A study of micromanufacturing process fingerprints in micro-injection moulding for machine learning and Industry 4.0 applications

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Abstract

This paper discusses micromanufacturing process quality proxies called “process fingerprints” in micro-injection moulding for establishing in-line quality assurance and machine learning models for Industry 4.0 applications. Process fingerprints that we present in this study are purely physical proxies of the product quality and need tangible rationale regarding their selection criteria such as sensitivity, cost-effectiveness, and robustness. Proposed methods and selection reasons for process fingerprints are also justified by analysing the temporally collected data with respect to the microreplication efficiency. Extracted process fingerprints were also used in a multiple linear regression scenario where they bring actionable insights for creating traceable and cost-effective supervised machine learning models in challenging micro-injection moulding environments. Multiple linear regression model demonstrated %84 accuracy in predicting the quality of the process, which is significant as far as the extreme process conditions and product features are concerned.

Keywords Micro-injection moulding · Injection moulding · Smart manufacturing · Process monitoring · Data acquisition · Process modelling · Industry 4.0

1 Introduction

Data-rich manufacturing, Internet of Things (IoT), and cloud manufacturing are becoming more and more prominent every day and are addressing challenges such as product quality improvement, cost-effectiveness, and sustainability for many different sectors in industry and research. One big area of interest is the smart manufacturing of high added value micro and nano featured products where different physical phenomena are exploited for various technological applications [1–4]. Manufacture of such products can be costly and demands challenging process environments. Hence, prominent micromanufacturing techniques such as micro-injection moulding (μ IM), micro-milling, hot embossing, and laser

micro-machining should be considered in conjunction with the emergence of data-rich manufacturing approaches for high quality and cost-effectiveness.

Concepts discussed in the literature such as cloud and data-driven smart manufacturing suggest integral and holistic approaches for addressing aforementioned challenges covering a large spectrum of data sources [5, 6]. The characteristics of big manufacturing data vary significantly according to Tao et al., since the sources can include the manufacturing equipment itself, logistics, sales, and end-user behaviours [5]. Another report classifies the data resources as hard, computational, and intellectual where the first one comprises of material and sensor-related information [7]. The authors discuss the challenges in accessing and encapsulation of perceived data such as filtering the irrelevant information. However, no particular method or approach were discussed in the work regarding the filtering or sorting of the collected data. This type of data refinement becomes even more challenging when considering the manufacture of miniature products.

Micro- and nano-scale product manufacture brings in extreme conditions specific to the processes. This makes the implementation of machine learning concepts such as data-

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rich manufacturing even more difficult [2, 8–10]. Such challenging environments and manufacturing methods require very capable data capturing devices and sensors that can record the highly dynamic physical phenomena which results in multiple channels of complex information. Consequently, currently available machine learning and data-rich manufacturing concepts should be scaled down and considered specifically to the individual micromanufacturing methods and data channels as far as the IoT and Industry 4.0 approaches are concerned. Moreover, data-rich manufacturing and characterisation of manufacturing processes can be significant in moving towards sustainable approaches and reducing the negative environmental impacts in relation to carbon footprints, labour, and time costs [11, 12].

We have noticed that another feature of most of the IoT and holistic approaches presented in the literature so far is that the manufacturing systems are treated as black box type of complex entities which is usually a prerequisite as reported by Wang et al. [6]. The authors acknowledge that the interpretation of this complex information is a challenge and should be addressed by manufacturing engineers. Therefore, smart manufacturing approaches can benefit from interrogation of process physics and dynamic aspects of the processes for increasing efficiency and overall quality of the products. These aspects can be modelled, and the knowledge extracted can help in identifying the data types to include in the models and which to discard. This can be achieved only if tangible, relatively easy to process and filter, yet effective quality or fail proxies which are extracted from the physical process data in terms of product dimensions or functionality.

In-line process monitoring has been used rigorously for product development, quality assessment, and fault detection in a variety of micromanufacturing processes [13]. Our group has been a pioneer in implementing real-time monitoring solutions for μ IM processes in the last 2 decades by attaching extensive sensor technologies on the machinery [2, 14–16]. μ IM associated data is highly dynamical and are obtained from state-of-the-art measurement devices. Moreover, the big data collected from μ IM conforms to the 4V rule presented by Liu et al. where value, velocity, variety, and volume of the data were emphasised which makes μ IM an excellent case study for smart manufacturing of products with high margins [17]. The challenge lies at the interpretation of μ IM data collected from the state-of-the-art sensors attached to the machinery, similar to the other reports based on big data usage in manufacturing. Metternich et al. discussed a guideline for data source selection in manufacturing processes [18]. A pool of potential data sources is presented in the work for a machine tool which is based on expert views. Process dynamics-related variables such as spindle current, spindle temperature, and image sensors are included; however, no detailed information is given regarding the selection reasons of these process features for the algorithms they implemented.

In the present work, we demonstrate micromanufacturing quality proxies so-called process fingerprints (PF) which can be extracted from the data collected from μ IM cycles for identifying patterns in the complex, multi-channelled data. As opposed to the reports available, we provide and discuss the required rationale for selection of such PFs and their physical interpretations. This approach can also by-pass a number of filtering or data sorting steps, since the selected quality proxies are well-thought and closely linked to the products in the first place. We believe that this systematic extraction of information patterns using process fingerprinting is essential for deep learning and smart manufacturing applications. After the manufacturing runs, products containing micro-features are inspected using off-line methods for the analysis of relationships between the part quality and PFs. As the last step of the study, PFs are also channelled into a multiple linear regression (MLR) method for the assessment of their suitability for inline quality assurance procedures, indirect measurement methods, and machine learning applications. An overview of our systematic approach is given in Fig. 1.

2 Process fingerprints in micro-injection moulding

PFs are distinct features of the captured data from a manufacturing process that can provide valuable information regarding the product quality. The data being discussed in the present work come from the sensors attached to the μ IM equipment and change dramatically within a machine cycle over time. We believe that it is of crucial importance to be able to understand the physical meanings and characteristics of the quality proxies before proposing any machine learning approaches or quality prediction models for state-of-the-art μ IM processes. PFs can be peak values, derivatives, or integral values of the data channels that are calculated or detected at specific intervals.

In the following, we provide details regarding the μ IM process and the data sources used in this work whilst discussing multiple data channels. Then, we classify the PFs according to their comparison methods and propose three different groups, namely standard, derived, and comparative PFs.

2.1 Process data collection in μ IM

The manufacturing equipment used in this work is a state-of-the-art μ IM machine (Wittmann-Battenfeld Micropower 15) which can be considered a scaled down version of regular injection moulding machines. However, the process itself is highly dynamic and dominated by various physical phenomena at the micro-scale due to the challenges in replicating extremely small mould cavities, providing components with only a few mg in masses for specific applications [19]. The details of the μ IM process for thermoplastics are discussed elsewhere [14, 20].

Fig. 1 Schematic showing the steps of the study involving the extraction of process fingerprints and establishment of multiple linear regression models

The main consideration in controlling a μ IM cavity filling process is to monitor the injection pressure (P_i) that is being recorded from a built-in strain gauge sensor (X-Sensors XB 120-1500) attached at the back of the injection piston which conveys the plasticised thermoplastic material. Another force sensor (Kistler 9210AA) is attached to the mould tool for recording cavity pressure (P_c) for each moulded part. The details of this sensor attachment is similar to our previous work in which the sensor was located at the back of an ejector pin towards the end of the moulding cavity [2]. P_c has been proved to be a very valuable data channel which can directly represent the quality of the micromoulded products as reported by several authors [8, 21]. The third data channel consists of the information coming from the encoder of the injection piston position which is readily available on the machine. The position data of the injection unit or the piston is also very important since this data is prone to the various physical processes such as friction and expansion. This makes this data channel capable of capturing cycle to cycle variations. These three data channels are connected to an ethernet network interface (National Instruments – cDAQ – 9185), and a custom-

built LabVIEW code was created for capturing the multi-channelled data for each cycle. Data acquisition has been synchronised using a common trigger signal coming from the machine. Figure 2 shows the multi-channelled process data collected from a μ IM cycle showing the main characteristics of the process.

Fig. 2 Multi-channelled process data collected from a single μ IM cycle

The multi-channelled process data taken from a μIM cycle are characterised by two important stages. The first one is the injection phase which occurs in the vicinity of $t = 6.5$ s where the molten polymer is injected to the mould cavity by the piston movement. This phase is characterised by the peaks in P_i and P_c curves. The second feature of interest in the graph is the packing phase which can be traced with the constant piston position just after $t = 6.5$ s. In the following, a brief information regarding the moulded product will be given, and individual PFs that can be an indicator of moulding quality will be extracted from the multi-channelled data with different approaches.

2.2 Part design and process details

The product used in the present study is based on a 0.5-mm-thick circular disc shape with 17 mm diameter which accommodates an array of microneedle cavities in 6×6 configuration in a μIM tool as discussed in our previous study [2, 22]. The quality proxy of the moulded products in this work has been defined as the microreplication efficiency of the microneedle features (M_μ) obtained from each part or manufacturing cycle. M_μ has been calculated by measuring the average microneedle height by using a telecentric optical machine vision system for one sample and dividing it by the average cavity depth of the needles on the mould insert which is $912 \mu\text{m}$. This results in M_μ values between 0 and 1 where 1 would correspond to a fully replicated array of microneedle protrusions from the substrate. The conical structures of the needles provided necessary draft angles in the ejection stages of the moulding, and 3-dimensional warpage or deformations were found to be negligible from process variation perspective. Approximately 200 mg shot size has been used for the moulding of the parts. This shot size and high-cooling rates allowed the process to reach a steady state after few cycles. P20 grade tool steel also provided sufficient mechanical strength to the mould tool which makes the mould deformation insignificant during the process.

A commercial acrylonitrile butadiene styrene (ABS) polymer resin (CYCOLAC - HMG94MD, Sabic) was used. This particular thermoplastic material is suitable for thin-walled medical parts manufacture with superior flow capabilities and relatively low shrinkage (%0.5–0.8 [23]). The processing conditions given in Table 1 have been used for experimentation. Packing pressure is applied on the moulded parts just

after the switch-over point, from velocity to pressure controlled regime for shrinkage compensation. One of the important considerations in process conditions is the mould temperature, where 3 different values were used, namely 50, 60, and 70°C . Twenty parts have been collected for each mould temperature and process data were recorded. Process fingerprints are studied for all 3 mould temperatures in a global approach for simplifying the assessments. At least 10 parts have been discarded for making sure that the temperature gradients and frictional affects are avoided while collecting the samples.

2.3 Standard process fingerprints (sPFs)

The sPFs are quality indicators that do not require any alterations to the data channel and can be extracted directly for each μIM cycle. One sPF has been selected from each data channel mentioned in Fig. 2. Maximum injection pressure value ($P_{i\text{-max}}$) has been taken as a PF representing the peak value of the injection pressure data (Fig. 3a). This particular FP gives insight regarding the deceleration of the injection piston after hitting a certain pressure threshold that can be affected by several phenomena during the process such as viscosity of the material and friction. Maximum cavity pressure value ($P_{c\text{-max}}$) has been extracted from cavity pressure data in a similar fashion to $P_{i\text{-max}}$. Intuitively, it can be stated that the cavity pressure is a more sensitive measurement than the P_i because of the measurement's proximity to micro-features due to its location in the cavity.

The 3rd PF has been extracted from the encoder data of the injection piston position where the amount of packing (Δx) has been calculated for each cycle after the injection unit decelerates. Δx is a measure of shrinkage compensation during the packing phase and can provide useful insights regarding the packing dynamics. Figure 3 is a zoomed-in version of Fig. 2 where the details for extracting sPFs are shown. The differences in the scales for Fig. 3 a and b show the important features of data channels. For instance, the packing behaviour and the resolution limit of the encoder can be seen, which is approximately $60 \mu\text{m}$ (see Fig. 3b).

2.4 Derived process fingerprints (dPFs)

The first derivatives of the pressure measurements and how they are sustained in the data channels shown in Fig. 2 might also be of interest for detecting cycle to cycle variations.

Table 1 Process parameters used in μIM experiments

Melt temperature ($^\circ\text{C}$)	Mould temperature ($^\circ\text{C}$)	Injection velocity (mm/s)	Switch-over pressure (bar)	Packing pressure (bar)	Packing duration (s)
235	50, 60, and 70	400	700	750	7.5

Fig. 3 Extraction of sPFs. **a** Graph indicating the P_{i-max} and P_{c-max} values taken from a cycle; **b** graph showing the details regarding the position data taken from the encoder and how the Δx values were calculated.

Notice that the same data were used for both graphs with different scales to show the important features

Derivatives and integrals within certain intervals were considered PFs for capturing these aspects of the data. For instance, the first derivative of cavity pressure data has been calculated (Fig. 4). Data taken from 3 random cycles in Fig. 4 show that the rate of increase during the injection varies considerably during the cycles. The rate of change in cavity pressure data can provide insights regarding the flow and hence the replication capability of the molten polymer. Thus, the maximum rate of cavity pressure increase ($[dP_c/dt]_{max}$) has been selected as a dPF.

Pressure sustained during at any stage of μ IM is of importance and can be a reliable process quality indicator [8, 22, 24]. Viscosity of a polymer can be considered as resistance to flow, and higher viscosities result in bigger pressure drops in

polymer processing. The viscosity of the polymers and hence the pressure sustained in the cavity during μ IM can differ significantly due to the extreme process conditions such as shear heating effects [25]. Lower viscosities during the moulding process will result in better replication of micro-features. Hence, pressure curves taken from μ IM can be integrated within certain intervals, and this property can be quantified for quality indication. For this purpose, P_i and P_c data that has been integrated in the vicinity of the pressure peaks and values have been taken as dPFs, namely $\int P_i$ and $\int P_c$. The integrations have been carried out within a 100 ms interval from the peak value towards the pressure decay using a numerical integration based on the functions present in the LabVIEW package. This calculation has been schematically depicted in

Fig. 4 Graphs depicting the first derivative of P_c data. $[dP_c/dt]_{max}$ values taken from 3 random cycles have been used for presenting the dramatic differences in FP values

Fig. 5 for P_i . The calculation for P_c was done in a similar way and omitted for preventing redundancy.

2.5 Comparative process fingerprints (cPFs)

Another way of extracting process quality proxies is to analyse the samples comparatively for being able to quantify the deviations. Initial analysis showed that only cavity pressure measurements are suitable for doing such a comparative analysis. The following steps were used for extracting comparative process fingerprints (cPFs), and the method is also depicted in a graphical format in Fig. 6:

- i. The best sample in terms of microreplication efficiency (M_{μ}) was determined, and the whole cavity pressure data of this particular sample has been taken as a reference point.
- ii. Cavity pressure data of all samples were subtracted from the “golden sample” mentioned in i. to quantify the deviance from the product with ideal quality.
- iii. Numerical integration has been applied to the resultant curves in ii. to quantify a deviation measure ($\Delta(t)$). Different integration ranges were used for determining the most relevant part of the data. Δ_{all} is the fingerprint representing the integration of the whole curve for 15 s, whereas $\Delta_{1.5s}$ and Δ_{3s} capture the dramatic increase and decays in $\Delta(t)$ in 1.5 and 3 s time intervals (see Fig. 6b), respectively.

Previous work in the literature covered how the process quality indicators could change according to the process parameters such as melt temperature, mould temperature, injection speed, and holding pressure [19, 20]. It was demonstrated that both process and quality proxies were dependent on the processing conditions. However, a cycle by cycle analysis has been missing in the literature with respect to characterising the dimensional features of the products. Moreover, the process

Fig. 5 Injection pressure data showing the calculation of the integral value for P_i

quality indicators or fingerprints can be changed significantly when a smaller or bigger mould cavity used. This changes the cooling rates, temperatures, and pressure measurements completely. For filling this gap in the literature, an approach based on cycle by cycle monitoring of the process fingerprints has been adopted.

These 9 process quality indicators or PFs are summarised in Table 2. They are extracted for each 60 cycles resulting in 9 PF series for individual products. PFs are analysed with corresponding M_{μ} values of the parts in the following section, and a ranking system has been made for evaluation of the process quality indicators. Finally, the resulting linear relationships are used for forming a MLR model for predicting the microreplication efficiency of the process.

3 Results and discussion

In the following, for each of the selected PFs, x-y scatter plots have been made, and PFs are analysed with respect to M_{μ} . The relationships between PFs and M_{μ} have been quantified using the R-squared (R^2) statistical parameter calculated from linear correlations, which is also called as coefficient of determination (COD). A ranking system also have been made to see which PF is linked to the process/product quality better, and discussions are also provided for the explanation of physical effects. In the last sub-section, process fingerprints will be evaluated by Pearson correlation coefficients (PCC) for their selection for the MLR model.

3.1 sPF analysis

Two of the sPFs (P_{i-max} and P_{c-max}) have been known to be linked to the dimensional features of the micromoulded products in the literature; however, no reports have been found citing their direct link to the micro-feature replication efficiency [8, 20, 21]. Data given in Fig. 7 a and b show that an obvious positive linear relationship is present between peak pressure values and M_{μ} . P_{c-max} resulted in a slightly higher R^2 (0.7819) than P_{i-max} as expected. Moreover, injection pressure (P_i) measurements are taken at the back of the injection piston, and these also include inertial effects due to mass of the whole injection unit resulting in slightly less relevant data than P_c data. Both PFs suggest that pressure measurements can provide high-quality data regarding M_{μ} . For instance, P_{i-max} and P_{c-max} change significantly for 950 to 1150 and 150 to 450 bar range, respectively. Any impact that can alter the flow or injection behaviour of the molten material will be manifested on these pressure values and be detected for fault prevention.

Fig. 6 Graphs showing the calculation of comparative process fingerprints. **a** The P_c profiles of the best and inferior sample used for calculation of the deviation curve; **b** calculation of Δ_{all} , $\Delta_{1.5s}$, and Δ_{3s} .

Δx data presented in Fig. 7c resulted in an R^2 value of 0.498 for predicting M_{μ} . This can be attributed to the relatively low resolution in the measurement of the position as shown in Fig. 3b. The encoders inability to measure displacements below 60 μm is evidenced by the exact same values detected for Δx . Certain accumulations in this particular scatter plot are due to the different mould temperatures employed and a linear relationship between the amount of packing and M_{μ} has been found, however with much lower correlation. Δx is a measure of the movement of the injection piston after the switch-over from speed controlled regime to the pressure controlled packing regime, where lower Δx values might suggest a relatively late switch-over or more material conveyance to the cavity due to dosage.

3.2 dPF analysis

$[dP_c/dt]_{\max}$ data shown in Fig. 8a represent a positive trend with respect to M_{μ} , however with low sensitivity and an R^2 of 0.4336. The similar behaviour is also valid for $\int P_i$. This behaviour might suggest that not enough data points were acquired while capturing the process data and shows that this particular PF types might require higher data capturing rates than usual as the increase and decreases happen very rapidly. $\int P_c$ data performed better than $[dP_c/dt]_{\max}$ and $\int P_i$, resulting in R^2 of 0.763. This shows that cavity pressure decay profiles occurring after a cavity filling event are the most reliable of the dPF containing information that can be linked to microreplication directly. The inferior performance of $\int P_i$ can also be explained by the fact that the injection pressure

Table 2 A summary of selected process fingerprints (PFs)

Type	Process fingerprint (PF)	Properties/features
Standard PFs (sPFs)	$P_{i-\max}$	Peak value of the injection pressure data taken from the strain gauge sensor
	$P_{c-\max}$	Peak value of the cavity pressure data taken from the piezoelectric cavity pressure sensor
	Δx	Amount of packing calculated from the data taken from encoder of the injection piston
Derived PFs (dPFs)	$[dP_c/dt]_{\max}$	Maximum value of the 1 st derivative of the cavity pressure data
	$\int P_i$	Integral of the injection pressure in the vicinity of the peak value within 100 ms
	$\int P_c$	Integral of the cavity pressure in the vicinity of the peak value within 100 ms
Comparative PFs (cPFs)	Δ_{all}	Integral value of the comparison curve that results from the comparative analysis from the whole interval
	$\Delta_{1.5s}$	Integral value of the comparison curve that results from the comparative analysis from a 1.5-s interval near the peak
	Δ_{3s}	Integral value of the curve that results from the comparative analysis from a 3-s interval near the peak

Fig. 7 Scatter plots depicting the correlations between sPFs and M_μ : **a** P_{i-max} vs M_μ ; **b** P_{c-max} vs M_μ ; and **c** Δx vs M_μ

overshoots near the piston (see Fig. 5) can vary significantly from cycle-to-cycle resulting in more scattered values especially for higher pressure integral values (614–618 bar.s) as illustrated in Fig. 8b. The high amount of momentum of the injection unit makes the control of the deceleration difficult leading to variable pressure overshoots and hence integral values.

3.3 cPF analysis

The quality indicators extracted from comparative analysis and their scatter plots are given in Fig. 9. The analysis shows that the main trends are mostly the same for the whole integration range, 1.5 s and 3 s. However, differences can be quantified by analysing the R^2 values. For instance, R^2 values of 0.750 and 0.789 corresponding to Δ_{all} and $\Delta_{1.5s}$, respectively, clearly show that the quantification of the comparative deviation near the peak (see Fig. 6b) is of more relevance to the microreplication quality detection. Once again, this can be attributed to the importance of cavity pressure decays as it is the case in $\int P_c$. A comment can be made that $\Delta_{1.5s}$ and $\int P_c$ are too similar and present no significant difference, albeit a 3.5% improvement in R^2 values is present while using the comparative analysis approach. The difference between $\Delta_{1.5s}$ and Δ_{3s} is only marginal at 0.89% which shows that the prior one is preferable for quality prediction and machine learning

purposes. In overall, cPF analysis of the cavity pressure data proved to be logical and resulted in best R^2 values amongst all PFs for representing the microreplication efficiency.

A Pearson correlation coefficient (PCC) matrix depicting the interactions between 9 process fingerprints and M_μ is given in Fig. 10. PCC between two variables takes values between -1 and 1 and is a statistical measure indicating the linear correlations between two variables. Positive values indicate a positive linear trend between two variables, whereas negatives represent a negative linear relationship. The intuitive approach could be the selection of best performing PFs from each class of process fingerprints in a multiple linear regression model involving PFs and quality prediction or monitoring of micro-products. However, lower correlations are favoured between the selected process quality indicators for building a multiple linear regression model for making it more realistic.

The best performing PFs from each class in terms of R^2 values are P_{c-max} , $\int P_c$, and $\Delta_{1.5}$ for predicting/monitoring microreplication during the μ IM process. These PFs are somewhat derived from the cavity pressure data and show strong correlations between each other. Three PCC values of P_{c-max} vs $\int P_c$, P_{c-max} vs $\Delta_{1.5}$, and $\int P_c$ vs $\Delta_{1.5}$ are 0.96, -0.99 , and 0.98, respectively. For making the multiple regression model for machine learning more realistic, and rather than flooding the model with redundant data, P_{i-max} , $[dP_c / dt]_{max}$, and $\Delta_{1.5}$ have been selected. These PFs not only provide useful insights from different channels but also represent a selection of

Fig. 8 Scatter plots depicting the correlations between dPF and M_μ : **a** $[dP_c / dt]_{max}$ vs M_μ ; **b** $\int P_i$ vs M_μ ; and **c** $\int P_c$ vs M_μ

Fig. 9 Scatter plots depicting the correlations between cPF and M_μ : **a** Δ_{all} vs M_μ ; **b** $\Delta_{1.5}$ vs M_μ ; and **c** Δ_{3s} vs M_μ

various PF extraction methods such as analysis of peak values (P_{i-max}), pressure increases rates ($[dP_c/dt]_{max}$), and comparative analysis ($\Delta_{1.5}$). Corresponding PCC values for P_{i-max} vs $[dP_c/dt]_{max}$, P_{i-max} vs $\Delta_{1.5}$, and $[dP_c/dt]_{max}$ vs $\Delta_{1.5}$ are 0.71, -0.89 , and -0.72 , respectively. Table 3 summarise the best PFs according to R^2 values and selected PFs for the multiple linear regression model.

3.4 Multiple linear regression (MLR) model

Linear regression is a statistical method that has been widely used for modelling process behaviours, product quality, and predictions based on dependant and independent variables [2, 10, 26]. More variables can be added to the linear regression models for training the predictive model towards a more accurate machine learning approach. In this case, the method becomes a multiple linear regression (MLR) combining the behaviours of different independent variables for predicting a

dependant variable which is usually a quality criterion of the product. This can be generalised as:

$$y = m_1x_1 + m_2x_2 + \dots + m_ix_i + c \quad (1)$$

where y is the dependant, x is independent variable with individual slopes (m_i), and c is the intercept of the curve. In our model, microreplication efficiency (M_μ) is the dependant variable that is being affected by the dynamic phenomena. The independent variables are the process fingerprints (PFs) which are the proxies of the physical processes from μ IM.

The PFs in Table 2 and M_μ are organised in data columns in a spreadsheet file for representing 60 moulding cycles and are processed using code written in Python using Jupyter Notebook IDE (integrated development environment) for creating the MLR model. The code can be found in the Appendix, and it assigns the columns of data to independent (PFs) and dependant (M_μ) variables followed by creating a test and training data groups. After the usage of the linear

Fig. 10 Pearson correlation coefficient matrix depicting the relationships between quality indicators

Table 3 A summary of the best performing and other selected PFs for the MLR model

Best performing PFs (based on R^2)	Selected PFs for MLR (based on PCCs)
P_{c-max} , $\int P_c$, $\Delta_{1.5}$	P_{i-max} , $[dP_c/dt]_{max}$, and $\Delta_{1.5}$

regression function in the code, all coefficients are calculated, and the MLR equation for the model can be stated as:

$$M_{\mu} = (1.356 \times 10^{-4})P_{i-max} + (-2.29 \times 10^{-7})\left[\frac{dP_c}{dt}\right]_{max} + (-9.7 \times 10^{-5})\Delta_{1.5} + 0.588 \quad (2)$$

To check the validity of the MLR model, a test size of 0.2 is set where 20% of the manufacturing cycles are randomly chosen by the code to test the model. After generating the code, the remaining 80% is used for training the model. The test dataset is then used as inputs in Eq. (2), and corresponding predicted M_{μ} values (M_{μ_pred}) are generated. Test values (M_{μ_test}) which were randomly selected in the beginning were then compared with predicted y values (M_{μ_pred}) which is the outcome of the training set. The scatter plot in Fig. 11 shows the relationship between M_{μ_test} and M_{μ_pred} . The test and predicted values are also provided. The success of the model is then quantified by the R^2 value calculated by the Origin Pro software.

The R^2 value of 0.835 has been found from the linear fit calculated from M_{μ_test} and M_{μ_pred} scatter plot. The result suggests that M_{μ_test} can be explained at about %84 accuracy by using predicted values generated by the MLR model. It can be concluded from the analysis that by training the MLR model with different PFs, the reliability and accuracy of the models can be increased as compared with single quality indicators vs M_{μ} as given in the previous sections. Moreover, since the MLR method

also includes testing datasets for checking the validity of the models, it is a fairer way of quantifying the behaviours of process fingerprints. A comment can be made that ~84% accuracy might not be appropriate for such a quality assessment procedure; however, the main purpose is to present that the quality proxies or PFs work in the first place and there is a lot of room for improvement such as using additional layers of instrumentations on the machine and using more quality indicators in the MLR models. Furthermore, relatively low accuracy of data-based in-line quality assurance models can still be very cost-effective since the PFs are directly physical metrics and they can change significantly in the case of mechanical or electrical failures on the machines. For instance, frictional effects in injection units, heater failures, or changes in the material viscosities can be thought as examples that can lead significant differences in the values of the PFs that can easily be detected and faulty products can be sorted. The cost-effectiveness of the models usually overshadows the low accuracies when it comes to manufacture of high added values micro-nano featured components due to their high margins.

Another aspect of the method presented can be its applicability in the shop floor and automation scenarios. The total time spent for DAQ system setup and process fingerprint extractions can be measured with a few days provided that some coding and data analysis skills are present. Moreover, the time investment for coding and data analysis is a onetime effort and provides the necessary flexibility in the shop floor for the manufacture of different products.

Fig. 11 Correlation between the predicted microreplication efficiency of the MLR model (M_{μ_pred}) and efficiency of the samples selected for testing the model (M_{μ_test}). Notice that the test data corresponds to real measurements

The following suggestions can be stated for making the model even more accurate:

- Additional sensor technologies can be added to the process in pursuit of better correlating PFs.
- Sampling rate at DAQ rate can be increased which could lead to capture of sensitive bits of process data. This feature should be considered carefully since the size of the data and storage can become problematic.
- More parts can be manufactured and samples for training set can be increased for better accuracy of the models.

4 Conclusions

Definitions and extraction methods of micromanufacturing process fingerprints in μ IM are presented in the work alongside with required rationale. The selection of such process quality indicators proved that the approach is effective from data-filtering point of view, where considerable amount of data is generated in each manufacturing run. These quality indicators can be used for various purposes in similar approaches which can reduce inspection efforts for micro-nano featured products and pave ways towards zero-defect manufacturing. The method can be employed for other manufacturing techniques where the big data coming from an established manufacturing system can be analysed and mined for machine learning applications. It was demonstrated that 9 different quality indicators extracted from the sensor data provided valuable information regarding the quality of the process.

Selected process fingerprints are also used in a multiple linear regression quality prediction or detection model for micro-featured parts in the work. The model proposed in the work predicted the quality of the process with %84 for such challenging geometrical features which emphasises its potential for in-line fault detection, pass-fail procedures, and data analysis. Creation of these models allows the users to present and use their findings effectively and provide actionable insights regarding their processes. Moreover, process fingerprinting also has the capability to decrease the lifecycle of a big chunk of process data by condensing them into well-defined quality proxies. Generation of process fingerprints in a way is one of the most simplistic, yet effective way of translating the complex information into distilled process fingerprint values for improving the responsiveness of the manufacturing systems. The implementation of such a method in a manufacturing scheme is feasible since generic machine learning and programming tools can be used for doing such an analysis provided that sufficient experience and know-how are present in μ IM.

A summary can be made as following to emphasise the main outcomes of this research:

- A process fingerprinting method for μ IM has been presented that can be exemplary as far as data-rich manufacturing and Industry 4.0 applications are concerned.
- Process fingerprints are classified according to their extraction methods and analysed with respect to microreplication efficiency of μ IM.
- A multiple linear regression model has been created for predicting the part quality or success of the moulding process.

Abbreviations μ IM, Micro-injection moulding; PF, Process fingerprint; MLR, Multiple linear regression; P_i , Injection pressure; P_c , Cavity pressure; M_{μ} , Microreplication efficiency; ABS, Acrylonitrile butadiene styrene; sPFs, Standard process fingerprints; P_{i-max} , Injection pressure maximum value; P_{c-max} , Cavity pressure maximum value; Δx , Amount of packing; dPFs, Derived process fingerprints; $[dP_c/dt]_{max}$, The maximum rate of cavity pressure increase; $\int P_i$, Integral value of the injection pressure; $\int P_c$, Integral value of the cavity pressure; cPFs, Comparative process fingerprints; $\Delta(t)$, Deviation measure; Δ_{all} , Integral value of the comparison curve that results from the comparative analysis from the whole interval; $\Delta_{1.5}$, Integral value of the comparison curve that results from the comparative analysis from a 1.5 s interval near the peak; Δ_3 , Integral value of the curve that results from the comparative analysis from a 3 s interval near the peak; COD, Coefficient of determination; PCC, Pearson's correlation coefficient; $M_{\mu-pred}$, Predicted microreplication efficiency; $M_{\mu-test}$, Test values for microreplication efficiency

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Availability of data and material Yes.

Code availability Yes, it is provided with the file named “Appendix.”

Declarations

Conflict of interest The authors declare no competing interests.

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