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Data-driven Model for CMM Probe Calibration to Enhance Efficiency and Sustainability

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Abstract

Ensuring precise measurement is critical for manufacturing industries; and a coordinate measuring machine (CMM) is widely used for automated inspection of critical and complex components. But there is a lack of clarity regarding optimal timepoint for CMM probe re-calibration. Too frequent calibrations increase the cost and an uncalibrated CMM probe affects the inspection quality. When to get a CMM probe calibrated is still an open question. It is important to accurately determine the optimal probe re-calibration intervals to mitigate the adverse effects on the quality and the time. This paper presents a novel data-driven approach to predict the optimal timepoint to re-calibrate a CMM probe. The data is collected at various levels to develop, train, and validate the predictive model, which includes numerical and categorical data-frame such as probe usage metrics, probe calibration environmental condition, probe specifications, workpiece data, probe calibrated dimension data and calibration requirement. The research potentially aims to reduce the CMM downtime without compromising the product quality variations that arise from the anomalies/errors related to the probe re-calibration thereby enhancing the inspection efficiency as well as sustainability.

Keywords: Probe Calibration; Data-driven model; Industry 4.0

1.Introduction

In a measurement system (CMM), probe is an integral sensory unit that links the machine and the part intended to be measured [1]. Several types of probing systems have been developed and they can be classified based on the way these devices sense the surfaces – analogue (measuring) probes; touch-trigger probes or tactile probes; continuous scanning probes; and non-contact systems [2]. Weckenmann et al. [1] have provided a systematic overview of the factors influencing the probing systems performance. The authors describe the performance of the probing system based on the operation principle (hard, touch-trigger measurement), measurement strategy (discrete-point data or scanning), main influences (surface characteristics, tip ball diameter, probing force) movement during probing (dynamic or static, active or passive), kinematics (series, parallel or directional response pattern DRP), environmental data (not controlled, controlled, compensation data), and qualification criterion (stylus bending, hertzian stress). The measurement strategy influences the probing systems performance, and it is highly dependent on the user. Chan et al. [3] investigated some of the influencing parameters that affect the accuracy of the coordinate measuring machine with touch- trigger probing system and are as follows:

- The overall length, cross sectional area, and the mechanical properties and mounting of the stylus.
- The approach direction, distance, and speed to the surface.
- The orientation of the workpiece.
- The probing force on the surface.
- The spring back pressure within the probe.
- The sphericity (form) of the stylus tip.
- The contact condition (tip or the master reference sphere contamination)

Probe calibration is performed to determine the effective diameter of the probe tip. The probe tip is generally made of a high wear resistance material such as ruby and the styli/ stem

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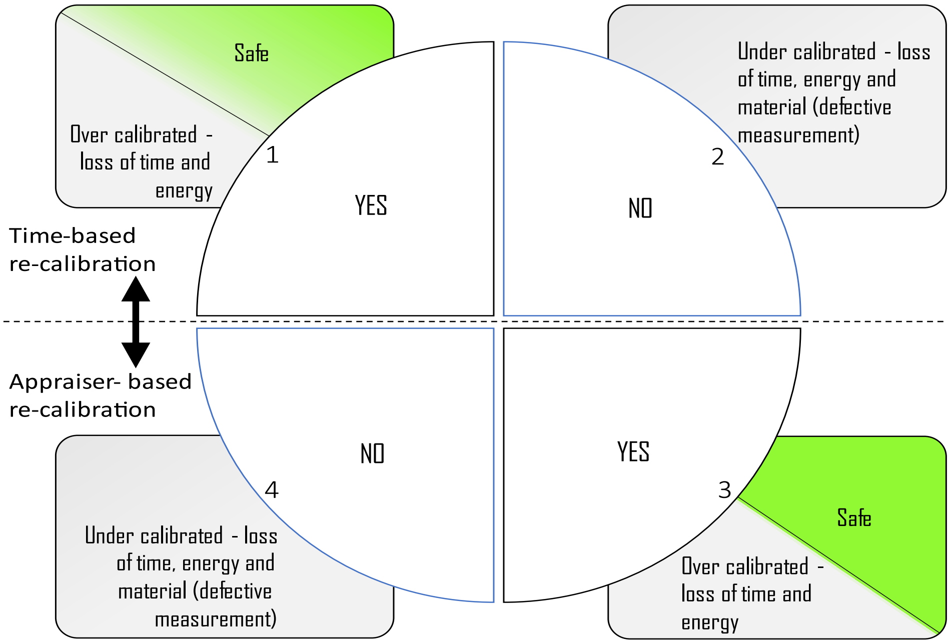

Fig.1 Re-calibration scenarios and their effect

would be a non-magnetic stainless steel, tungsten carbide or carbon fibre. Further the probe is calibrated with a calibrated reference sphere whose certified dimensions are fed into the software while ensuring the artefact and probing system is scrupulously clean. To maintain measurement accuracy and the performance of the probe, 'calibration' or 'probe-qualification' and its re-qualification are highly necessary.

CMMs are utilized in several fields to perform inspection of the part geometry(s), but the utilization rate varies for different organizations. With diverse range of applications, it becomes challenging to determine a fixed frequency of probe re-calibration and pose a question "when to re-calibrate the CMM probe?" that needs to be addressed. Although the industry experts and the machine manufacturers suggest maintaining a scheduled probe re-calibration frequency as a solution, it becomes potentially inadequate when measurement strategy is considered. This is because of lack of specific information regarding the measurement strategies. The factors influencing the performance of the probing system are discussed in literature, but challenges remain when considering the measurement strategy. The potential scenarios and the disadvantages of time-based and appraiser-based re-calibrations are further discussed.

This article aims to address the challenge of the re-calibration frequency of a CMM touch-trigger probe based on the machine learning approach. The studies were conducted to quantitatively standardise the data and develop a data-driven model to predict whether re-calibration is required or not based on the historical data within the organisational limits (use case). The model developed recognises the pattern of usage to decide, which enhances the appraiser's ability, save time, inspection cost, and provide reliable measurement results.

2. Research background

This section discusses the probe errors and performance influencing factors and summarizes the literature and brings out the research gap. Kumar et al. [4] and Wozniak et al. [5] conducted a literature survey on the research area and provided information regarding analysis and estimation of the probe errors. Cauchick and King [6] provided the details of the factors influencing the performance of the probe. It also concludes that the calibration of the probe qualification sphere is important to reduce the uncertainty of the measurement results caused due to the variations in the size and form of the calibration sphere [7]. Further the paper from Renishaw [8] has discussed about the wear comparison of the standard ruby styli and a diamond-styli based on the scanning method to extract the part feature. Summarising the literature, time-based probe calibration technique is commonly suggested, but the limitations of the time-based technique are evident on wider application of CMM.

In an industry where calibration is performed on periodic (daily/weekly/monthly) basis irrespective of whether the calibration was necessary or not. This technique is independent of the machine usage thereby leading to various scenarios as depicted in fig. 1. Figure 1 is the visualisation of the confusion matrix for time-based and appraiser-based re-calibration process in which four scenarios could be witnessed. These four scenarios have their own merits and demerits and the corresponding sustainability challenges as given below:

1. Time demands re-calibration and the probe was calibrated. This can further lead to two scenarios: one, over calibration; two, safe calibration. But this safe calibration is a chance calibration as the re-calibration requirement depends upon the actual condition of the probe, which further depends upon the utilization, environment and the type of products as seen in the table 1. It is safe yet the appraiser is not certain about the need of the calibration. The over calibration scenario leads to unnecessary consumption of energy and time. The clean rooms required for the calibration have a large amount of carbon footprints as their ambient conditions are strictly controlled and the energy requirements for this may

become large particularly in low temperature, high temperature, humid and dusty environment.

2. Time demands re-calibration and the probe was not calibrated – defective measurements (false acceptance / rejection) leading to loss in time, energy and material. Again, this leads to high carbon footprint.
3. Appraiser decides to re-calibrate and the probe was calibrated. It leads to two scenarios. One, over calibration leading to loss in resources (time and energy) as explained above. Two, the calibration is done as and when required by the condition of probe. The present paper develops a technique and decision support system to reach to this scenario always so that over calibration and under calibration can be avoided.
4. Appraiser decides not to re-calibrate and the probe was required to calibrate- under calibration condition leading to defective measurements which leads to higher carbon footprints as in scenario 2.

As per the convention if the ambient conditions are controlled, the probe re-calibration could be avoided as there would be stability in the temperature gradient and humidity, vibration isolation and scrupulously clean inspection room. But in real practice it is highly impractical to maintain all the conditions precisely and yet there may be a requirement of re-calibration due to other external factors unaccounted. Therefore, implementing purely a time-based or purely appraiser-based model incurs loss in several areas as explained above.

Overall, the inference leads to an understanding that the probe qualification is to be done whenever the stylus is newly mounted with an extension, loosened or tightened the probe threads, the probe head is indexed for different configurations, recovering the CMM from accidents or crash, while defining the new probe build. But the research gap to address the challenge of probe re-calibration frequency in an industry to minimise the resources, inspection cost and loss incurred due to faulty inspection remains. Based on the entities driving the whole scenario of the time-point of the probe calibration it could be categorised based on the time and machine usage.

The proposed data-driven model based on the measurement strategy attempts to enhance the appraiser decision relying upon the identified data frame composed of numerical and categorical data that could be utilised to determine whether the re-calibration of the probe is essential or not before the measurement process. The proposed data-driven model attempts to develop the data frame considering the probe usage matrix; the probe calibrated dimension; workpiece material hardness value; and the probe re-calibration status. The underlying patterns in the datasets could aid the appraiser to decide the requirement of re-calibration. A machine learning model approach capable of solving complex problems [9] is most suited for the current problem as the application demands generalisation-make predictions on to unseen data, flexibility-to learn and adapt to the data patterns even without any predefined mathematical functions, scalability-to handle larger and high-dimensional dataset.

3. Research Methodology

The current research adopts a combination of the inspection process using CMM and the general methodology to develop a ML model. The flowchart (fig.2) represents the overview of the workflow of the probe re-calibration prediction model developed. It involves data acquisition, data pre-processing of the dataset, algorithm selection, hyperparameter tuning to enhance the model, training, testing and validation of the model.

3.1. *Data acquisition and pre-processing*

The data acquisition to develop the ML model is cautiously selected as it plays a crucial role in emphasizing the historical

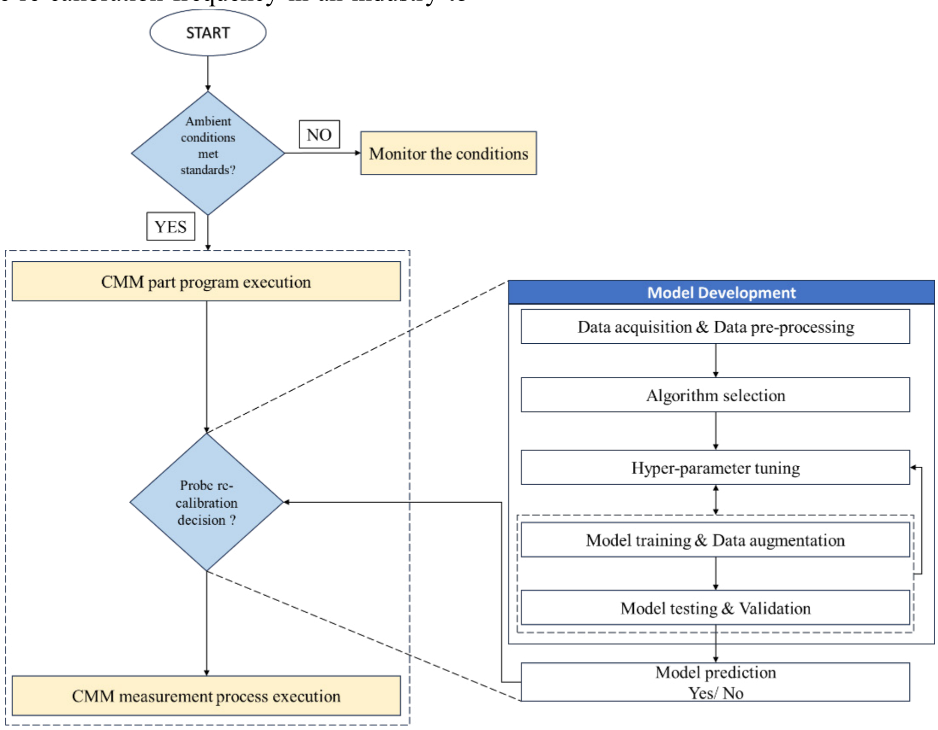

Fig.2 Methodology flow-diagram adopted for the probe re-calibration prediction model

information of the CMM probing system. As discussed in section 2, the probing system data could be obtained from various sources such as the calibration certificate(s), sensors, technical specifications, etc. The dataset could be classified into numerical or categorical, and some among them take up constant values and others are variables. The present research work aims to provide information on the database that account to the requirement of the probe re-calibration (table 1) and further the data class that could be enhanced for various analyses.

Based on the inference drawn from the database table 1, the part of the database is selected to develop the ML model: the number of data points (D_p); probe tip dimension value after each calibration (C_d); workpiece hardness value (H_w). Re-calibration status ($S_{re\text{-}c}$) data is incorporated to develop the model to compute the prediction based on the historical data. The quantified data are from the operations performed by a 2-millimetre diameter synthetic ruby crystal probe and the data is re-structured to suit the requirements as presented in figure 3.

Table 1. Database and necessary details of probe re-calibration

Data Superclass	Data Sub class	Data Acquisition source	Data type	Constant or variable	Remarks
Probe Usage Matrix	Number of data points (discrete data points)	Touch-trigger probe sensor (Kinematic resistive/ strain gauge sensor)	Quantitative	Variable	Total number of data points collected during measurement process was recorded.
	Distance travelled during the measurement process	Scanning probe sensor	Quantitative	Variable	Scanning operation was not performed
	Probe tip dimension value after each calibration	Algorithmic computation	Quantitative	Variable	Considered as part of the dataset
	Measurement speed	Recommended optimal value	Quantitative	Variable	3mm/s set as default
	Measurement force	Manufacturer specified	Quantitative	Constant	/
Probe specification	Stylus type	Manufacturer-technical specification	Qualitative	Constant	/
	Stem material		Qualitative	Constant	
	Holder material		Qualitative	Constant	
	Tip material		Qualitative	Constant	
	Overall length		Quantitative	Constant	
	Ball tip diameter		Quantitative	Constant	
	Thermal expansion coefficient		Quantitative	Constant	
	Extension specifications		Quantitative	Constant	
Ambient condition data during calibration and measurement process	Effective Temperature	Sensors- Traceability certificate/ measurement reports	Quantitative	Assumed to be constant, as the ambient condition is maintained as per the recommended standards prior/ during the calibration/ measurement process	Temperature: (20±4)° C Std
	Humidity		Quantitative		Relative Humidity : (50±10) %
	Vibrations		Quantitative		Vibration data was not considered as part of dataset
	Pressure		Quantitative		Pressure data was not considered as part of dataset
Workpiece data	Material properties	Datasheet/consumer	Quantitative	Variable	Hardness values were considered as part of dataset
	Surface characteristics	Prior knowledge/ Consumer	Quantitative	Variable	/
Reference sphere data	Technical specifications	Manufacturer datasheet	Quantitative & Qualitative	Constant	/
Chaotic conditions	Accidents	Appraiser/ limiting sensors	Quantitative & Qualitative	Variable	Re-calibrations/ replacement of the probe is compulsory depending on the situations
	Other unlikely events			Variable	
Re-calibration Status		Appraiser	Qualitative	Variable	Re-calibration history based on the user experience

	Matreial hardness (HV)	Data point count	Calibrated probe dimension	Re-calibration status
0	25.9	0	1.9887	1
1	25.9	228	1.9887	2
2	25.9	482	1.9887	2
3	25.9	736	1.9887	2
4	25.9	990	1.9887	2
...	...	...	...	...
215	25.9	1346	1.9855	2
216	25.9	1620	1.9855	2
217	25.9	1786	1.9855	2
218	25.9	562	1.9857	1
219	25.9	1124	1.9857	2

220 rows × 4 columns

Fig.3 Data-structure

Data pre-processing is performed to identify the missing values and the data transformation (Feature scaling) is performed on the necessary data columns (D_p, C_d, H_w). Data encoding is performed on S_{re-c} categorical variable to label the data (1- re-calibration was performed, 2- calibration was not performed). Data splitting is performed on the dataset for training, testing and validation in the proportion of 70:15:15 percentage. Further the dataset is passed to the machine learning algorithms to perform the prediction.

3.2. Algorithm selection and Hyperparameter tuning

This section describes the algorithm selection and the hyper-parameter tuning process. Since the current research focuses on the prediction of re-calibration requirement of the CMM probe tip, which is discrete in nature, a supervised classification model is opted for the application. Random Forest classifier, a machine learning algorithm to handle numerical dataset [10] is used to train, test, validate the probe re-calibration prediction model.

A machine learning algorithm's prediction precision and accuracy depends on the hyper-parameters. The maximum depth/level of the decision tree, the maximum number of features, number of trees in the forest, random state, are some of the Random-Forest classifier input parameters. Since these hyper-parameters take up a combination of values to optimize the prediction model, a grid search cross validation method is utilised to fine tune the hyper-parameters to enhance the precision and accuracy of the prediction model.

3.3. Model Training and Data augmentation

The model training is performed on the existing dataset. The classification results obtained were effective for the probe calibration status '2' and highly inefficient for '1' (see figure 4a). It was identified that the data class '1' was imbalanced due to the limited data and the model had bias towards the majority class '2' which led to a misleading accuracy. Further the issue of imbalanced data class was resolved by data augmentation. The oversampling of the minority class was performed by synthetic majority over-sampling technique (SMOTE) [11]. The accuracy and the precision of both the classes were enhanced which made the classification model robust (figure 4b). Although the accuracy before data re-sampling is higher it is not found to be robust, whereas re-sampling increased the robustness of the prediction model.

3.4. Model testing and Validation

The developed classification model is evaluated based on the F1-scores (accuracy) and the precision of the prediction during the training, testing and the validation phase for all the classes. By balancing the data class with data augmentation, the precision of the prediction model is improved, the bias is removed, and the robustness of the prediction model is enhanced.

3.5. Model prediction

The final prediction model could be deployed to perform instantaneous predictions upon entering the user input in an appropriate sequence. The prediction model thus provides a class of the re-calibration status (1- Yes and 2-No) as the output, this output is looped to the measurement process thus enhancing the appraiser decision and further the process could be executed.

4. Discussion and conclusions

A novel data-driven model is developed utilizing random forest machine learning algorithm to perform the prediction of CMM probe re-calibration. Re-calibration of the CMM probe is one of the debatable topics among the quality experts. An appraiser-based decision could be subjective and may incur loss. A time-based re-calibration can lead to losses due to high maintainability cost of the equipment, whereas re-calibration not performed on a long run may increase the chance of false acceptance or rejections of the parts produced. The present developed data-driven prediction approach aids the CMM user as a decision support system.

An informed decision always enhances the ability of the CMM appraiser to perform the inspection process efficiently by improving the utilization of the inspection time, cost, and the human resources, thus contributing to the sustainability.

The proposed model had a limitation of the dataset that enforced the authors to perform data augmentation. The prediction model does not incorporate the factors such as any un-natural events. These factors may require further investigation and quantification of factors is a complex task. The accuracy and reliability of the prediction model can be further enhanced by incorporating more data sources such as scanning data, surface characteristics etc... Overall, the present research attempts to enhance the appraiser decision(s) in re-calibration of the CMM probe which directly impacts the potential outcomes of sustainability in quality management domain.

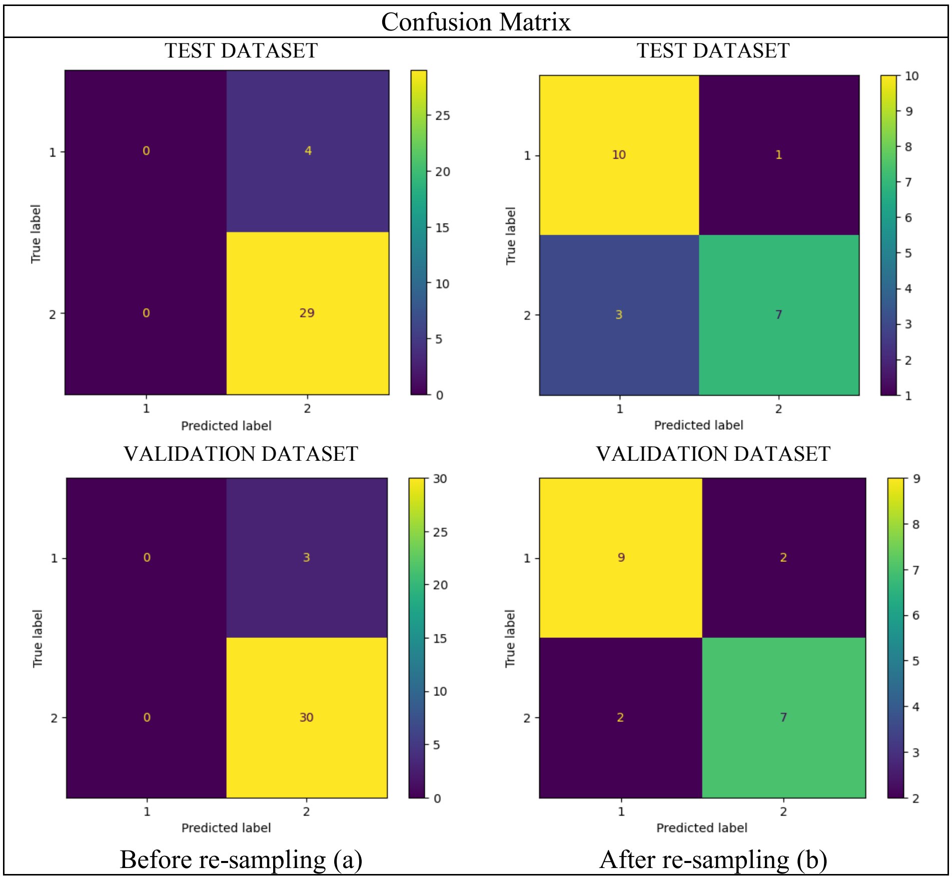

Fig. 4 Confusion matrix for before and after re-sampling data

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