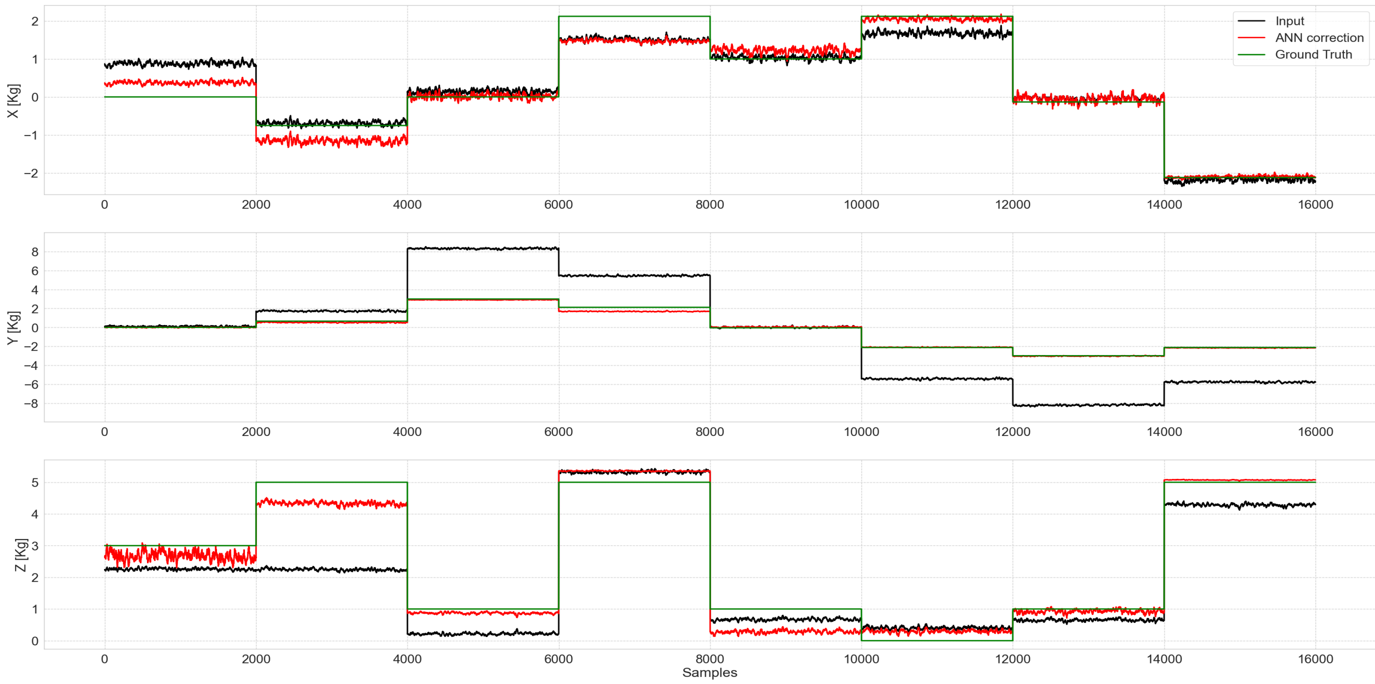

Fig. 6. ANN correction of the artificial signal

As a next step, the system will undergo dynamic testing, i.e. changing weights in a continuous manner. We will also attempt to correct the force over a full polishing run with the developed models and use this to predict the material removal rate.

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