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Abstract

Process and product fingerprints are unique process and product characterisation parameters, respectively. They need to be controlled to ensure that manufactured parts are within their specifications to achieve the required functions. The process and product fingerprints are developed to reduce production time and efforts for metrology and process optimisation. The existing methods to identify process and product fingerprints are usually developed for particular machining processes. They are often performed manually which make them time-consuming. In addition, the existing methods are strongly influenced by human decisions. As a result, the fingerprints identified by these methods may have poor correlations with product functionality or the surface quality/dimension characteristics. For the first time, a unique machine learning-based framework is presented in this paper to automatically identify process and product fingerprints. The new framework can shorten fingerprint development time and reduce complexity of process control and product characterisation. A CTER index which is the ratio of correlation and testing error ratio has been proposed to determine the best fingerprint in the framework. The performance of the proposed framework has been validated using data obtained from manufacturing superhydrophobic structures on stainless steel using a nanosecond laser. The correlation of product functional characteristics with fingerprints identified using the proposed framework is observed better than existing fingerprints developed purely based on the physics of the machining process. In addition, the proposed framework can also be used for process optimisation and prediction of functional characteristics/measurement tolerances, which has also been presented in this paper.
Keywords: Smart Manufacturing, Quality Control, Machine Learning, Process Fingerprint, Product Fingerprint

Introduction

A manufactured product's geometrical or functional characteristics depend on many individual process parameters and dependence among them. In addition, surface characterisation parameters for surface roughness and surface integrity directly affect the product functional characteristics. It is very difficult to establish clear links among process control parameters, surface characterisation parameters and product functional characteristics. Hence, the generation of the most sensitive process parameters and surface characterisation parameters that is critical to the functionality of precision components is still an iterative process based on experience [1–3]. The "process/product manufacturing fingerprint" concept has been recently developed to solve this challenge [4]. Process fingerprints refer to unique process parameters which need to be controlled to achieve desired functional/surface characteristics. In contrast, product fingerprints refer to unique surface characterisation parameters which correlate to product functional characteristics [5]. Identification of process and product fingerprints reduces significantly product wastages, metrology and optimisation efforts [6]. The identified fingerprints enable designers to sense customer needs and realise in-line surface quality feedback control in smart manufacturing systems. Many works have been reported for identifications of process and product fingerprints for particular machining process in recent years. For example, Cai et al. [5] developed the process and product fingerprints for the nanosecond pulsed laser ablation process used to fabricate superhydrophobic structures. Baruffi et al. [7], Giannekas et al. [8], and Luca et al. [9] developed process and product fingerprints for the microinjection moulding process. Kuriakose et al. [6], Cannella et al. [10], Bellotti et al. [11], Swiercz et al. [12], and Suárez et al. [13] developed process and product fingerprints for micro extrusion, electro sinter forging, micro EDM drilling, EDM and wire arc additive manufacturing process, respectively.

The aforementioned works for the development of process and product fingerprints have made significant contributions to gain an in-depth understanding of the intrinsic link among process control, surface characterisation and product functionality for particular manufacturing approaches and
products. However, they have some drawbacks. First, the proposed methods for identification of process and product fingerprints are manual and time-consuming. Second, these fingerprints are developed for a particular machining process which would possibly limit their utilisation. Different method needs to be developed if machining process changes which again takes time. Third, the proposed methods of fingerprints identification require prior machine and process knowledge. Fourth, the proposed physics-based process and product fingerprints development methods may not fully learn machining process behaviour. Hence, a poor correlation has been observed between the proposed fingerprints and product functional characteristics under certain conditions.

Machine learning (ML) has the potential to overcome these deficiencies. Recent studies show that machine learning can be used for the automation of different industries [14–19]. This paper will present a machine learning-based framework that can automatically identify the process and product fingerprints. No expert or domain knowledge is required for these fingerprints' identification in the proposed ML framework. The framework only needs few experimental datasets performed for different levels of process parameters for a particular machining process. Hence, the proposed framework is generic and can be applied to any machining process. The framework identifies the important parameters, interaction among these parameters and simultaneous optimisation of parameters affecting the product functionalities. The random forest regression (RFR) based ML model will be used in the proposed framework as it gives good prediction accuracy and is partially interpretable compared to other ML models such as support vector machine (SVM), artificial neural network, etc. The proposed framework can establish the relationship between the fingerprints and product functional characteristics. This relationship will be used to predict product functional performance for a given value of process and surface characterisation parameters. The proposed framework is also used for process optimisation to determine the best level of in-line monitored process control parameters to obtain desired functional performance.

The process parameters, surface characterisation parameters, and functional performance data obtained from the superhydrophobic structures on AISI 316L stainless steel generated by using a nanosecond pulse laser ablated machine have been considered to show the performance of the proposed ML-based
process and product fingerprints development framework. The correlation between the proposed process and product fingerprints with functional performance is carried out to show its significance compared to fingerprints previously developed using the physics of the machining process.

The remainder of this paper is organised as follows: Section 2 discusses the proposed machine learning-based framework for automatic process and product fingerprints identification. Section 3 outlines the experimental setup and data used for proposed framework validation. Process and product fingerprints identified using the proposed framework are discussed in Section 4. In addition, process optimisation and product functional characteristics prediction results are discussed in this section. The conclusion drawn based on the proposed work is outlined in Section 5.

Proposed Framework for Automatic Identifications of Process and Product Fingerprints

Driven by the ever-increasing need for higher integration and performance, high precision three-dimensional products/parts such as head-up displays, micro lens arrays, surveillance cameras, microfluidics and lidar for autonomous vehicles, etc. are designed. Parameter's optimisation and metrology-based quality control is a critical but time-consuming task due to the complexity of these products/parts. A framework is needed which can identify a minimum number of process and surface characterisation parameters to maximise the production efficiency and meet the manufacturing tolerances and functional characteristics. The concepts of process and product fingerprints were recently developed for this purpose.

There could be multiple process parameters that affect product surface morphology and functional characteristics. It becomes difficult to control all process parameters together to fabricate a product within desired specifications. The process parameters that have the highest correlation to product functional characteristics can be identified as process fingerprints. Thus it's become easy to assure quality control in-line by controlling this process fingerprint value [7]. The surface morphology has a significant effect on the functional characteristics of the product. Many surface features need to be measured at the same time to characterise the surface, which is again time-consuming. Hence, a minimum number of measurable surface characterisation parameters with the highest correlation to
product functional characteristics can be identified and termed product fingerprints. The product fingerprints attempt to explain the underlying mechanism of the effect of surface topography on its functional characteristics. The product fingerprint is a bridge to connect process parameters and their functional performance [5]. The product fingerprint is sensitive to process variation settings and, therefore, to the overall product quality.

In previously reported works [5–13,20], the best process/product fingerprints were identified manually. These developed methods are application and process specific, and different material/structure/process/dimensional ranges and class of components may give different process/product fingerprints or their relations. Hence, the manual identification of these fingerprints is time-consuming and requires significant domain knowledge. There is a need to establish a robust and generic framework for automatic identification of process and product fingerprints. Figure 1 shows a machine learning-based framework developed in this study for automatic identification of process and product fingerprints. The proposed framework is divided into five following steps.

(a) Identify product functional performance, process and surface characterisation parameters for a particular machining process.

(b) Perform a few experiments for different levels and combinations of process parameters and measure and record functional performance and surface characterisation parameters value.

(c) Based on the given number of process and surface characterisation parameters, potential candidates for process and product fingerprints will be generated in this step. The individual process/surface characterisation parameters could be process/product fingerprint for a given machining process/system.

\[ y = f(P_{mi}) \]  

\[ y = \{y_1, y_2, \ldots, y_m\}, P \text{ and } i \text{ are product functional characteristics, process/surface characterisation parameters, and index for particular process/surface characterisation parameters, respectively. The index } m \text{ represents the number of experimental datasets available for process/product fingerprint development. Here } f \text{ is a fixed but unknown function of process/surface characterisation parameters } P_{m1}, P_{m2}, \ldots, P_{mi}. \]
However, there could be interaction among these parameters which jointly affects product functional performance. Hence cross terms should also be considered, i.e., products of the first-order process/surface characterisation parameters (e.g. Process Parameter 1 × Process Parameter 2 × ... ... ... Process Parameter n).

\[ y = \prod_{i=1}^{n} f(P_{mi}) \]  

where, \( n \) is the number of process/surface characterisation parameters.

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**Figure 1** Proposed machine learning-based framework for automatic identification of best process and product fingerprints
The introduction of cross-terms allows representing the non-linear functional relationship between product functional characteristics and process/surface characterisation parameters. In this student we want to discover a relationship between process/surface characterisation parameters. In our previous work based on study of physics of machining process [5], best process fingerprint was found in both cross-terms (i.e., Laser Power × Exposure Time) and exponential forms (i.e., \( \text{Pitch}^2 \)). Hence, the exponential forms are adopted in this study as they characterise the machining process better than the linear relation. Either negative or positive exponential (e.g. \( b^{th} \) order) terms for an individual process/surface characterisation parameter may give a better relationship with product functional characteristics rather than a first-order term. In addition, if exponentially forms are not significant for any particular process/surface characterisation parameter, they will be automatically eliminated based on the procedure given in Figure 1.

Considering exponent terms (e.g. \( \text{Product Functional Characteristics} \propto f(\text{Process/Surface Characterization Parameter}^b) \)), Eq. (2) will be represented as:

\[
y = \prod_{i=1}^{n} f(P_{mi}^b)
\]

(3)

where, \( b \) is the exponent value considered for the particular process/surface characterisation parameter. The exponent \( b \) can have any real number values lies between \(-\infty \) and \( \infty \).

Based on given exponent values and cross-term relationships, all possible combinations would be considered during the process and product fingerprint development. These combinations would be \( k^n \); \( k \) (e.g. \( k \) will be five if \( b \) is assumed as -2, -1, 0, 1 and 2) is the number of exponent values considered. These all \( k^n \) would be potential candidates for process and product fingerprints. The number of exponents depends on the exponent upper limit, exponent lower limit and step size, which can be mathematically expressed as

\[
k = \left( \frac{\text{exponent upper limit} - \text{exponent lower limit}}{\text{step size}} \right) + 1
\]

(4)

In summary, while developing fingerprint, we have considered all three effects, i.e., linear \((P_{m1}, P_{m2}, \ldots, P_{mn})\), interaction \((P_{m1} \times P_{m2} \times \ldots \times P_{mn})\) and exponential \((P_{m1}^b \times P_{m2}^b \times \ldots \times P_{mn}^b)\).
Train a machine learning model using the leave one out cross-validation (LOOCV) approach. In the LOOCV approach, a single observation is held out of validation. The machine learning algorithm using the LOOCV approach will be applied for each experiment. All other experimental datasets will be used as training sets. A selected single experiment will be used as a test set. For example, a total of 30 (i.e., \( m \)) experimental datasets are available for model training and validation. If data from experiment 1 is used as a test/validation set, then data from experiments 2 to 30 (i.e., \( m - 1 \)) will be used for model training. Similarly, if data from experiment 2 is used as a test/validation set, then data from experiments 1 and 3 to 30 will be used for model training. This procedure will be repeated thirty times, i.e., equal to the total number of experiment datasets that are available. The LOOCV approach therefore, addresses the drawback of using small training datasets. During model training and testing, the process/product fingerprints candidates will be considered in the model inputs, i.e., independent variables and functional performance would be output, i.e., dependent variable.

Calculate testing error based on the LOOCV approach. The candidate with which the least testing error is observed could be considered the desired process/product fingerprint for the particular machining process. However, correlation among the fingerprints and functional characteristics is also equally important. The fingerprint should have minimum testing error and maximum correlation with product functional characteristics. Hence, the correlation and testing error ratio (i.e., correlation/testing error) (CTER) has been considered for evaluating the process/product fingerprint candidates. The testing error has been calculated based on the following expression.

\[
Testing\,\,error = \frac{Actual\,\,Functional\,\,Characteristics - Predicted\,\,Functional\,\,Characteristics}{Actual\,\,Functional\,\,Characteristics} \times 100
\]

The Pearson correlation coefficient has been used to determine the correlation among fingerprints and functional characteristics. Its mathematical expression is given as:

\[
CC\,(FP, FC) = \frac{|m \sum FP_m FC_m - \sum FP_m \sum FC_m|}{\sqrt{(m \sum FP_m^2 - (\sum FP_m)^2)(m \sum FC_m^2 - (\sum FC_m)^2)}}
\]

where, \( CC, FP, FC \) represents the correlation coefficient, fingerprints and functional characteristic parameter, respectively. The \( FP_m \) and \( FC_m \) represents fingerprint and functional characteristic parameters for the \( m^{th} \) experiment.
The candidate with the highest CTER could be considered the desired process/product fingerprint. The highest CTER may be obtained for the candidate who considers the maximum number of in-line monitored process parameters or surface characterisation parameters. Other candidates have a CTER value almost near to candidates for which the highest CTER has been observed. But they might use fewer parameters than candidates with the highest CTER value. This whole study aims to identify the minimum number of parameters that need to be controlled/measured to reduce metrology and process optimisation efforts. Hence, $0.90 \times$ maximum CTER is chosen as the threshold. The candidates who have CTER above this threshold and use a minimum number of parameters will be selected. The candidate with the highest CTER will be considered the final process/product fingerprint for a particular machining process among the selected candidates.

**Figure 2** RFR model for process and product fingerprints development

The selection of the machine learning model is also very important in the proposed framework. The random forest regression (RFR) model has been considered in this study among the available machine learning models. This model is preferred due to reasons such as high prediction accuracy and better interpretability compares to other ML models such as artificial neural network (ANN), support vector
machine (SVM), etc. [21]. Figure 2 shows the architecture of the RFR model used in this study for process/product fingerprint development. The RFR is an ensemble learning-based method that combines prediction from the $T$ number of decision trees to make more accurate predictions (i.e., $t$ in Figure 2) than individual decision trees [22]. More details about the working of this methodology can be found in [21]. For better understanding, the algorithm for implementation of the proposed ML framework for best process/product identification is given in Table 1.

### Table 1 Algorithm for implementation of the proposed ML-based framework for best process and product fingerprints identification

1. **Generate process/product fingerprint candidates (step $a$, $b$ and $c$)**

   **Input:** A set of data of the form, $y = \{y_1, y_2, \ldots, y_m\}$ (Vector $y$ of size $(m \times 1)$ contains product functional characteristics values)

   $$P = \begin{bmatrix} P_{11} & P_{12} & \cdots & P_{1n} \\ P_{21} & P_{22} & \cdots & P_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ P_{m1} & P_{m2} & \cdots & P_{mn} \end{bmatrix}$$  (Matrix $P$ of size $(m \times n)$ contains values of $n$ process/surface characterisation parameters for $m$ number of experiments)

   **Initialise:** $k = \{b_1, b_2, \ldots, b_k\}$ (Number of exponent values considered)

   $c = k^n$ (Total number of process/product fingerprint candidates)

   Let $d = 0$

   **Output** the fingerprint candidates in matrix $FP$ (Matrix $FP$ of size $(m \times c)$)

   **Iterate for** $j = 1$ to $\text{length}(k) - 1$

   **for** $p = 1$ to $\text{length}(k)$

   $: $

   **for** $q = 1$ to $\text{length}(k)$ (Number of loops will be equal to the number of process/surface characterisation parameters)

   $$FP[m, d + q] = \{P_{m1}^{b_j} \times P_{m2}^{b_p} \times \ldots \times P_{mn}^{b_q}\}$$

   $end$

   $d = d + q$

   $: $

   $end$

2. **Train RFR ML model using LOOCV approach (Input: FP matrix, Output: y) (step $d$)**
Output the error recorded in matrix \( er \) (Matrix \( er \) of size \( [m \times c] \) contains error values for prediction of \( y \) based on unseen \( FP \) values)

3. **Identified Process/Product Fingerprint (step e)**

\[
\text{corr} = \text{correlation}(FP, y) \quad \text{(Correlation among fingerprint candidates and FC)}
\]

\[
\text{CTER} = \text{corr} / er \quad \text{(Calculate CTER for all fingerprint candidates)}
\]

\[
\text{Threshold} = 0.90 \times \text{maximum}(\text{CTER})
\]

\[
\text{SFP} = FP(FP > \text{CTER}) \quad \text{(Selected fingerprints)}
\]

\[
\text{Best selected fingerprint} = \text{SFP(maximum CTER)}
\]

3. **Experiment Details**

Due to properties such as self-cleaning, corrosion resistance, anti-icing and drag reduction, artificial superhydrophobic surfaces have received significant attention in the last few years [23–29]. The nanosecond pulsed laser ablation process has been recently used to create such surfaces. Figure 3 shows a hybrid (micro milling and laser micromachining) ultra-precision machine used to fabricate a superhydrophobic surface on AISI 316L stainless steel. The laser source shown in the experimental setup has a central emission wavelength, average output power and maximum pulse repetition rate of 1064 nm, 20 W and 200 kHz, respectively. All experiments were performed at a constant feed rate of 200 mm/min and pulse repetition rate of 100 kHz.

The process parameters such as laser power, exposure time and pitch are varied to fabricate gaussian holes type patterns on the stainless steel specimen. Superhydrophobic surfaces have a water contact angle larger than 150º and can be measured by a liquid droplet deposited on a smooth surface. A drop shape analyser with a water droplet volume of 5 µL was used to measure functional characteristics, i.e., static contact angle on surfaces. The contact angle was measured three times, and the average value is considered as the final contact angle value. Figure 4 shows the surface morphology and shape of water drops on specimens with a different value of contact angle. The surface morphology has a significant effect on the functional characteristics of the product. Hence, the surface characterisation parameters such as arithmetical mean height (\( Sa \)), maximum height (\( Sz \)), Kurtosis (\( Sku \)), developed interfacial area ratio (\( Sdr \)), root mean square gradient (\( Sdq \)), and \( R_{hy} \) which is defined as the average ratio of maximum height of profile (\( R_z \)) to the mean width of profile elements (\( R_{sm} \)) in [5], were measured using a 3D...
laser scanning confocal microscope. More details about experimental setup, process parameters and surface characterisation definition can be seen in [5].

Figure 3 Experimental setup for hybrid ultra-precision nanosecond laser-ablated machine

![Experimental setup for hybrid ultra-precision nanosecond laser-ablated machine](image)

Figure 4 Surface morphology and shape of water drops on specimens with a different value of contact angle

![Surface morphology and shape of water drops on specimens](image)

Table 2 lists the value of surface characterisation parameters and contact angle obtained for experiments performed at different values of process parameters. All process and surface characterisation parameters are potential candidates for process and product fingerprints. This work aims to develop an automatic
process and product fingerprints framework that is sensitive to the product's functional characteristics, i.e., hydrophobicity of the microstructure surface in the present case.

**Table 2** Process parameters, surface characterisation parameters and corresponding functional characteristics for nanosecond laser machining experiments

<table>
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<tr>
<th>Exp No.</th>
<th>Process Parameters</th>
<th>Surface Characterisation Parameters</th>
<th>Functional Characteristics</th>
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<td></td>
<td>Laser Power (W)</td>
<td>Exposure Time (seconds)</td>
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<td></td>
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<td>Pitch (μm)</td>
<td>Sa (μm)</td>
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### 4. Results and Discussion

In the proposed ML-based framework, the model is trained/tested against candidates for process/product fingerprints (i.e., candidates generated based on process parameters laser power, exposure time and pitch or candidates generated based on surface characterisation parameters $S_a, S_z, S_{dr}, S_{ku}, S_{dq}$ and $R_{hy}$) and functional characteristics, i.e., contact angle in the present case.

#### 4.1 Process and Product Fingerprint Results

For process fingerprint candidates, the number of process parameters are three (i.e., $n = 3$ in Table 1). The number of exponent combinations for these parameters is assumed from -2 (i.e., exponent lower...
limit) to 2 (i.e., exponent upper limit) in a step of 0.25 (-2, -1.75, -1.5, 1.25, -1, -0.75, -0.5, -0.25, 0, 0.25, 0.5, 0.75, 1, 1.25, 1.5, 1.75, 2 (i.e., \( b \) in Table 1); total combinations would be 17 (i.e., \( k = 17 \) in Table 1)). Hence the total number of candidates for process fingerprints would be \( 17^3; 4913 \) (i.e., \( c \) in Table 1). From Table 2, a total of 40 (i.e., \( m \) in Table 1) experimental data points is available for model training and testing. As discussed earlier in Figure 1 and Table 1, the LOOCV approach is used during model development and testing. The ML model is trained and tested against all these 4913 candidates for process fingerprints. Based on the procedure explained in Table 1, the best process fingerprint is observed when the exposure time parameter is excluded from the model and laser power, and pitch parameters are considered in the power of 1 and -0.75, respectively. Hence, the process fingerprint obtained using the proposed ML-based framework is given as

\[
\text{Proposed Process Fingerprint} = \frac{\text{Laser Power}}{\text{Pitch}^{0.75}} \tag{7}
\]

Figure 5(a) shows the variation of the proposed process fingerprint with functional performance, i.e., contact angle. Almost a linear relationship between the proposed process fingerprint and contact angle is observed. This relationship has been quantified using a correlation coefficient, which is obtained as 0.93. This shows that the process fingerprint identified using the ML framework perfectly correlates to the product's functional characteristics. Cai et al. [5] recently developed the process fingerprint \( I_s \) based on physics of the machining process, which is given below

\[
I_s = \frac{\text{Laser Power} \times \text{Exposure Time}}{\text{Pitch}^2} \tag{8}
\]

Figure 5(b) shows the variation of process fingerprint proposed in [5] with functional performance, i.e., contact angle. A poor correlation (i.e., 0.63) of process fingerprint proposed in [5] with product functional characteristics has been observed. In addition, this method of process fingerprint identification is time-consuming and requires domain knowledge. Comparatively, the automatic process fingerprint developed in this work based on the ML framework has an excellent correlation (i.e., 0.93) with product functional characteristics.
Following a similar procedure, the product fingerprint has been identified. From Table 2, for the present experimental study, the number of surface characterisation parameters are six (i.e., $n = 6$ in Table 1). The number of exponent combinations for these parameters is assumed from -2 to 2 in a step of 0.5 (-2, -1.5, -1, -0.5, 0, 0.5, 1, 1.5, 2 (i.e., $b$ in Table 1); total combinations would be 9 (i.e., $k = 9$ in Table 1)). Hence the total number of candidates for product fingerprints would be $9^6; 531441$ (i.e., $c$ in Table 1). Considering these candidates for product fingerprints as input and product functional characteristics as output, the ML model is trained and tested against all these 531441 candidates. Following the procedure given in Table 1, the best product fingerprint is identified when Sa and Sku parameters are excluded from the model and Sz, Sdq, Sdr, and Rhy parameters are considered in the power of 0.5, 1, -2, and 1, respectively. Hence, the product fingerprint obtained using the proposed ML-based framework is given as

$$\text{Proposed Product Fingerprint} = \frac{S_z^{0.5} \times S_{dq} \times R_{hy}}{S_{dr}^2} \quad (9)$$

Figure 6(a) shows the variation of the proposed product fingerprint with functional performance, i.e., contact angle. The product fingerprint identified using the proposed ML framework is almost linearly correlated (i.e., 0.83) to functional performance, i.e., contact angle. The performance of this product fingerprint compares with fingerprint $C_{hy}$ proposed by Cai et al. [5]. The mathematical expression for product fingerprint $R_{hy}$ is given below

**Figure 5** Contact angle variation with process fingerprint (a) proposed in this work (b) proposed in [5]
\[ R_{hy} = \frac{\text{Maximum height of profile}}{\text{Mean width of the profile elements}} \]  \tag{10}

Figure 6(b) shows the variation of product fingerprint proposed in [5] with functional performance, i.e., contact angle. A correlation (i.e., 0.80) of product fingerprint proposed in [5] with product functional characteristics has been observed. Comparatively, the product fingerprint identified using the proposed ML framework is better correlating (i.e., 0.83) to the functional performance. Table 3 reported the correlation of these fingerprints with product functional characteristics.

![Contact angle variation with product fingerprint](image)

**Figure 6** Contact angle variation with product fingerprint (a) proposed in this work (b) proposed in [5]

<table>
<thead>
<tr>
<th>Process Fingerprint</th>
<th>Product Fingerprint</th>
</tr>
</thead>
<tbody>
<tr>
<td>Identified using ML framework</td>
<td>Identified using physics of machining process</td>
</tr>
<tr>
<td>0.93</td>
<td>0.63</td>
</tr>
<tr>
<td>Identified using ML framework</td>
<td>Identified using physics of machining process</td>
</tr>
<tr>
<td>0.83</td>
<td>0.80</td>
</tr>
</tbody>
</table>

**Table 3** Correlation of process and product fingerprints with product functional characteristics

The choice of exponent values, limits and steps sizes are very important for finding the important process and product fingerprints. Based on design of experiment, the total number of process/surface characterisation parameters will be fixed. Higher limits and smaller step sizes will increase the number of potential candidates for process and product fingerprint development. However, the computational time for finding the best fingerprint will increase with the increase in the number of potential candidates.
In general, low-order exponent values are used to describe mechanical process behaviour. The literature shows that a mechanical process that needs to be presented using a more than 2nd order polynomial model is highly unusual. Therefore, in this study, we focused on limits between +2 and -2.

The step size may depend on the number of process/surface characterisation parameters that are available for the development of fingerprint. If a higher number of process/surface characterisation parameters are available, then the step size may be larger and vice versa for a smaller number of process/surface characterisation parameters. This step size process is iterative, and step size can be reduced unless no significant increase in CTER will be observed from the previously considered step size. However, the computation time also needs to be considered while reducing the step size.

For example, in the present study, the number of process parameters are three and a step size of 0.25 is chosen during the development of process fingerprint. The total number of candidates for product fingerprints would be $17^3 \cdot 4913$ (i.e., $k = \left(\frac{2^{-(-2)}}{0.25}\right) + 1 = 17; n = 3$). The computation time for processing 4913 fingerprint candidate using the RFR model is approximately 10.64 minutes. Whereas, if step size is reduced to 0.10, the number of candidates for process fingerprint would become $41^3 = 68921$. The computation time for 68921 candidates would be approximately 2.5 hours. However, with the present experimental data, no significant improvement in CTER value has been observed when the step size varies from 0.25 to 0.1. We therefore choose the step size of 2.5 in this study to consider computational efficiency without comprising accuracy during the development of process fingerprint.

Six surface characterisation parameters and a step size of 0.5 are chosen during the development of product fingerprint. The total number of candidates for product fingerprints would be $9^6 \cdot 531441$ (i.e., $k = \left(\frac{2^{-(-2)}}{0.5}\right) + 1 = 9; n = 6$). The processing time for 531441 fingerprint candidates is approximately 19.19 hours. If the step size is reduced to 0.25, then the number of candidates for product fingerprint would be $17^9 \cdot 24137569$. The computation time for 24137569 fingerprint candidates would be increased to 871.6 hours (i.e., 36.3 days). Again, the step size of 0.5 is chosen to consider computational efficiency without comprising accuracy during the development of product fingerprint.
In summary, the process/product fingerprint developed in this work based on the ML framework has an excellent correlation with product functional characteristics. Figure 7(a) shows the variation of the proposed process fingerprint with the proposed product fingerprint. The proposed process and product fingerprint are almost linearly correlated with a correlation of 0.87. Whereas the process and product fingerprint developed using the same data set based on the physics of the machining process are poorly correlated with a correlation of 0.75.

Figure 7 Process and product fingerprint variation (a) proposed in [5] (b) proposed in this work

In addition, the proposed framework can also be used for optimising the process parameters and predicting the functional characteristics discussed in the following sections.

4.2 Process Optimisation Results

The process and product fingerprints can be used as an objective function in determining the required surface topography and process parameters for the particular functional performance [5]. The choice of
process parameters and their upper and lower limits in design of experiment are based on the expert knowledge that is available in the literature. In the optimisation tool, the upper and lower limit of the process variables can be chosen based on the designed experiment.

The optimisation process in the proposed framework can be attempted to achieve the highest desirability, and different combinations were looked for, maximising/minimising the model functions. In the present study, the process parameters are laser power, exposure time and pitch. However, from Eq. (4), it is found that exposure time has no significant effect on functional characteristics prediction. Hence, only laser power and pitch process parameters need to be controlled to obtain the best optimum functional characteristics.

In this work, the objective of the optimisation study is to find the process parameters values that maximise the contact angle. The lower and upper limit of the process variables is chosen based on the given experiments’ levels. From Table 2, the lower and upper limit for the process variable laser power is chosen as 4 and 20, respectively. At the same time, the lower and upper limit for the process variable pitch is chosen as 70 and 150, respectively.

Figure 8 shows the obtained process parameter optimisation results. From Figure 8, the maximum value for process variable laser power, i.e., 20W and minimum value for process variable pitch, i.e., 70µm, gives the maximum contact angle, i.e., 160 in the present case.
4.3 Prediction of Product Functional Characteristics

The proposed framework can also be used to predict product functional characteristics. Figure 9 shows the prediction results obtained when fingerprints identified using ML framework and physics of machining process are used as input in the proposed RFR model. From Figure 9, the contact angle is predicted more precisely when both process and product fingerprints are identified using the ML framework.

![Graph showing prediction results](image)

**Figure 9** Product functional characteristics prediction results based on (a) process fingerprint (b) product fingerprint

Table 4 report the obtained percentage error in prediction. The percentage error in prediction is 3.23 and 6.86 when process fingerprints identified using the proposed ML framework and physics of the machining process is used as an input, respectively. Whereas the percentage error in prediction is 3.7 and 6.62 when product fingerprints identified using the proposed ML framework and physics of machining process are used, respectively. The lowest error in prediction is obtained when both process and product fingerprints are identified using the proposed ML framework, which shows the significance of chosen process/product fingerprint based on this framework.
Table 4 Percentage error in functional characteristics prediction

<table>
<thead>
<tr>
<th>Using Process Fingerprints</th>
<th>Using Product Fingerprints</th>
</tr>
</thead>
<tbody>
<tr>
<td>Identified using ML framework</td>
<td>Identified using physics of machining process</td>
</tr>
<tr>
<td>3.23</td>
<td>6.86</td>
</tr>
</tbody>
</table>

To evaluate the effectiveness of the proposed RFR model, its model performance has been compared with other machine learning models such as artificial neural network (ANN), support vector machine (SVM) and decision tree (DT). The evaluation metrics used in this study include testing error, identified fingerprint correlation with functional characteristics, CTER (ratio of correlation to testing error), and computational time. Table 5 shows the performance results obtained during the development of process fingerprint. R programming language has been used for developing all ML models. The computational time has been calculated on a computer with an i-7 processor and 32 GB RAM. Table 5 shows that the DT model takes the least computation time than other ML models. However, the fingerprint identified using DT has the highest testing error and least correlation with functional characteristics, hence the least CTER value. The most critical metric for model selection in the present study is CTER. The highest CTER value is obtained when using the RFR model comparing to ANN, SVM, and DT models. Hence, the RFR model is preferred in this study for fingerprint development. In addition, the RFR model is selected over SVM and ANN due to its much interpretability.

Table 5 Comparisons of performance of RFR, ANN, SVM and DT models during the development of process fingerprint

<table>
<thead>
<tr>
<th>Model</th>
<th>RFR</th>
<th>ANN</th>
<th>SVM</th>
<th>DT</th>
<th>Overall</th>
</tr>
</thead>
<tbody>
<tr>
<td>Testing error (%)</td>
<td>3.23</td>
<td>3.5</td>
<td>3.6</td>
<td>3.6</td>
<td>RFR&lt;ANN&lt;SVM/DT</td>
</tr>
<tr>
<td>Correlation</td>
<td>0.93</td>
<td>0.93</td>
<td>0.93</td>
<td>0.87</td>
<td>RFR/ANN/SVM&gt;DT</td>
</tr>
</tbody>
</table>
In summary, this ML-based process/product identification framework is robust and generic. It can identify process/product fingerprints automatically based on a given experimental dataset without any prior domain knowledge.

5. Conclusion

The need for high productivity, high-quality parts and low manufacturing costs leads to the automatisation of machining operation in smart manufacturing systems. This study proposed a unique and robust machine learning-based framework, the first of its kind for automatic identification of process and product fingerprints for smart manufacturing systems. The proposed framework is generic and requires no substantial prior domain knowledge. It can significantly reduce efforts for metrology and production control. Among the available machine learning models, the random forest regression (RFR) methodology has been used in the proposed framework due to the advantages such as high prediction accuracy and better interpretability. The process and product fingerprint identified using the proposed framework is highly correlating to product functional performance with a correlation coefficient of 0.93 and 0.83, respectively. Whereas, correlation of the process and product fingerprints identified based on the physics of the machining process were only 0.63 and 0.80, respectively. In addition, the results have shown that using the proposed framework, the machining process parameters can be optimised to meet the desired functional characteristics or manufacturing tolerances by keeping the in-line monitored parameters within the desired range. The product functional characteristics can also be predicted by the proposed framework with inputs of the in-line monitored process parameters. Based on the identified process and product fingerprints, the proposed framework can predict the product functionalities for the given laser machining process dataset with an error of 3.23% and 3.7%, respectively.
Future work will be focused on the validation of the proposed framework for different of machining processes. As such, a unique health indicator for machine tool health monitoring can be established in the near future based on this framework.

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Data Statement


References


