Available online at www.sciencedirect.com

ScienceDirect

Procedia CIRP 138 (2026) 346–351

www.elsevier.com/locate/procedia

18th CIRP Conference on Intelligent Computation in Manufacturing Engineering

Non-Intrusive Monitoring of Machining Processes for In-Process Product Health Prediction based on Machine Learning

Moschos Papananias

Department of Mechanical and Aerospace Engineering, Brunel University London, Kingston Lane, Uxbridge, Middlesex UB8 3PH, UK

E-mail address: moschos.papananias@brunel.ac.uk

Abstract

Intelligent monitoring systems for machining processes have been gradually developed for various scenarios, such as tool condition monitoring, chatter detection and product health prediction. Existing approaches of monitoring machining processes for quality assurance typically rely on intrusive sensor systems, such as dynamometers and spindle accelerometers, to obtain informative signals for training an algorithm, thus limiting their widespread adoption in industry. This paper presents a non-intrusive machining process monitoring method for in-process product health prediction with uncertainty information using Gaussian Process Regression (GPR). The performance of the proposed method is demonstrated on the prediction of dimensional deviations of a milling process.

Peer-review under responsibility of the scientific committee of the 18th CIRP Conference on Intelligent Computation in Manufacturing Engineering (CIRP ICME '24)

Keywords: Intelligent manufacturing; Machining process monitoring; Non-intrusive instrumentation; Machine learning; Gaussian process regression

1. Introduction

Subtractive machining processes typically involve a sequence of processing operations, such as milling, drilling and grinding, to transform a starting workpiece into a final part with desired geometry and surface finish quality. These operations are influenced by various sources of errors, such as tool wear, thermal errors, geometric and kinematic errors, cutting force induced errors, and fixturing errors [1], [2]. Therefore, in-process and post-process inspections are usually required to determine whether the machined parts meet their design specifications [3]. In addition to inspection processes, machining processes are increasingly instrumented with various sensors, such as force, vibration, power and Acoustic Emission (AE) sensors, to increase machining productivity, improve product quality and reduce manufacturing costs in accordance with Industry 4.0 principles [4]-[6]. The sensing and Data Acquisition (DAQ) hardware, however, must be flexible in configuration and able to provide informative signals without being costly and intrusive to the machining environment for widespread adoption in a variety of production processes. Cutting force measurement systems, such as piezoelectric dynamometers mounted on the machine table, can provide valuable insight into the machining process, but they are costly and not practical for installation on Computer Numerically Controlled (CNC) machining centres. Also, vibration measurement is widely used in machining process monitoring systems. Vibration during machining is most commonly measured using piezoelectric accelerometers mounted on the spindle housing, workpiece, fixture, or other locations. Nevertheless, careful consideration must be given to ensure that the sensing hardware supports the monitoring system objectives, is robust to uncertainties, and is minimally intrusive to the manufacturing process [7].

Peer-review under responsibility of the scientific committee of the 18th CIRP Conference on Intelligent Computation in Manufacturing Engineering (CIRP ICME '24)
10.1016/j.procir.2026.01.060

Machining processes are typically designed and set up by manufacturing engineers and machinists based on their theoretical understanding of the cutting process, off-line simulations, experience and heuristic rules to ensure the safety and quality of machining operations. However, they often suffer from conservative operating conditions, frequent human intervention and re-work, and despite these efforts, the process may still produce parts that are below the required quality standards [8]. Therefore, being able to predict key process variables, such as tool and part condition, as part of the machining cycle can be particularly valuable for zero-defect manufacturing and online machining process control functions without human intervention. Indeed, this can enable intelligent process control schemes with active learning features embedded within the machining cycle through real-time monitoring and diagnosis based on data-driven modelling techniques, such as machine learning, thus improving the productivity and capability of machining processes while reducing extensive in-cycle gauging and post-process inspection. However, machining processes are characterized by uncertain and nonlinear dynamics, multimodal behavior, and randomness. These features coupled with tight tolerances under conditions of high levels of uncertainty inevitably increase the complexity of intelligent machining process monitoring and control technology, and the resource efforts required to accomplish them.

The prediction of part quality from in-process monitoring signals has been a long-held problem in the published literature of machining process monitoring systems [4]-[6]. Existing product health monitoring methods for machining processes typically rely on sensing and DAQ solutions that are neither practical for industrial deployment nor flexible in terms of configuration and extension with further signal sources and different sensors. Therefore, the main contribution of this paper is the development of a dimensional product health monitoring system based on non-intrusive instrumentation and DAQ hardware that is easy to install, configure and extend with plug-and-play simplicity for different applications which require several mixed sensor types and sensor bandwidths. The proposed product health monitoring method can provide valuable data to an intelligent manufacturing metrology informatics system for machining processes in order to complement current machining process control technologies that apply closed-loop metrology feedback to the machining process using post-process inspection data. This will be an important step towards smart manufacturing with practical, cost-saving technology that can verify the machining process without the need to remove the part from the machine tool due to lack of reliable metrological information.

The remainder of the paper is organized as follows: Section 2 presents the background of the research. Section 3 presents the basic theory for the machine learning algorithm employed in this research. Section 4 provides a detailed description of the instrumentation, DAQ system and experiment performed to capture multi-sensor data from a CNC machining process for in-process product health prediction based on machine learning. Section 5 presents and discusses the results obtained by the developed product health monitoring method. Section 6 draws conclusions and provides suggestions for further research.

2. Background

Manufacturing informatics is a thriving field that underpins the digitalization of manufacturing processes and the development of intelligent manufacturing systems with high levels of autonomy through in-process metrology and Artificial Intelligence (AI) technologies. Subtractive machining processes are expected to achieve accurate parts under conditions of uncertainty, with a minimum time delay between machining and inspection operations and with as little operator intervention as possible. On-Machine Probing (OMP) is an established and valuable measurement technology in the machining industry to reduce part variation and improve productivity. Machine tool probes, such as spindle-mounted touch-trigger probes, can be used to set up workpieces before machining and measure them while still clamped in the machine tool as part of the machining cycle for rapid process verification and finished part inspection. This approach can detect sources of process variation and improve product quality [9]. However, due to the fact that the same machine tool is used for both machining and inspection, OMP adds cycle time and is sensitive only to errors that are not common to both processes. The latter is particularly important in practice because OMP will not detect certain errors, including machine tool geometry errors, thermal distortions and errors in thermal corrections applied to the machine tool, which are common to both the machining and the inspection process [10]. Therefore, OMP is typically supplemented by independent accurate measurements with Coordinate Measuring Systems (CMSs), notably Coordinate Measuring Machines (CMMs) and automated comparative gauging systems [11]. Such CMSs can be used with different probe types, such as touch-trigger probes and scanning probes, to assess the stability of the manufacturing process and determine the conformance/non-conformance of manufactured parts to the specified design tolerances with a high level of confidence.

Owing to global competition pressure, today’s manufacturing enterprises increasingly understand the value of data produced by a range of indirect sensors during manufacturing, and the need to constantly improve their decision-making processes by using AI techniques. This is leading to new intelligent machining processes with process control loops and in-process quality assurance technologies that can meet ever tighter tolerances, while reducing human intervention, production times, and the volume of non-value-added processes, such as CMM inspection [3]. Indeed, intelligent process and product health monitoring systems are crucial in facilitating autonomous machining, maintaining the required part quality according to the tolerance specifications, and eliminating the high fixed costs associated with redundant operations when the required tolerance specifications are not achievable. A range of sensors, such as dynamometers, accelerometers, current/power and AE, are available to provide real-time information about the process state. However, the wide range of machine tool configurations and machining processes, each with their own inherent uncertainty and modes of operation, inevitably brings with them abundant implementation challenges. For example, these may include: i) the intrusive nature and high cost of piezoelectric multicomponent dynamometers for cutting force measurement; ii) the practical difficulties, including the accessibility of the machine tool, in measuring spindle and tool vibrations; and iii) the reliability of the sensor frequency bandwidths and the generalization performance of the developed data-driven models, particularly for machining operations that exhibit different performance characteristics and are subject to higher levels of uncertainty, which are difficult to quantify. Therefore, developing a robust product health monitoring system for machining processes using a data-driven approach requires a practical and flexible instrumentation and DAQ system, and a sufficient amount of multi-sensor data, collected under different cutting conditions which occur in practice, for training a learning algorithm.

In the machining process monitoring literature, many research studies have focused on finding input-output mappings using machine learning algorithms for various application areas, such as tool wear [12], chatter vibrations [13], surface metrology parameters [14], and dimensional metrology characteristics, which are the concern of this study. In previous research studies, it has been shown that the volume of dimensional inspections can be reduced significantly by adopting the method of inspection by exception [15] and conformance probability-based part quality monitoring with probabilistic machine learning and information fusion [16], [17]. It should be noted, however, that barriers to the adoption of intelligent product health monitoring systems in a production setting still exist, such as the reduction in robustness and generalization performance of the system due to different process settings, uncontrollable variations and process drift, the cost and practical issues involved in acquiring sensor signals from close to the cutting zone, and the compatibility of the monitoring system with the machining environment. This paper aims to address these barriers by developing and implementing a sensing system, including multiple sensors mounted on the workholding device, and a probabilistic machine learning modelling methodology, which can generalize well to novel machining conditions during industrial deployment. The study in this paper focuses on the modelling of diameter deviations using Gaussian Process Regression (GPR).

3. Gaussian process regression

Gaussian Processes (GPs) are a powerful tool for probabilistic machine learning [18]. Consider a set of m input-output training points $\mathcal{D} = \{\mathbf{X}, \boldsymbol{y}\} = \{(\mathbf{x}_i, y_i)\}_{i=1}^{m}$, where $\mathbf{x}_i \in \mathbb{R}^n$ is an n-dimensional vector of covariates and $y_i \in \mathbb{R}$ is the response variable. Suppose that the response y can be modelled as:

$$y = f(\mathbf{x}) + \epsilon, \tag{1}$$

where $f(\mathbf{x})$ is an unknown regression function of covariates and ϵ represents a random effect, such as measurement noise, with $\epsilon \sim \mathrm{N}(0, \sigma^2)$. The main idea of GPs for learning input-output mappings is to treat the regression function $f(\mathbf{x})$ as a random function and then set up a prior distribution for $f(\mathbf{x})$ using a GP parametrized in terms of a mean function:

$$m(\mathbf{x}) = \mathbb{E}[f(\mathbf{x})], \tag{2}$$

and a covariance function:

$$k(\mathbf{x}, \mathbf{x}') = \mathbb{E}\big[\big(f(\mathbf{x}) - m(\mathbf{x})\big)\big(f(\mathbf{x}') - m(\mathbf{x}')\big)\big]. \tag{3}$$

A GP model is denoted as:

$$f(\mathbf{x}) \sim \mathcal{GP}\big(m(\mathbf{x}), k(\mathbf{x}, \mathbf{x}')\big). \tag{4}$$

Assuming that $f(\mathbf{x})$ is a zero-mean GP and the variance contribution of the vector $\boldsymbol{\epsilon}$ is given by $\sigma^2\boldsymbol{I}$, the joint distribution of the observed response values $\boldsymbol{y}$ and the function values $\boldsymbol{f}$ at novel test inputs $\mathbf{X}_*$, denoted by $\boldsymbol{f}_*$, is as follows:

$$\begin{bmatrix} \boldsymbol{y} \\ \boldsymbol{f}_* \end{bmatrix} \sim \mathrm{N}\left(\mathbf{0}, \begin{bmatrix} K(\mathbf{X}, \mathbf{X}) + \sigma^2\boldsymbol{I} & K(\mathbf{X}, \mathbf{X}_*) \\ K(\mathbf{X}_*, \mathbf{X}) & K(\mathbf{X}_*, \mathbf{X}_*) \end{bmatrix}\right), \tag{5}$$

where $\boldsymbol{I}$ is the $m \times m$ identity matrix, $\mathbf{X}$ is the $m \times n$ matrix of the training inputs, $\mathbf{X}_*$ is the $m_* \times n$ matrix of test inputs, $K(\mathbf{X}, \mathbf{X})$ is the $m \times m$ covariance matrix, and $K(\mathbf{X}, \mathbf{X}_*)$ $K(\mathbf{X}_*, \mathbf{X})$ and $K(\mathbf{X}_*, \mathbf{X}_*)$ denote the matrices of the covariances evaluated at all pairs of training and test points, test and training points, and test points solely, respectively. The covariance function $k(\mathbf{x}, \mathbf{x}')$ can be defined by various kernel functions parametrized in terms of a set of kernel parameters or hyperparameters, $\boldsymbol{\theta}$. Given a training set of input-output data $\mathcal{D}$, the hyperparameters $\boldsymbol{\theta}$ and residual variance σ^2 of the GPR model can be estimated by maximizing the likelihood $p(\boldsymbol{y}|\mathbf{X})$ as a function of $\boldsymbol{\theta}$ and σ^2, i.e., $\widehat{\boldsymbol{\theta}}, \hat{\sigma}^2 = \arg\max_{\boldsymbol{\theta}, \sigma^2} \log p(\boldsymbol{y}|\mathbf{X}, \boldsymbol{\theta}, \sigma^2)$. The log marginal likelihood is as follows:

$$\log p(\boldsymbol{y}|\mathbf{X}, \boldsymbol{\theta}, \sigma^2) = -\frac{1}{2}\boldsymbol{y}^{\mathrm{T}}(K(\mathbf{X}, \mathbf{X}) + \sigma^2\boldsymbol{I})^{-1}\boldsymbol{y} - \frac{1}{2}\log|K(\mathbf{X}, \mathbf{X}) + \sigma^2\boldsymbol{I}| - \frac{m}{2}\log(2\pi). \tag{6}$$

The posterior distribution of $\boldsymbol{f}_*$ at novel test input data $\mathbf{X}_*$ is:

$$\boldsymbol{f}_*|\mathcal{D}, \mathbf{X}_* \sim \mathrm{N}\left(\bar{\boldsymbol{f}}_*, \mathrm{cov}(\boldsymbol{f}_*)\right), \tag{7}$$

with mean function:

$$\bar{\boldsymbol{f}}_* = K(\mathbf{X}_*, \mathbf{X})[K(\mathbf{X}, \mathbf{X}) + \sigma^2\boldsymbol{I}]^{-1}\boldsymbol{y}, \tag{8}$$

and covariance function:

$$\mathrm{cov}(\boldsymbol{f}_*) = K(\mathbf{X}_*, \mathbf{X}_*) - K(\mathbf{X}_*, \mathbf{X})[K(\mathbf{X}, \mathbf{X}) + \sigma^2\boldsymbol{I}]^{-1}K(\mathbf{X}, \mathbf{X}_*). \tag{9}$$

4. Experimental approach and setup

This section presents the development and testing of a non-intrusive and low-cost, multi-sensor monitoring system for machining processes. The sensing hardware included four sensors: a passive piezoelectric AE sensor (Vallen Systeme VS150-K3) with a frequency range of 100-450 kHz, a triaxial accelerometer (PCB 604B31) with a frequency range (±3 dB) of 0.5-5000 Hz, a uniaxial accelerometer (PCB 352A60) with a frequency range (±3 dB) of 5-60000 Hz, and a microphone system (PCB 378C01), which was excluded for this research study. The frequency response of VS150-K3 AE sensor is characterized by a peak at 150 kHz where it exhibits a resonance. The DAQ measurement hardware included a National Instruments (NI) cDAQ-9174 USB chassis with different voltage input modules depending on the required sampling rates (e.g., NI-9222, NI-9223, NI-9775). For signal conditioning, a PCB 482C05 4-channel signal conditioner was used for both accelerometers and an AEP5 pre-amplifier with a DCPL2 decoupling box for the AE sensor. An EMCO MAXXMILL 350 machining center was used in the experimental trials for milling holes under dry and varying process conditions with different feed rates and spindle speeds, including 400, 420 and 440 mm/min, and 1592, 1672 and 1752 rev/min, respectively, such that a wide range of process conditions can be covered. An indexable milling cutter was used with three interchangeable inserts (APKT 1003PDTR-76 IC328), which were replaced at irregular intervals to represent typical machining conditions. EN3B steel was selected as the workpiece material due to its low cost and use in many commercial applications, such as machinery parts and low stress engineering applications. The AE sensor, the triaxial accelerometer, and the high-frequency accelerometer were mounted on the vise, close to the cutting zone, using magnetic holders to derive a portable multi-sensor monitoring solution for machining processes. The NI LabVIEW SignalExpress software was used to acquire all the sensor signals simultaneously at 500 kHz, allowing frequency content up to 250 kHz to be observed during machining. A Mitutoyo CMM, equipped with MCOSMOS software, was employed in a metrology lab to measure each milled hole using the SP25M scanning probe as a touch-trigger probe. In total, 396 diameters were determined for this research study using four contact points each. A general overview of the experimental setup is shown in Fig. 1. The experiment was carried out at the University of Portsmouth. Fig. 2 shows the histogram of CMM measurements with a normal density fit. The sample mean and standard deviation of CMM data are 35.1288 mm and 0.0638 mm, respectively.

5. Modelling results and analysis

The acquired sensor signals were pre-processed in MATLAB to extract only the useful, cutting condition data and improve the signal-to-noise ratio. Then, a variety of features were computed in the time-domain for each signal, particularly 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. The extracted process features were standardized to have a mean of 0 and a standard deviation of 1 prior to training a GPR model. The response data vector $\boldsymbol{\mathscr{y}} = (\mathscr{y}_1, \dots, \mathscr{y}_m)^{\mathrm{T}}$ was obtained by calculating the absolute difference between the CMM measured value, y_i , and the nominal diameter value, $\tilde{y} = 35$ mm, thus $\mathscr{y}_i = |y_i - \tilde{y}|$ for $i = 1, \dots, m$.

One of the most commonly used covariance functions in GPR is the Squared Exponential (SE) covariance function defined by:

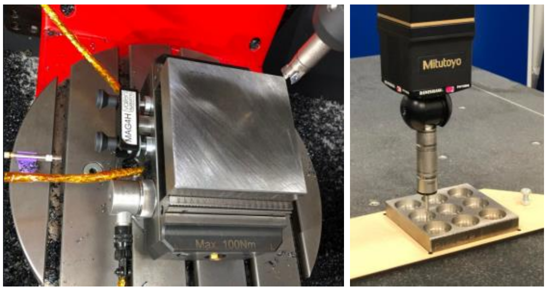
$$k_{SE}(\mathbf{x}, \mathbf{x}') = \sigma_f^2 \exp\left[-\frac{r^2}{2\ell^2}\right], \tag{10}$$

where σ_f and ℓ are both hyperparameters and $r = |\mathbf{x} - \mathbf{x}'|$ is the Euclidean distance between $\mathbf{x}$ and $\mathbf{x}'$. The hyperparameter σ_f is known as the signal standard deviation and controls the magnitude of the function, while the hyperparameter ℓ controls the smoothness of the function and is commonly referred to as the characteristic length-scale. Another important kernel function is the SE with a separate length-scale for each predictor. This is known as the Automatic Relevance Determination-Squared Exponential (ARD-SE) kernel defined by:

$$k_{ARD\ SE}(\mathbf{x}, \mathbf{x}') = \sigma_f^2 \exp\left[-\frac{1}{2}\sum_{j=1}^{n}\frac{\left(\mathrm{x}_j - \mathrm{x}_j'\right)^2}{\ell_j^2}\right]. \tag{11}$$

where the hyperparameters are $\boldsymbol{\theta} = \left(\sigma_f, \ell_1, \dots, \ell_n\right)$. A very large length-scale value implies that the corresponding predictor variable may be irrelevant to the response variable or have little impact on it and may therefore be removed from the model because the covariance function becomes almost independent of that predictor.

The dataset was randomly partitioned into a training set containing 90% of the dataset and a testing set containing the remaining 10% of the dataset. The training set was used to train the learning algorithm and the testing set was used to measure its generalization performance. Two GPR models were obtained to map the extracted process features to the product health diameter metric deviations: a GPR model using the SE kernel function and a GPR model using the ARD-SE kernel function, which assigns an individual weight to each predictor. The Root-Mean-Squared-Error (RMSE) was utilized to evaluate the performance of the models on the training and testing data. As can be seen from the results of Figs. 3-6, both GPR models yield accurate prediction results without overfitting to the training data. Overfitting refers to the phenomenon where the performance of a machine learning algorithm in the training set is misleadingly higher than its performance in an independent test set. Also, comparing the two models, the results suggest that the model with the SE kernel is slightly less accurate in terms of the RMSE than the model with the ARD-SE kernel. Fig. 7 and Fig. 8 show the actual diameter deviations, the predicted diameter deviations and the 95% prediction intervals for the model with the ARD-SE kernel, where it can be seen that the trained model accurately predicts the diameter deviations and provides reasonable uncertainty estimates, given the high variability of the data, for both the training data and the testing data.



(a) (b)

Fig. 1. (a) CNC machining; (b) CMM inspection.

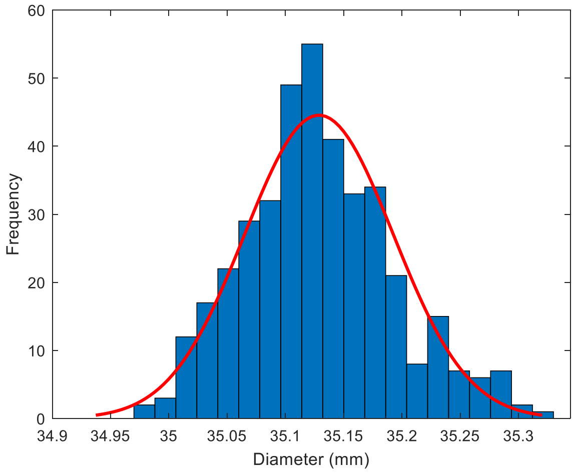


Fig. 2. Histogram of diameter values with a normal density fit.

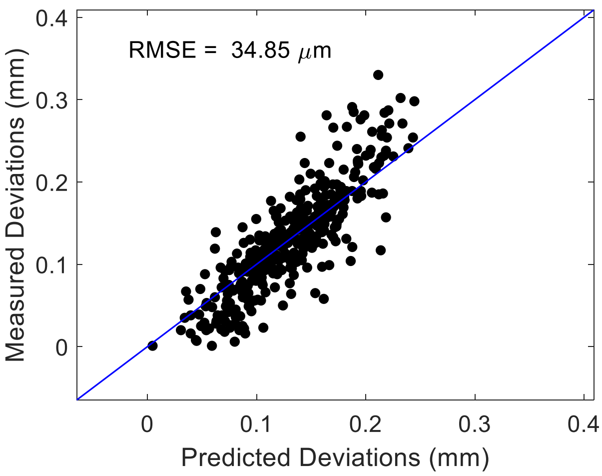


Fig. 3. Performance of the model with the SE kernel on the training data.

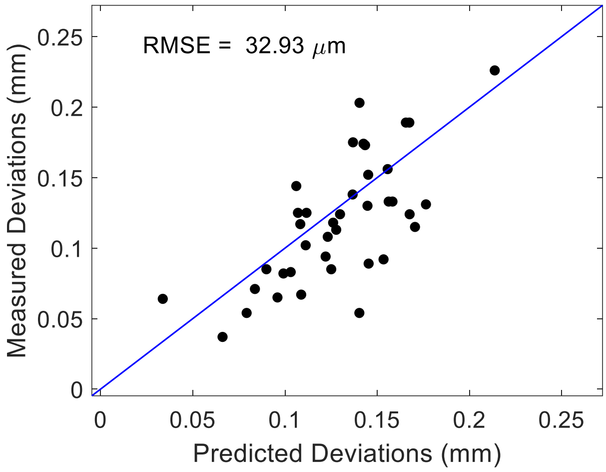


Fig. 4. Performance of the model with the SE kernel on the testing data.

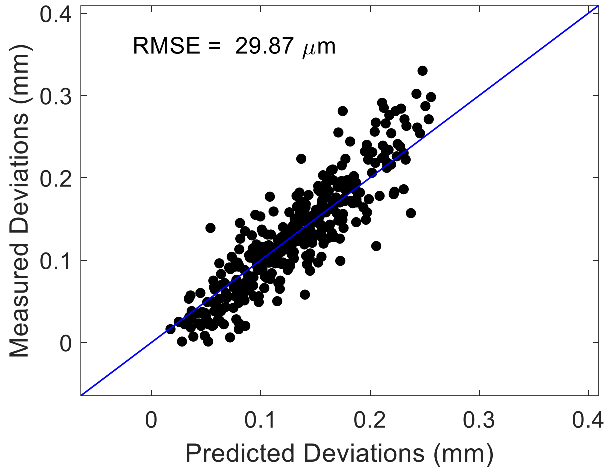


Fig. 5. Performance of the model with the ARD-SE kernel (training).

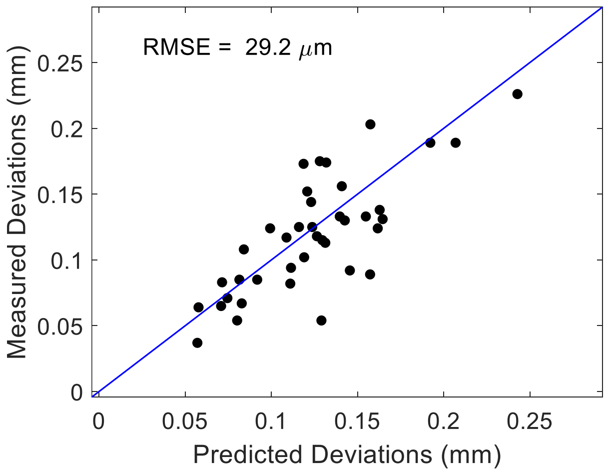


Fig. 6. Performance of the model with the ARD-SE kernel (testing).

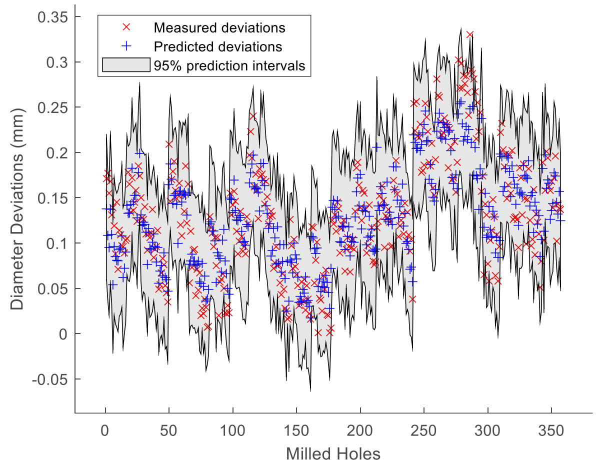


Fig. 7. GPR model with ARD-SE kernel (training dataset).

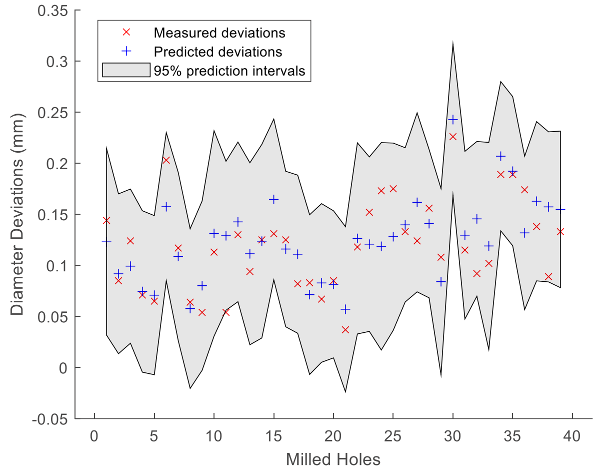


Fig. 8. GPR model with ARD-SE kernel (testing dataset).

6. Conclusions and suggestions for future work

With the advent of Industry 4.0, machining processes are evolving towards even more advanced manufacturing processes that yield higher quality products while giving a reduction in machine downtime, human intervention, scrap and re-work. This paper has presented a probabilistic product health monitoring method for machining processes using non-intrusive instrumentation, including two accelerometers and an AE sensor installed in fixturing, and a modular DAQ system that allows multiple expansions of the monitoring system with additional measurement modules, thus making it easily transferable to other manufacturing processes. The proposed method relies on signal processing and feature extraction algorithms, and a Bayesian non-parametric approach using GPR to provide the in-process condition state of the part and the associated uncertainty. Two GPR models with different kernel functions (SE and ARD-SE) were developed and evaluated using the RMSE performance metric. The GPR model with the ARD-SE kernel provided an improved performance compared to the GPR model with the SE kernel. Future work will look to apply the proposed monitoring method for machining processes to further manufacturing processes, which can benefit from sensor-based monitoring and probabilistic machine learning solutions for a range of monitoring scopes.

Acknowledgements

The author gratefully acknowledges the Royal Society for the grant RGS\R2\222098.

References

[1] Ramesh R, Mannan MA, Poo AN. Error compensation in machine tools—a review: part I: geometric, cutting-force induced and fixture-dependent errors. Int J Mach Tools Manuf 2000;40:1235-56.
[2] Ramesh R, Mannan MA, Poo AN. Error compensation in machine tools—a review: part II: thermal errors. Int J Mach Tools Manuf 2000;40:1257-84.
[3] Papananias M, McLeay TE, Mahfouf M, Kadirkamanathan V. A Bayesian framework to estimate part quality and associated uncertainties in multistage manufacturing. Comput Ind 2019;105:35-47.
[4] Liang SY, Hecker RL, Landers RG. Machining process monitoring and control: the state-of-the-art. J Manuf Sci Eng 2004;126:297-310.
[5] Abellan-Nebot JV, Romero Subirón F. A review of machining monitoring systems based on artificial intelligence process models. Int J Adv Manuf Tech 2010;47:237-57.
[6] Teti R, Jemielniak K, O'Donnell G, Dornfeld D. Advanced monitoring of machining operations. CIRP Annals 2010;59:717-39.
[7] McLeay TE, Turner MS, Worden K. A novel approach to machining process fault detection using unsupervised learning. Proc Inst Mech Eng Pt B: J Eng Manuf 2021;235:1533-42.
[8] McLeay TE. Unsupervised monitoring of machining processes. PhD Thesis. University of Sheffield; 2016.
[9] Groover MP. Automation, production systems, and computer-integrated manufacturing. 4th ed. Pearson; 2015.
[10] Hocken RJ, Pereira PH. Coordinate measuring machines and systems. 2nd ed. CRC Press; 2012.
[11] Papananias M, Fletcher S, Longstaff AP, Forbes AB. Uncertainty evaluation associated with versatile automated gauging influenced by process variations through design of experiments approach. Prec Eng 2017;49:440-55.
[12] Karandikar J, McLeay TE, Turner S, Schmitz T. Tool wear monitoring using naïve Bayes classifiers. Int J Adv Manuf Technol 2015;77:1613-26.
[13] Yesilli MC, Khasawneh FA, Otto A. Chatter detection in turning using machine learning and similarity measures of time series via dynamic time warping. J Manuf Proc 2022;77:190-206.
[14] Obajemu O, Mahfouf M, Papananias M, McLeay TE, Kadirkamanathan V. An interpretable machine learning based approach for process to areal surface metrology informatics. Surf Topogr: Metrol Prop 2021;9:044001.
[15] Papananias M, McLeay TE, Obajemu O, Mahfouf M, Kadirkamanathan V. Inspection by exception: a new machine learning-based approach for multistage manufacturing. Appl Soft Comput 2020;97:106787.
[16] Papananias M, McLeay TE, Mahfouf M, Kadirkamanathan V. A probabilistic framework for product health monitoring in multistage manufacturing using unsupervised artificial neural networks and Gaussian processes. Proc Inst Mech Eng Pt B: J Eng Manuf 2023;237:1295-310.
[17] Papananias M, McLeay TE, Mahfouf M, Kadirkamanathan V. A Bayesian information fusion approach for end product quality estimation using machine learning and on-machine probing. J Manuf Proc 2022;76:475-85.
[18] Rasmussen CE, Williams CKI. Gaussian processes for machine learning. MIT Press; 2006.