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Intelligent Monitoring of Machining Processes using Gaussian Process Regression and On-Machine Comparator Measurement

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***Abstract*—This paper presents an intelligent machining process monitoring approach with emphasis on On-Machine Comparator Measurement (OMCM) and the effect of remastering on dimensional accuracy. Comparator measurement applies the comparator principle by referencing each measurement to a calibrated master part. In this approach, a mastering procedure is first performed by measuring the calibrated master part to establish a reference. By directly comparing the test part with the master part under repeatability conditions, constant systematic errors in the measurement system are effectively cancelled when determining deviations from the master part. However, the accuracy of this method depends on the time interval between mastering and subsequent production measurements. An experimental study is conducted on a vertical milling centre using non-intrusive sensing. Gaussian Process Regression (GPR) is employed to model Coordinate Measuring Machine (CMM) measured diameter deviations and the associated uncertainty. OMCM is implemented, and the effect of remastering is discussed. The results demonstrate that measurement accuracy deteriorates when remastering is not performed prior to significant system drift, whereas timely remastering improves accuracy and reduces uncertainty, highlighting the critical role of remastering in maintaining measurement reliability with OMCM.**

***Keywords*— Gaussian Process Regression, Intelligent Manufacturing, Machining Processes, On-Machine Comparator Measurement, Process Monitoring and Control**

I. Introduction

Industry 4.0 is driving the evolution of manufacturing through the integration of in-process metrology with emerging technologies, such as digital twins, Cyber-Physical Systems (CPS), the Industrial Internet of Things (IIoT), Artificial Intelligence (AI), big data analytics, and cloud computing [1]. Manufacturing companies face many challenges in achieving full automation and 'lights-out' production in order to make sustainable improvements and stay competitive. To achieve this, the manufacturing sector must develop cutting-edge manufacturing systems that bring significant improvements in the ratio of value-added to non-value-added production time and drive efficiency throughout the manufacturing chain [2].

Machining is a material removal process in which a cutting tool removes material from a workpiece to achieve the required geometry, dimensional accuracy, and surface finish [3]. Such processes rely heavily on manual intervention and post-process inspection, such as Coordinate Measuring Machine (CMM) inspection, to ensure end-product conformance with specified tolerances [4]. Assessing whether a part meets its tolerance specifications using a CMM is inherently subject to error [5]. This is due to incomplete geometric characterisation of workpiece features, as measurements are acquired at a finite number of contact points, as well as to measurement uncertainty associated with the CMM process and its propagation into the computed results [6]. Conformance assessment under measurement uncertainty is therefore a fundamental problem in precision manufacturing, since even small deviations and measurement uncertainties can significantly influence conformity decisions.

Conventional CMMs are primarily used for post-process inspection in stable, temperature-controlled environments to ensure reliable, accurate results. However, such conditions are unlikely to be met on the shop floor, thereby limiting the suitability of CMM-based inspection for effective feedback to the production loop [7]. Increasing demands for in-process feedback have motivated the development of closed-loop process control strategies based on comparator measurements, in which machined parts are measured relative to a calibrated master part of identical nominal geometry. Examples include Renishaw Intelligent Process Control (IPC), which uses Equator™ gauging data to update offsets directly on machine tool controls, thereby compensating for common causes of process instability (e.g., tool wear and thermal drift), as well as approaches based on On-Machine Comparator Measurement (OMCM) [8]. An Equator comparator measurement system can be positioned next to the machine tool on the shop floor, enabling close-to-manufacturing measurement [9]. In contrast, OMCM is performed directly on the machine tool that produced the part, allowing immediate verification without part relocation and potentially reducing reliance on dedicated Coordinate Measuring Systems (CMSs), such as CMMs and automated comparator gauges, for dimensional inspection.

In these comparator-based approaches, a mastering procedure is first performed by measuring the calibrated master part in order to establish a reference state for the measurement system. Subsequent measurements of production parts are then evaluated as relative deviations from this reference. As a result, constant systematic effects associated with the system are largely cancelled through the principle of mastering [10]. However, since comparator measurement relies on relative measurements with respect to the master part, any variation in the system between the time the master part is measured and the time the test part is measured reintroduces error. Regular remastering is therefore required in current industrial practice to maintain measurement accuracy and traceability [11].

Advances in sensing and computing technologies are driving the transition toward Industry 4.0. In this paradigm, real-time monitoring of processes and product quality using machine and deep learning models plays a central role in reducing non-value-adding operations, production bottlenecks, rework, scrap, and cost. To support this objective, a wide range of sensing techniques has been developed and applied in the field of machining process monitoring [12]. However, most existing methods for machining process monitoring, particularly those aimed at product quality prediction, rely on expensive and intrusive sensors such as dynamometers, which limits their industrial applicability [13].

To address these limitations, this work employs OMCM in combination with non-intrusive sensor-based monitoring, supported by Gaussian Process Regression (GPR), as an effective approach for in-process quality monitoring. In this study, attention is given to the influence of remastering on OMCM performance. The proposed framework is designed to support continuous in-process improvement throughout the machining cycle and to reduce the time required to integrate different sensors within a process and across different machines and machining applications. These capabilities directly support Industry 4.0 manufacturing technologies, including the development and deployment of digital twin systems for machining process monitoring and control [14].

Section II presents the experimental work for machining process monitoring and dimensional inspection. Section III describes the GPR modelling approach. Section IV presents and analyses the modelling results. Section V discusses the OMCM and remastering. Section VI draws conclusions and outlines directions for future work.

II. Machining Process Monitoring and Dimensional Inspection

In the High-Value Manufacturing (HVM) sector, manufacturers are increasingly investing in Industry 4.0-enabled digital technologies to enhance quality, productivity, and operational efficiency. This digital transformation is driven in part by the development of intelligent process monitoring and control systems with active learning capabilities for autonomous fault and defect detection within the manufacturing cycle. Current research and industrial efforts therefore focus on providing continuous in-process information on the machining process and the part being manufactured to enable intelligent, unattended machining operations with integrated in-process Quality Assurance (QA). This approach relies on real-time data acquired from multiple sensors, such as dynamometers, accelerometers, and Acoustic Emission (AE) sensors, to continuously monitor the cutting process rather than relying solely on post-process inspection.

Experimental trials were conducted on an EMCO MAXXMILL 350 vertical milling centre to machine holes in EN3B engineering steel blocks under dry cutting conditions. Process variability was introduced using a full factorial design with two factors (feed rate and spindle speed) at three levels each (400, 420, and 440 mm/min; 1592, 1672, and 1752 rev/min). An indexable milling cutter with interchangeable inserts was employed and insert changes were made at irregular intervals to introduce additional process variability. With three replicates of the experimental design, 27 parts were produced, each containing 18 holes machined from both sides of the workpiece, resulting in a total of 486 holes. Of these, 396 holes from 22 parts were utilised in this study. A non-intrusive multi-sensor monitoring system was implemented, consisting of an AE sensor (Vallen Systeme VS150-K3) and uni- and tri-axial accelerometers (PCB 352A60 and PCB 604B31, respectively) [8, 15]. All sensors were mounted on the machine vice using magnetic holders. Signals were acquired simultaneously at a sampling rate of 500 kHz using a National Instruments (NI) Data Acquisition (DAQ) system (cDAQ-9174 USB chassis) equipped with voltage input modules (NI-9222, NI-9223, and NI-9775) selected according to the required sampling rate. Hole diameters were measured using On-Machine Probing (OMP) with a Renishaw OMP 40-2 probe system and a laboratory-based Mitutoyo CMM with a Renishaw SP25M probe system. Four probing points were used per hole in both inspection approaches. A master part was also manufactured for comparator measurements. All experiments were carried out at the University of Portsmouth. The experimental setup is shown in Figs. 1 and 2.

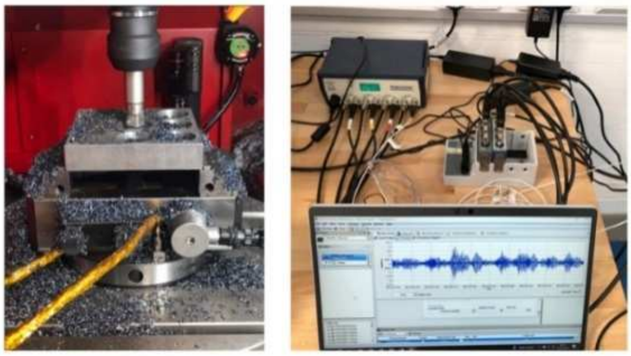

Fig. 1. Machining process equipped with sensors (left) and Data Acquisition hardware and software (right).

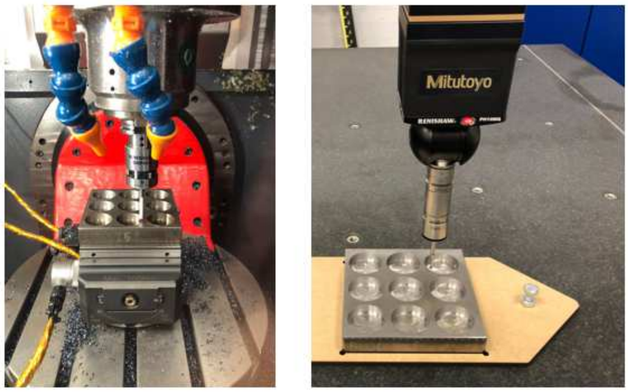

Fig. 2. On-Machine Probing (left) and Coordinate Measuring Machine (right) inspection.

III. Gaussian Process Regression

Consider an input-output training dataset D of m observations, $D = \{(\mathbf{x}_i, h_i)\}_{i=1}^{m}$, generated according to:

$$h_i = f(\mathbf{x}_i) + \epsilon_i, \tag{1}$$

where each $h_i \in \mathbb{R}$ is a scalar target value, $\mathbf{x}_i \in \mathbb{R}^n$ is an n-dimensional input vector, $f(\mathbf{x}_i)$ is an unknown regression function of $\mathbf{x}_i$, and ϵ_i is a random effect described by a Gaussian distribution with zero mean and variance σ_ϵ^2,

$\epsilon_i \sim \mathrm{N}(0, \sigma_\epsilon^2)$. GPR treats f as a random function and places a Gaussian Process (GP) prior over it, defined by a mean function $\mu(\mathbf{x}) = \mathbb{E}\big(f(\mathbf{x})\big)$ and a covariance function (kernel) $k(\mathbf{x}_i, \mathbf{x}_j) = \mathrm{cov}\Big(f(\mathbf{x}_i), f(\mathbf{x}_j)\Big)$, for $i, j = 1, \dots, m$. This is written as [16-17]:

$$f(\mathbf{x}) \sim \mathcal{GP}\left(\mu(\mathbf{x}), k(\mathbf{x}_i, \mathbf{x}_j)\right). \quad (2)$$

It is common to assume a zero mean function and specify a kernel function with hyperparameters $\boldsymbol{\theta}$, which are learned from the training data, $D = \{\mathbf{X}, \boldsymbol{h}\}$. The hyperparameters $\boldsymbol{\theta}$ and the noise variance σ_ϵ^2 are estimated by maximising the log marginal likelihood, $\widehat{\boldsymbol{\theta}}, \hat{\sigma}_\epsilon^2 = \arg\max_{\boldsymbol{\theta}, \sigma_\epsilon^2} \log p(\boldsymbol{h}|\mathbf{X}, \boldsymbol{\theta}, \sigma_\epsilon^2)$, where the log marginal likelihood is:

$$\log p(\boldsymbol{h}|\mathbf{X}, \boldsymbol{\theta}, \sigma_\epsilon^2) =$$

$$-\frac{1}{2}\boldsymbol{h}^{\mathrm{T}}(\boldsymbol{K} + \sigma_\epsilon^2\mathbf{I})^{-1}\boldsymbol{h} - \frac{1}{2}\log|\boldsymbol{K} + \sigma_\epsilon^2\mathbf{I}| - \frac{m}{2}\log 2\pi. \quad (3)$$

Here, $\boldsymbol{K}$ is the $m \times m$ covariance matrix with entries $K_{i,j} = k(\mathbf{x}_i, \mathbf{x}_j)$, and $\mathbf{I}$ is the $m \times m$ identity matrix. For a set of test inputs $\mathbf{X}_*$, the predictive distribution is Gaussian

$$\boldsymbol{f}_*|\mathbf{X}, \boldsymbol{h}, \mathbf{X}_* \sim \mathrm{N}\left(\bar{\boldsymbol{f}}_*, \mathrm{cov}(\boldsymbol{f}_*)\right), \quad (4)$$

with predictive mean $\bar{\boldsymbol{f}}_* = \boldsymbol{K}(\mathbf{X}_*, \mathbf{X})(\boldsymbol{K}(\mathbf{X}, \mathbf{X}) + \sigma_\epsilon^2\mathbf{I})^{-1}\boldsymbol{h}$ and predictive covariance $\mathrm{cov}(\boldsymbol{f}_*) = \boldsymbol{K}(\mathbf{X}_*, \mathbf{X}_*) - \boldsymbol{K}(\mathbf{X}_*, \mathbf{X})(\boldsymbol{K}(\mathbf{X}, \mathbf{X}) + \sigma_\epsilon^2\mathbf{I})^{-1}\boldsymbol{K}(\mathbf{X}, \mathbf{X}_*)$. In this study, the covariance function was defined using the Automatic Relevance Determination-Squared Exponential (ARD-SE) kernel, which extends the SE kernel by introducing a separate length-scale parameter for each predictor variable:

$$k_{ARD-SE}(\mathbf{x}_i, \mathbf{x}_j|\boldsymbol{\theta}) = \sigma_f^2 \exp\left[-\frac{1}{2}\sum_{d=1}^{n}\frac{(\mathrm{x}_{id} - \mathrm{x}_{jd})^2}{\ell_d^2}\right], \quad (5)$$

where $\boldsymbol{\theta} = (\sigma_f, \ell_1, \dots, \ell_n)^{\mathrm{T}}$ denotes the vector of kernel hyperparameters. The parameter σ_f is the signal variance and controls the overall magnitude of the covariance. Each hyperparameter ℓ_d represents the characteristic length-scale associated with the d-th predictor variable and controls the smoothness of the function along that input dimension. Hence, the values of $\ell_1, \dots, \ell_n$ determine the relevance of the corresponding input variables to the output variable. This allows the model to automatically assess the relevance of each predictor. A very large length-scale value indicates that the corresponding predictor has little influence on the response, since the covariance function becomes nearly independent of that predictor. Such predictors may therefore be regarded as weakly informative or irrelevant and could potentially be excluded from the model without degrading predictive performance.

IV. Modelling Results and Analysis

The acquired sensor signals were pre-processed in MATLAB to isolate the cutting-related signal components and improve the signal-to-noise ratio. Subsequently, a range of time-domain features was extracted from each signal, including the mean, standard deviation, Root-Mean-Square (RMS), kurtosis, skewness, shape factor, peak value, clearance factor, crest factor, impulse factor, signal-to-noise ratio, and signal-to-noise-and-distortion ratio. These features capture key characteristics of the machining process, such as signal magnitude or power (e.g., RMS), variability (standard deviation), and higher-order statistical properties (kurtosis and skewness), which are widely used in condition monitoring due to their sensitivity to changes in cutting conditions, tool wear, and process stability. As a result, these features are commonly used as indicators of machining state and are often correlated with machining quality. The extracted process features and the associated cutting parameters were used as input variables to the GPR model and were standardised to zero mean and unit variance prior to model training. The CMM-based product quality metric deviations, $h_{\mathrm{e}} = h_{\mathrm{m}} - \gamma$, were used as the output data, where h_{m} denotes the CMM measured diameter and $\gamma = 35$ mm is the nominal diameter. Fig. 3 shows the histogram of CMM measured diameter deviations with a normal density fit. The sample mean and standard deviation are 0.1288 mm and 0.0638 mm, respectively.

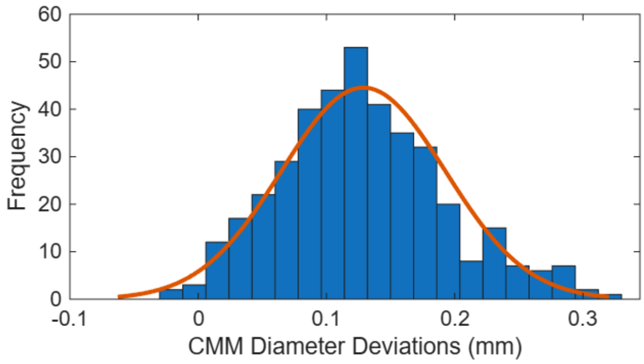

Fig. 3. Histogram of CMM measured diameter deviations with a normal density fit.

The dataset was randomly partitioned into a training set comprising 90% of the samples and an independent test set containing the remaining 10%. A GPR model with an ARD-SE kernel was employed to map the process conditions to the CMM product quality metric deviations. The ARD-SE kernel was used to facilitate the identification of the most relevant covariates. The performance of the model was evaluated using the Root Mean Squared Error (RMSE), which provides an interpretable measure of prediction accuracy. The model achieved an RMSE of 24.36 µm on the training set and 25.42 µm on the test set, indicating consistent predictive performance and good generalisation. Figs. 4 and 5 present the measured versus predicted plots for the training and test sets, respectively. In both cases, the predictions closely follow the measured values and cluster around the 45° reference line, indicating good agreement between predicted and experimental values. The comparable performance between the training and test sets indicates that the GPR model does not exhibit overfitting. Overfitting arises when a model fits noise or irrelevant patterns in the training data, resulting in poor generalisation to unseen samples. Figs. 6 and 7 illustrate the actual diameter deviations alongside the corresponding GPR predictions and the associated 95% prediction intervals, obtained using the ARD-SE kernel, for the training and test sets, respectively. The results demonstrate that the model not only provides accurate point predictions but also produces realistic uncertainty estimates, given the high variability of the measurements. Figs. 8 and 9 show the histograms of the residuals for the training and test sets, respectively, with residuals centred around zero, similarly spread, and approximately Gaussian in distribution.

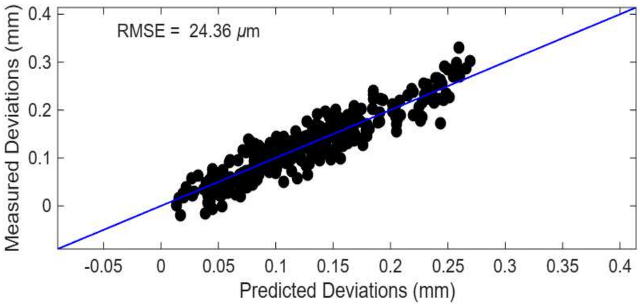

Fig. 4. GPR model performance on the training set.

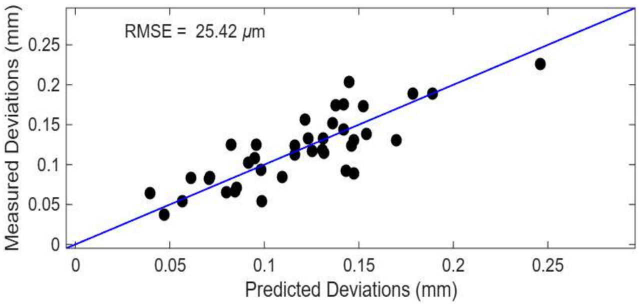

Fig. 5. GPR model performance on the test set.

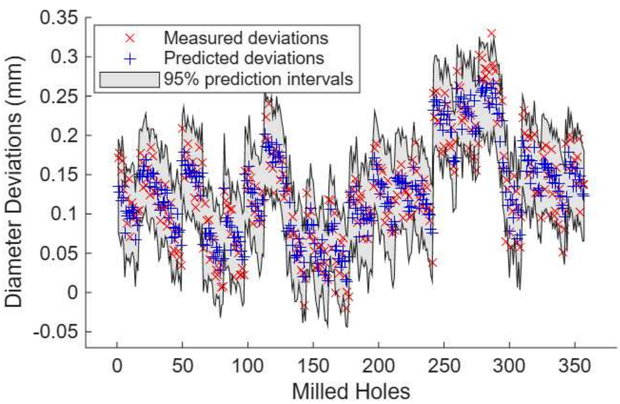

Fig. 6. GPR model prediction results for the training set.

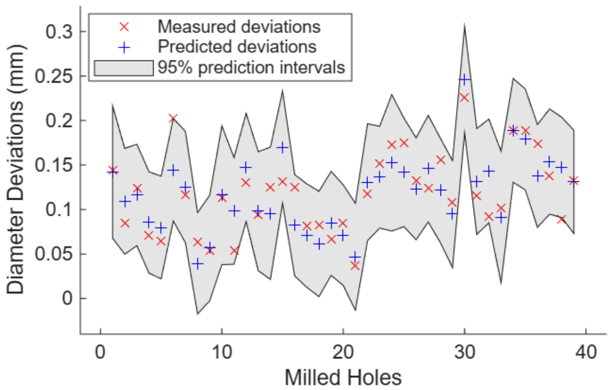

Fig. 7. GPR model prediction results for the test set.

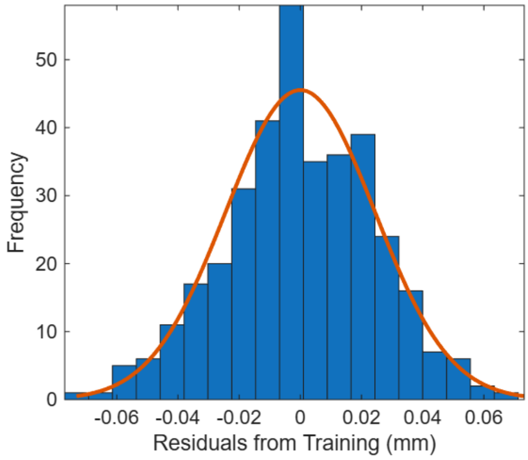

Fig. 8. Histogram of residuals with a normal density fit for the training set.

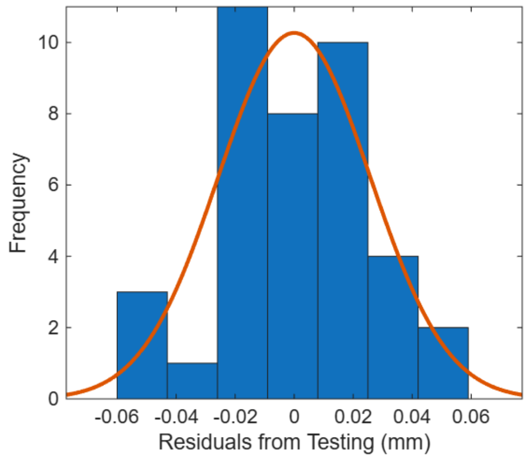

Fig. 9. Histogram of residuals with a normal density fit for the test set.

The performance of the GPR model depends on representative training data and may require retraining when process conditions change, leading to shifts in the data distribution. GPR was selected primarily because it provides probabilistic predictions with quantified uncertainty. This is essential for the proposed framework, where prediction uncertainty is used to support decision-making and determine when additional inspection is required. While other machine learning models may achieve comparable predictive performance, they typically require additional techniques to estimate uncertainty, whereas GPR inherently provides this capability within its probabilistic formulation.

V. On-Machine Comparator Measurement and Remastering

OMP can be employed using the comparator principle to compensate for constant systematic effects associated with the measurement system. In OMCM, a master part with nominally identical geometry to the test parts is first calibrated using a CMM under stable, temperature-controlled conditions, typically at 20 °C, and with the same probing strategy as that applied to the test parts. The calibrated master part is then measured on the machine tool using OMP with the same probing strategy. Let η_{cal} denote the OMP measurement of the master part, and h_{cal} its CMM calibrated value. The systematic error is estimated as the difference between the OMP measured value and the CMM calibrated value of the master part, $c = \eta_{\mathrm{cal}} - h_{\mathrm{cal}}$, or between their respective mean values in the case of repeated measurements. The OMP measurement of each test part is then corrected by subtracting this systematic error, i.e., $\eta_{\mathrm{m}}^* = \eta_{\mathrm{m}} - c$, where η_{m} is the OMP measurement. This procedure enables relative measurement with respect to the master part, thereby reducing the influence of constant systematic errors. The combined uncertainty associated with OMCM should account for: (i) the uncertainty of the CMM calibration of the master part, (ii) the uncertainty associated with the estimation of the systematic error from repeated On-Machine Measurements (OMMs) of the master part, (iii) the uncertainty of the applied measurement procedure, evaluated from repeated measurements of the test parts, and (iv) the uncertainty due to material and manufacturing variations [18].

OMCM improves conventional OMM by using a calibrated master part to compensate for constant systematic errors in the measurement system. Since OMCM relies on the assumption that the systematic error remains constant between the measurement of the master part and the measurement of production parts, any variation in the machine tool, probing system, or environment will reintroduce measurement error. Consequently, periodic remeasurement of the calibrated master part is required to update the correction value and preserve measurement accuracy and traceability. This procedure is commonly referred to as remastering and is an essential requirement of OMCM-based inspection. During remastering, the calibrated master part is remeasured on the machine tool to update the estimate of the systematic error.

OMCM combined with sensor-based monitoring can support timely decision-making within the production loop by providing in-process information on part conformity relative to specified tolerance limits. This capability can reduce the likelihood of producing extended sequences of nonconforming parts and can contribute to improved process stability and productivity. Moreover, performing comparator-based dimensional inspection directly on the machine tool can reduce reliance on external metrology systems, such as CMMs and Equator comparator gauges, for dimensional inspection.

Let Y denote the measurand regarded as a random variable, and let η be a possible value of Y. In Bayesian statistical inference, unknown parameters are modelled as random variables rather than fixed but unknown quantities, as assumed in frequentist inference. This formulation allows the incorporation of prior knowledge through a prior probability distribution. Prior knowledge about the measurand Y is encoded in a prior Probability Density Function (PDF) $g_0(\eta)$. Suppose that OMCM of Y yields the measured quantity value η_{m}^*. According to Bayes' theorem, the posterior PDF $g(\eta|\eta_{\mathrm{m}}^*)$ for Y, given this new information, is proportional to the product of the likelihood function $l(\eta_{\mathrm{m}}^*|\eta)$ and the prior PDF $g_0(\eta)$:

$$g(\eta|\eta_{\mathrm{m}}^*) \propto l(\eta_{\mathrm{m}}^*|\eta) g_0(\eta). \tag{6}$$

If no prior information is available, knowledge of the measurand Y is provided entirely by OMCM. Following the measurement, the probability that Y is no greater than a is given by the Cumulative Distribution Function (CDF), $P(Y \le a|\eta_{\mathrm{m}}^*) = G(a) = \int_{-\infty}^{a} g(\eta|\eta_{\mathrm{m}}^*)\, d\eta$. It follows that the probability p that Y lies within the interval $[a, b]$, with $a < b$, is $p = P(a \le Y \le b|\eta_{\mathrm{m}}^*) = \int_a^b g(\eta|\eta_{\mathrm{m}}^*)\, d\eta = G(b) - G(a)$. Knowledge about Y is therefore represented by the posterior PDF $g(\eta|\eta_{\mathrm{m}}^*)$. Let C denote the set of permissible (conforming) values of Y. The probability of conformance, denoted by p_c, is then defined as $p_c = P(Y \in C|\eta_{\mathrm{m}}^*) = \int_C g(\eta|\eta_{\mathrm{m}}^*)\, d\eta$, and the probability of nonconformance is $\bar{p}_c = 1 - p_c$ [19].

In the proposed framework, the GPR model is first used to predict the product quality characteristic and its associated uncertainty from in-process sensor data. When the predictive uncertainty is sufficiently small and the predicted quality characteristic is clearly within or outside the specified tolerance limits, a direct accept or reject decision can be made based on the GPR output alone. If the GPR prediction exhibits high uncertainty or if the predicted value lies close to the tolerance limits, OMCM can be applied as an intermediate inspection step to reduce uncertainty and update the model predictions using Bayesian statistical inference.

The selective application of OMCM reduces unnecessary inspections while providing rapid verification with reduced measurement uncertainty. In this context, the remastering strategy can be guided by in-process sensor data and data-driven models to maintain measurement accuracy while avoiding unnecessary recalibration, thereby supporting efficient and reliable operation of the measurement system. Figs. 10 and 11 demonstrate the effect of remastering on measurement accuracy for a randomly selected test part, assuming Gaussian distributions and without information fusion. Previous studies have shown that combining OMP-based [20] or OMCM-based [8] product quality estimates with machine learning model predictions can improve the accuracy and robustness of end-product quality estimation. In the absence of remastering (Fig. 10), the OMCM result deviates from the CMM measurement. This deviation is reduced when remastering is applied (Fig. 11), demonstrating a significant improvement in measurement accuracy, with results approaching those obtained by CMM. In practice, remastering can be triggered based on indicators of system drift or increasing model uncertainty. This enables a more informed and adaptive remastering strategy compared to fixed scheduling.

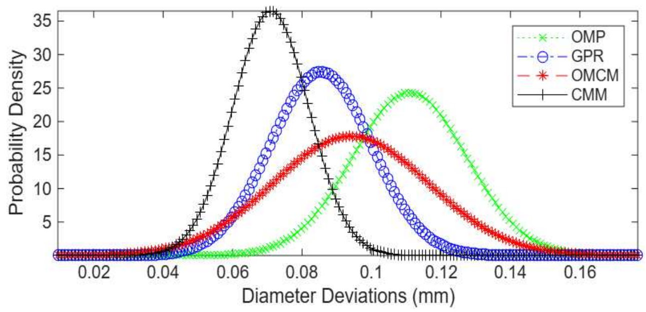

Fig. 10. Gaussian distributions of the measurand (without remastering).

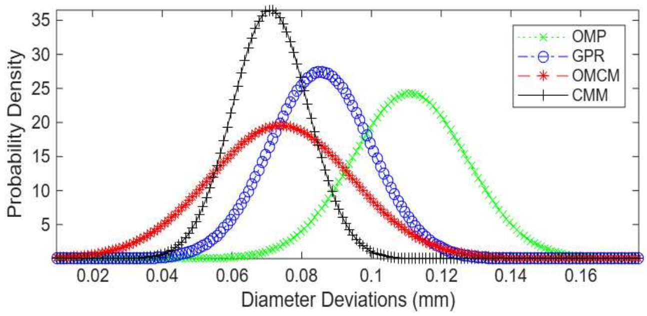

Fig. 11. Gaussian distributions of the measurand (with remastering).

VI. Conclusions and Future Work

This paper has demonstrated an intelligent machining process monitoring framework, with particular focus on OMCM and the influence of remastering on dimensional accuracy. OMCM effectively compensates for constant systematic effects immediately after mastering by referencing measurements to a calibrated master part. However, when remastering is not performed at appropriate intervals, variations in the machine tool, probing system, and environmental conditions reintroduce systematic error. The results therefore confirm that timely remastering is required to preserve the validity and reliability of OMCM-based inspection. By leveraging non-intrusive sensor data and GPR modelling to generate probabilistic predictions of product quality deviations, the proposed framework enables in-process quality assessment, providing predictive insight into process drift and supporting timely decision-making regarding remastering. This reduces reliance on post-process inspection and contributes to more efficient manufacturing operations.

Future work will focus on integrating the proposed framework with digital twin architectures to support intelligent autonomous machining and advanced quality control systems, as well as incorporating Bayesian decision-making approaches for conformity assessment using OMCM. Furthermore, since the experimental validation was conducted using a single machine tool under laboratory machining conditions, additional studies involving different machine tools and extended operating periods are required to further evaluate the scalability, robustness, and industrial applicability of the proposed framework.

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