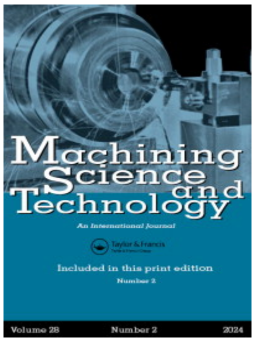

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Machining Science and Technology
An International Journal

ISSN: (Print) (Online) Journal homepage: www.tandfonline.com/journals/lmst20

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MACHINING SCIENCE AND TECHNOLOGY
https://doi.org/10.1080/10910344.2024.2348481

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ABSTRACT

Identification of chatter is mostly carried out offline after capturing the machining signals or by analyzing the machined surface after completing or interrupting the machining process. The offline methods for analyzing the machined signals are tedious and not very useful for microcomponents attributed to permanent deformation of thin-wall if chatter has already been occurred during process. Real-time information is necessary to monitor and control the micromilling process. Consequently, a smart manufacturing framework has been developed in the present work to monitor the chatter onset and the deviation in geometrical shape of the thin-wall during micromilling. An interactive web interface has been developed to project the real-time information necessary to monitor the micromilling process. The excitation of natural modes of the thin-walled structure of Ti6Al4V has been observed in real-time on the web browser for micromilling at 80 μm radial depth of cut, 50,000 rpm and a feed rate of 3 μm/flute. The maximum permanent deformation of 97.43 μm for thin-wall has been obtained at 130 μm radial depth of cut. The developed layout of web browser can be used for real-time monitoring of any other machining process as well.

KEYWORDS

Chatter; micromilling; process monitoring; real-time information; smart manufacturing; web application

Introduction

Smart manufacturing is the way forward to control and reconfigure different manufacturing processes. It is an integral part for implementing Industry 4.0 in the manufacturing process (Frank et al., 2019). Adoption of smart manufacturing in micromachining can immensely benefit through the detection of abnormalities like micro cutting tool wear, chatter, deviation in geometry and dimension, etc. (Rahimi et al., 2021). Note that the micro-cutting tool used for the micromachining process is susceptible to instability like chatter; if it is not controlled, it can lead to catastrophic failure (Malekian et al., 2009b). However, in-situ chatter onset identification is

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not trivial in the micromilling process, attributed to the low magnitude of chatter, frequency bandwidth and limitation of frequency resolution for available sensors (Malekian et al., 2009a). Alternatively, the offline method of chatter onset identification based on machined surface analysis is one of the effective methods (Singh et al., 2015, 2017). This offline method can be tedious and alter the accuracy of the machining set-up if the workpiece is unfixed from the feed table to measure the surface topography of the machined surface for chatter identification. Different sensors like accelerometers, microphones and acoustic sensors with high-frequency bandwidth have been used for identifying the chatter in the micromilling process. Moreover, the multi-sensor-based approach can be one of the most effective ways of chatter onset detection in the micromilling process. Different methods of chatter identification with the captured signals from the sensors require the analysis of signals. Signal analysis methods like wavelet transformation, frequency domain analysis, power spectrum analysis, short-time frequency analysis, entropy analysis, etc. of the signal captured from the sensors have been carried out to detect the chatter (Yun et al., 2011; Jin and Altintas, 2013; Ribeiro et al., 2020). A statistical method of chatter identification has also been carried out to detect chatter in the micromilling process. One of the major issues in all these signal analysis methods is in-situ signal analysis, which is attributed to being time-consuming and delayed sharing of critical information after signal analysis. In-situ analysis of the machining signal captured *via* sensors and projection of the critical parameters for chatter identification with the progress of machining can be highly effective in carrying out the machining without any abnormalities (Frank et al., 2019). The projection of the critical parameters for chatter identification in real-time with the progress of machining can also leverage the process to correct itself through actuators, or the process can be corrected by altering the machining process parameters.

Furthermore, projecting critical parameters requires pre-analysis of all available signals to detect necessary abnormalities in the machining process. It may require projecting the multiple signals of real-time machining to arrive at the conclusion of the type of process abnormalities. Information about the type of process abnormalities can make the machinist take the most appropriate action to control the machining process to manufacture the product with the required accuracy and quality.

Consequently, the present work analyses the data from different sensors to monitor process abnormalities and it has also been projected online on both local and in cloud for real-time information. First, a literature review has been carried out for different works related to smart manufacturing, followed by proposing a smart manufacturing framework for real-time identification of process abnormalities in the micromilling process. In the subsequent section, the micromilling process set-up with details of experimental conditions has been discussed. The workpiece dynamics, which are necessary to identify the micromilling process, have also been estimated using experimental modal analysis, followed by a discussion of the effect of process parameters on the micromilling process stability. Finally, a dash app developed to detect process abnormalities has been detailed, and a method for projecting it in the cloud has also been discussed.

Literature review

The integration of sensors for smart manufacturing has become an integral part of original equipment manufacturers, as analyzed in Tao et al. (2019), Cui et al. (2020), Lu et al. (2020a, 2020b). Micro, small and medium enterprises (MSMEs) require the integration of sensors and actuators to realize the concept of smart manufacturing (Ahuett-Garza and Kurfess, 2018; Pivoto et al., 2021). De Felice et al. (2018) carried out a pilot study to implement smart manufacturing and showed that real-time information can reduce operator or human error. All the simulations for digitalizing the warehousing operation industries were carried out using Flexsim® (De Felice et al., 2018). The repair time of the components was shown to be reduced by 41% through real-time information. The transmission of data to achieve the objectives of layers in a process can also increase the flexibility of the production facility (Rossit and Tohmé, 2018). A real-time feature of the manufacturing process signal will be required to implement corrective action for manufacturing the components within specified tolerances. Guo et al. (2021) proposed an architecture to monitor the assembly line and the movement of materials between the assembly lines. They proposed smart gateways to capture the real-time status of the assembly process. Luo et al. (2015) proposed a method of scheduling the job by using the real-time data captured from the wireless radio frequency identification technique. The real-time information was collected from different gates located on the shop floor and also from other machines.

Sensors play a vital role in capturing real-time data in any manufacturing process and hence, it is one of the layers in the basic architecture of smart manufacturing (Boyes et al., 2018). The same sensors cannot be used for multiple processes or machines. Nguyen and Dugenske (2018) developed a low-cost architecture for conditioning monitoring of a band saw machine. This low-cost architecture was developed using an Inter-integrated circuit communication protocol. Signals from multiple sensors can be combined and compressed to monitor real-time information (Nguyen and Dugenske, 2018). Hence, the configuration of multi-sensors to capture the real-time machine condition and machining performance is necessary for developing a framework for smart manufacturing. Damjanovic-Behrendt and Behrendt (2019) found open-source software and hardware integration to be the most versatile way to develop a digital twin for smart manufacturing. The cost of a smart manufacturing setup and flexibility were two of the main reasons behind the selection of open-source software and hardware. Moreover, an open-source interface is highly useful for the flexibility and adaptability of smart monitoring systems, and it can also be used for virtual simulation of process planning for the manufacturing of components (Shin et al., 2016). An open-source interface based on MTConnect and step numerical control has been developed by Shin et al. (2016) to simulate the performance of the manufacturing step during the process planning stage. The open-source software and hardware-based system will also allow small-scale enterprises to implement digitalization in factories at lower cost. Hence, Wang et al. (2022) proposed a web-based platform with open-source software to visualize and interpret the captured signal data in the manufacturing process. They also deployed data analytics to transform the data in frequency and time-frequency domains to monitor the manufacturing process in smart manufacturing.

Digital twin was also found to be highly useful for predicting and monitoring process information in smart manufacturing. However, one of the main challenges for the successful implementation of digital twins was found to be the computational and network requirements of smart manufacturing. Successful implementation of smart manufacturing is a function of information flow through network integration of various activities in the manufacturing process. Hence, the major hurdles in designing and developing a universal framework for smart manufacturing are the continuous upgradation of information and communication technology (ICT) and manufacturing technology (MT) (Li et al., 2018). The flow of information must be upgraded to maintain the pace with the development of manufacturing technology for the successful adaption of smart manufacturing (Li et al., 2018). A bottom-up approach on the shop floor is necessary for the seamless transfer of data between different stages of a manufacturing cycle to realize smart manufacturing digitalization (Lu et al., 2020a, 2020b). Furthermore, the seamless integration of all information in the manufacturing process is critical for successfully implementing smart manufacturing concepts. Lu et al. (2020a, 2020b) also found an open source-based smart manufacturing framework more successful in its implementation.

One of the key requirements for implementing smart manufacturing is real-time information capability in the manufacturing process and system as devised in the framework of smart manufacturing (Mittal et al., 2019). This real-time information capability is necessary to interpret the captured data or signal during the manufacturing process to make the process autonomous. Cao et al. (2019) developed an ontology-based approach for monitoring different manufacturing process activities. They obtained the critical value of statistical parameters, like kurtosis, root mean square and crest factor, for condition monitoring of bearings in the rotary machine during manufacturing. The value of statistical parameters of the captured signal was calculated and projected on a web-based platform to identify the defect in the bearing. However, the proposed method needed to be more accurate when the statistical value became closer to the critical importance of statistical parameters.

Hanchate et al. (2023) developed a framework for graphical representation to map the sensing schemes using various sensors to different faults associated with different components of the machine tools. The faults were mapped to different components according to different standards and domain knowledge. They also used this developed method for fuzzing data from multi-sensors for early prediction of the health conditions of components of machine tools for preventive maintenance. A sensor wrapper scheme combining data from various sensors, like a dynamometer, accelerometer, acoustic sensor and imaging camera, can extract the process characteristics in a manufacturing process. The scheme was named smart manufacturing multiplex (SMM) and this SMM can be combined with artificial intelligence tools to carry out different manufacturing operations on a single machine tool (Botcha et al., 2020). The fusion of signals captured using different sensors can also be used to predict surface roughness in finishing operations. Cheng et al. (2015) used Gaussian regression to fuze the vibration signal from the force sensor and vibration sensor to predict the real-time surface roughness in ultra-precision machining.

The optimization of system performance can be achieved to increase the production rate of industries by analyzing the real-time signals from the sensor. This real-time information can be given as feedback to the machine by humans to take action to minimize the non-production time, and it optimizes the manufacturing process (Wang et al., 2016). Maintenance of devices on the shop floor is critical to achieving the efficiency of the manufacturing process. A decision on maintaining the manufacturing equipment can be taken by receiving feedback from the analyzed signal in the architecture of smart manufacturing. Real-time feedback can be generated by capturing the data continuously (Trentesaux et al., 2016; Penas et al., 2017). Production data during the production of a product may be collected from the production plant in real-time, and it may be compared with customer requirements and production planning and control data to track the status of the product. An RFID can be integrated with the material for which the production is going; the RFID data can be continuously monitored, and any deviation from the planned production of the material can be corrected manually (Tao et al., 2018). Furthermore, any deviation in the shape of a product or delay in the production of the product can trigger an alarm to alert the operator for necessary corrective action to be carried out (Stock et al., 2018).

A sustainable product and overall sustainability in the manufacturing process can also be achieved by reducing wastage through real-time monitoring of the product and indicating the requirement of maintenance through real-time feedback. The maintenance of machines and equipment through real-time feedback will ensure that power consumption is maintained as per the requirement. The real-time information in smart manufacturing also increases the flexibility in handling the product, optimizing the resources required for producing an effect (Cheng et al., 2015).

It can be seen that very little literature is available on developing or implementing smart manufacturing architecture in the micromilling process. Most of the work reported in the field of micromilling is in the domain of machine learning and intelligent approaches for monitoring different attributes of the micromilling process. Zhu and Yu (2017) proposed a region-growing method to separate the worn-out area of the micro-cutting tool to analyze the tool wear in the micromilling process. Kiswanto and Christiand (2020) proposed a digital twin to monitor tool wear in the micromilling process. They concluded that the digital twin could also be used in Industry 4.0 framework for real-time data analysis of the micromilling process. A principle component-back propagation-based prediction model was developed to include the cutting tool life for evaluating sustainability in the micromilling process (Zhang et al., 2022), which can be integrated within the framework of smart manufacturing. Kundu et al. (2022) developed a machine learning-based smart manufacturing framework for characterizing the process and product with the aim of obtaining the relationship between the intended application of the manufactured part and its defect. The analysis was carried out during the fabrication of a hydrophobic surface on 316 L using a laser ablation process. The proposed framework has also been found to be suitable for monitoring the machining process for its effect on the geometrical tolerances of the part. The proposed framework has found the random forest-based algorithm to be the most suitable machine learning method for predicting performance as a function of different machining conditions. Rao et al. (2014) proposed a recurrent predictor neural network (RPNN) and Bayesian particle filter (PF) based approach to predict the onset of surface variation in the ultra-precision machining process. They combined signals from both vibration and force sensors to predict the surface variation. The proposed method, based on RPNN-PF, can also handle the nonlinearity and stochastic nature of the machining process. The use of micro-cutting tools in the micromilling process makes the machining process highly susceptible to the instability of the workpiece and cutting tool. There can be a catastrophic failure of the cutting tool if the chatter onset is not detected in real-time during the machining process. Most of the work for aligning the sensor proposed in smart manufacturing for the macro-machining process cannot be adopted directly in the micromilling process, like a dynamometer cannot be used to monitor the process due to its limited bandwidth. Different sensors, like displacement, accelerometer, microphone, etc., have been used for monitoring and detection of chatter in the micromilling process, but the low magnitude of vibration in micromilling is not trivial to identify owing to their low signal-to-noise ratio. However, identifying chatter by combining signals from two sensors can be highly effective in identifying process abnormalities in the micromilling process. Additionally, if the vibration can be combined with machined surface roughness in real-time, it can further increase the accuracy in identifying abnormalities in the micromilling process. Hence, in the present work, the signals from accelerometers and displacement sensors have been used to identify the chatter. Furthermore, a support vector machine algorithm based on the displacement of the workpiece and the surface roughness of the machined surface has been used in real-time to classify the machining process into stable and chatter-dominant unstable conditions for micromilling the thin-walled workpiece Ti6Al4V. The real-time identification has been carried out on a web-based interface using the DASH app and it can be accessed from anywhere using html address to monitor the machining process.

Methods

First, the experiments have been carried out by performing micromilling of the thin-walled workpiece of Ti6Al4V. Different signals of micromilling have been measured using an accelerometer and laser displacement sensor. The captured signals from accelerometer have been analyzed in the frequency domain to find the critical parameters which may indicate chatter onset. The displacement of the thin-wall has also been analyzed in the time domain to estimate the permanent deformation of the thin-walled workpiece. Furthermore, the analyzed spectrum of acceleration and deflection from displacement sensor has been projected on a web browser by developing an analytical and interactive web application in python. Different layouts of web browsers have been proposed to visualize the real-time machining characteristics of the machining process as per the requirement of the operator or machinist. The methodology for the present work is shown in Figure 1.

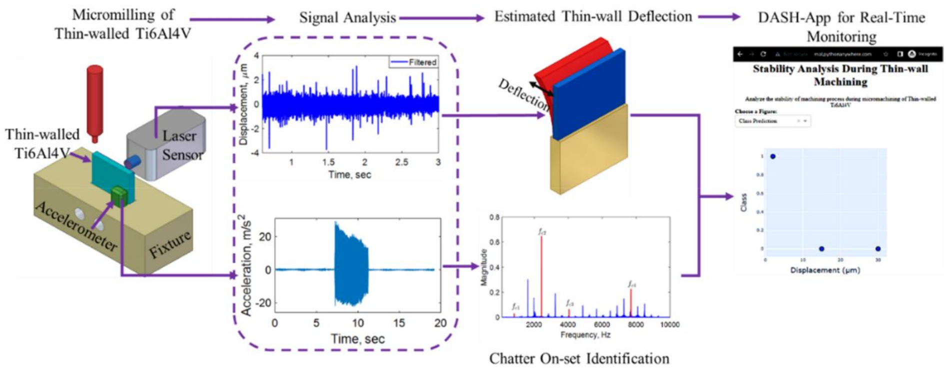


Figure 1. Methodology for the present work.

Framework for smart manufacturing

The development of a framework is important to obtain real-time information about the machining process. An analysis of real-time signals from the machining process needs to be carried out for effective monitoring and to assist the operator in carrying out the machining process with the required accuracy and quality. Furthermore, a critical parameter has to be estimated from the collected signals to detect abnormalities in the micromilling process. Combining the signals from sensors for machining with different process parameters can reveal changes in the pattern of the machining process, and any significant mismatch in pattern indicates a deviation from the stable machining process. A time domain signal is not sufficient to measure the deviation in the produced shape of the micromilled components and hence, signal transformation is required to detect the abnormalities in the machining process. An estimation of deviation in geometrical shape of the machined components during machining process requires the fusion of signals from different types of sensors and hence, heterogeneous signals are required to be combined to monitor the micromilling process. A basic framework for monitoring the machining process has been proposed, as shown in Figure 2.

The first requirement is to collect data from the sensors. MTConnect can collect the data from manufacturing process and deliver the data to different locations *via* internet of things. A different approach, where the signals from the sensors are captured continuously with the data acquisition system, has been proposed in the present work. However, two sensors – accelerometer and a laser displacement sensor – have been used to collect the continuous signal during high-speed micromilling of thin-walled workpiece. The data acquisition systems (DAQs) has to be placed not very far from the sensors of the micromachining center, as placing far the DAQs need a longer wire for the BNC cable to connect the sensors to the DAQs. The captured signal from DAQs can be saved in different formats, like .lvm,

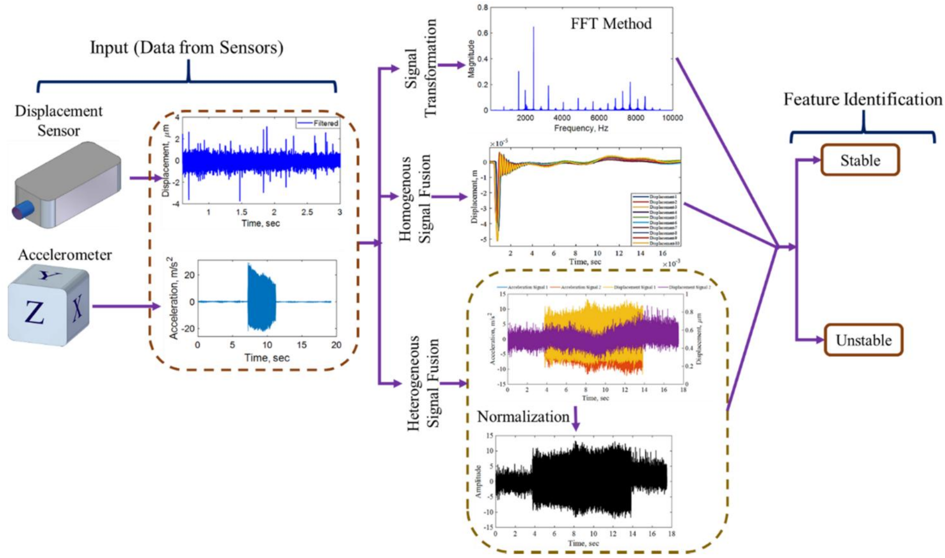


Figure 2. General frame for abnormalities detection.

text, .xls, JSON and XML. The stored signal can further be accessed using matlab, python, mathematica or any other signal processing tool to analyze the signal. Different statistical and dynamical parameters will be extracted by carrying out the signal analysis to indicate the status of the machining process. This status of the machining process can indicate that machining is carried out without any abnormalities, which ensures the machine components are produced without any geometrical or dimensional error. Note that the abnormalities identification in high-speed micromilling is not trivial due to the low magnitude of vibration and catastrophic failure of the micro- cutting tool due to its low diameter (less than 500 µm).

Furthermore, the machining of thin-walled structure reduces its stiffness as machining progresses, which make the thin-wall workpiece less stiff than the micro-cutting tool. Consequently, it is critical to monitor the signal for monitoring the deflection in the geometrical shape of the micromilled, thin-walled workpiece. Parallel to monitoring of the deflection of thin-walled workpiece, the monitoring of the chatter during machining process will also be useful to control the cutting tool wear to get the desired surface finish. Hence, acceleration signal has been used in the present work to monitor chatter onset and displacement signal has been used to monitor the deflection in shape of workpiece. The signals from different sensors should be combined and it may be projected on a common platform like web for effective monitoring of different phenomena taking place during the micromilling process. Real-time monitoring will help the machinist take the necessary actions, like changing the machining process parameters or cutting tools to carry out the machining without deviation in the shape of the machined components. The projection of analyzed machining signal can be projected to a web like on HTML. An app known as Dash, which has been developed *via* Python language in the present work, displays the signal in HTML with a port number. This Dash app has also been configured to display the signal in real-time with all the necessary information to monitor the machining process. Multiple signals from both accelerometer and laser displacement sensor have been configured to this app. Different signals captured using both sensors at different machining conditions with the progress of machining process has been combined and overlapped to understand the change in patterns in signal to detect abnormalities in the machining process. Moreover, the time domain signal has also been converted to frequency domain to identify the dominant amplitudes at different frequencies to detect the onset of chatter. The change in dominant amplitude will also be updated with the progress of the machining process to obtain real-time information. A filtering of tooth passing frequency has also been carried out in the captures displacement of thin-walled workpiece to estimate the permanent deformation in the thin-walled shape. This deviation in shape indicates the wear of the micro-cutting tool and hence, the information can be used to change the cutting tool. The proposed architecture is shown in Figure 3.

Experimental set-up

A high-speed micromilling experiment has been carried out at the micromachining center at the BIT-Pilani, Hyderabad campus. The micromachining

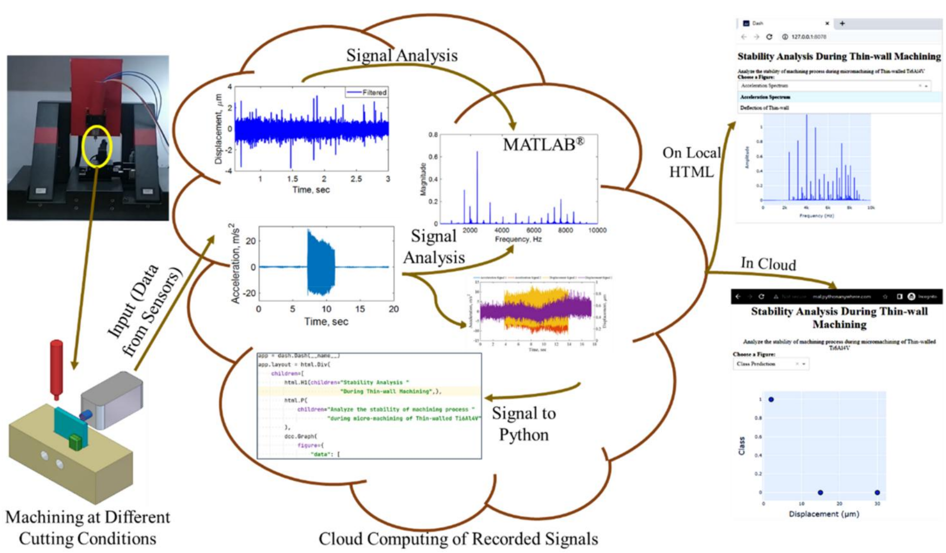
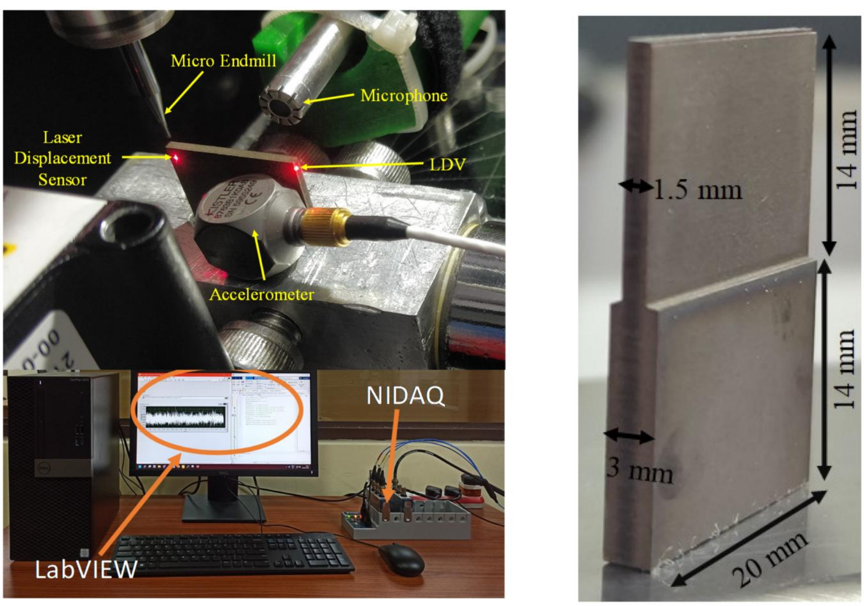


Figure 3. The proposed architecture for smart manufacturing.

center has three axes, where two axes (X and Y-axes) are used for feed table and radial depth of cut and the third axis (Z-axis) is for giving the required axial depth of cut. The spindle is also mounted on the Z-axis, and this spindle can rotate up to 80,000 rpm with a maximum torque of 11.9 N-cm. The spindle rotates in ceramic bearing and hence, high thermal stability can be achieved at higher cutting speed. All three axes are driven by AC servo motor. The resolution and the accuracy of X and Y-axes are 0.15 µm and ±2 µm, respectively. Tri-axial controller with RS232/USB communication has been used to control all three-axes. The high-speed micromachining center is placed on a granite structure for high damping and structural stability. The experimental set-up is shown in Figure 4. Different radial machining has been carried out on thin-walled workpiece of Ti6Al4V. The thickness of the thin-wall is 1.5 mm (Figure 4b). Two fluted micro-end mills of diameter 500 µm have been used for the experiments without the assistance of lubrication. The micromilling of thin-walled Ti6Al4V has been carried out at cutting speeds of 20,000, 50,000 and 80,000 rpm and at three different radial depths of cuts: 30, 55, 80, 105 and 130 µm. A constant feed rate of 3 µm/flue has been used for all the experiments. The axial depth is maintained at 50 µm for all the experiments. All the machining experiments have been repeated twice. The vibration of the thin-walled workpiece has been measured using tri-axial accelerometer (Kistler, 8763B1K0AB). Deflection of the thin-wall has been measured with laser displacement sensor (OptoNCDT,



(a) (b)

Figure 4. (a) Experimental set-up; (b) Thin-walled workpiece of Ti6Al4V.

ILD-2300-2). The signal from the sensors has been measured using National Instruments data acquisitions (NI 4474). LabVIEW 2020 has been used to store the signal from sensors. All the signals have been recorded at the sampling frequency of 20 kHz. All the captured data from LabVIEW has been analyzed in Matlab and all the analyzed data has been transferred to Python for developing a Dash app, which has been projected to the web *via* an HTML address.

Thin-walled workpiece and micro-end mill dynamics

The modal parameters of the thin-walled workpiece and an micro-end mill have been estimated by carrying out an experimental modal analysis. Modal parameters are required to study the stability of the machining process. A miniature impact hammer (Dytran 5800 SL) has been used to impact the free-end of the thin-wall at 10 different positions. The corresponding displacement of the free-end of thin wall has been measured using laser displacement sensor. An average of all the ten measurements has been taken to determine the frequency response function (FRF) of thin-walled workpiece. A peak-picking method has been used to estimate the modal parameters at the free-end of the thin-walled workpiece. The experimental FRF and the reconstructed FRF with estimated modal parameters (Table 1) are shown in Figure 5a.

The micro-end mill dynamics have been obtained by impacting the micro-end at a shank, and the velocity has been measured at the impact location and at the tip of the tool to determine the FRF at the tip of the micro-end mill. The impact has been given by an impact hammer (Dytran 5800 SL), and the velocity has been measured by a Laser Doppler Vibrometer (LDV, Polytech VGO-200). The frequency response function for the micro-end mill measured experimentally and reconstructed from the estimated modal parameters (Table 2) is shown in Figure 5b.

Results and discussion

Acceleration signal analysis

Acceleration signal has been analyzed to detect instability during the radial micromilling of thin-walled workpiece. The frequency domain transformation of the acceleration signal has been carried out by taking the Fast Fourier transformation. A dominance of spindle rotational frequency and

Table 1. Modal parameters for thin-walled workpiece.

Mode (s)	Frequency (Hz)	Stiffness (MN/m)	Damping factor
1	2265.62	0.38	0.181
2	4453.13	0.183	0.04

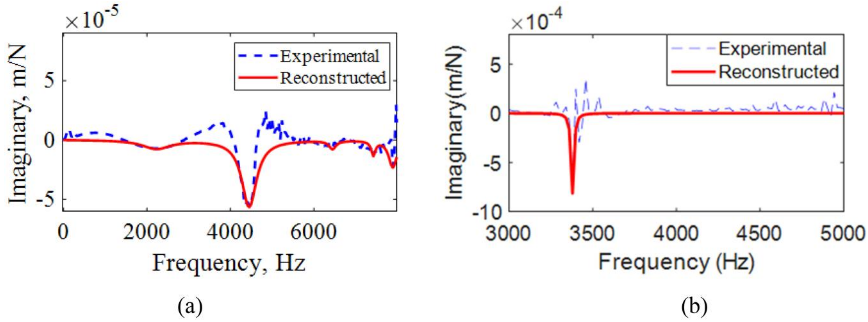


Figure 5. Frequency response function (a) for thin-walled workpiece; (b) Micro-end mill.

Table 2. Modal parameters for micro-end mill.

Mode	Frequency (Hz)	Stiffness (MN/m)	Damping factor
1	3378.91	0.2125	0.0029

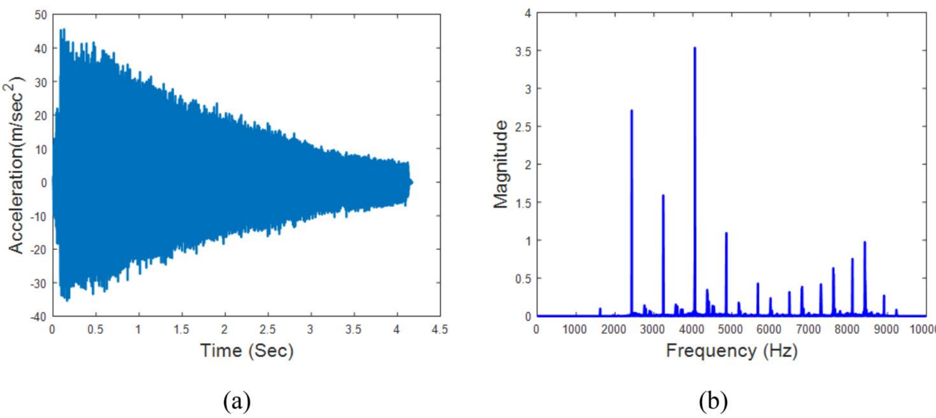


Figure 6. (a) Acceleration signal; (b) Acceleration spectrum for micromilling at 50,000 rpm, 30 μm radial depth of cut and a feed of 3 μm/flute.

tooth passing frequency indicates tool run-out and forced vibration, respectively. Hence, spindle rotational frequency and tooth passing frequency have been filtered by a second-order high pass Butterworth filter.

The time-domain acceleration (Figure 6a) signal for micromilling at 30 μm radial depth of cut shows high value of acceleration initially due to presence of tooth passing frequency and it reduces further with an increase of time. The acceleration spectrum after filtering the tooth passing frequency (1666.67 Hz) shows the presence of harmonics in the tooth passing frequency (Figure 6b). The presence of only tooth passing frequency and its harmonics shows the dominance of forced vibration due to cutting force generated during the machining process (Eppel et al., 2010; Huang and Wang, 2010; Dikshit et al., 2017; Caliskan et al., 2018). Hence, chatter during micromilling of thin-walled structure at 30 μm radial depth of cut has not occurred (Figure 6b) attributed to absence of workpiece's natural

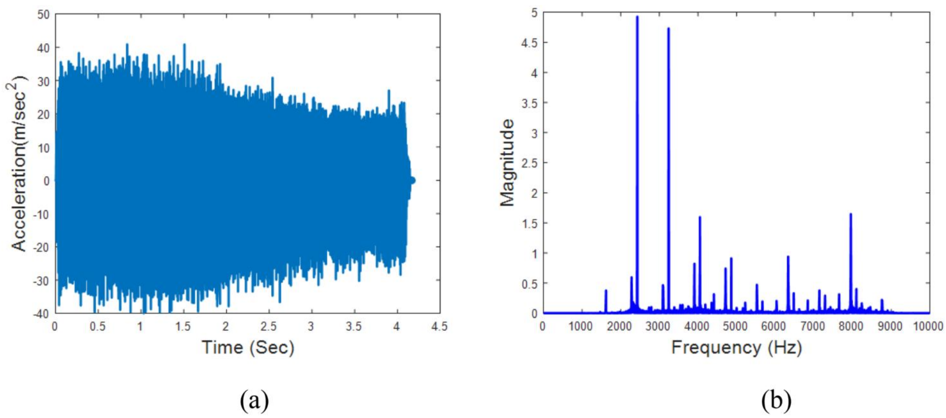


Figure 7. (a) Acceleration signal; (b) Acceleration spectrum for micromilling at 50,000 rpm, 80 μm radial depth of cut and a feed of 3 μm/flute.

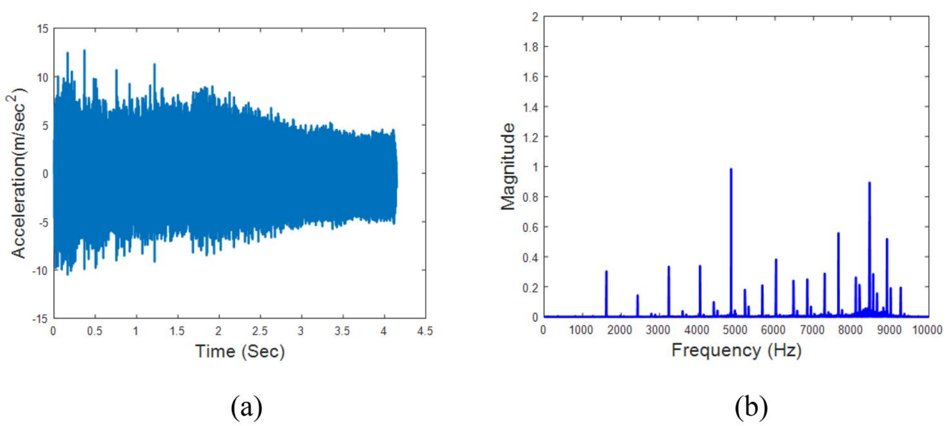


Figure 8. (a) Acceleration signal; (b) acceleration spectrum for micromilling at 50,000 rpm, 105 μm radial depth of cut and a feed of 3 μm/flute.

frequency in acceleration spectrum (Li et al., 2018). An increase in amplitude of acceleration for thin-walled structure has been achieved at 80 μm radial depth of cut (Figure 7a) compared to acceleration at 30 μm radial depth of cut. This increase in acceleration has excited the first natural mode of the thin-walled workpiece, attributed to the dominant magnitude at the frequency of 2429 Hz, which is near the first natural mode of the workpiece (2265 Hz) (Figure 7b). The presence of dominant magnitude near the first natural mode (2265 Hz) of the workpiece indicates the beginning of instability at the 80 μm radial depth of the cut.

A further increase in radial depth of cut to 105 μm has reduced the magnitude of vibration near the workpiece natural frequency (2265.62 Hz) attributed to cutting tool wear (Figure 8b). Note that the presence of cutting tool wear has been found to reduce the effect of chatter in the

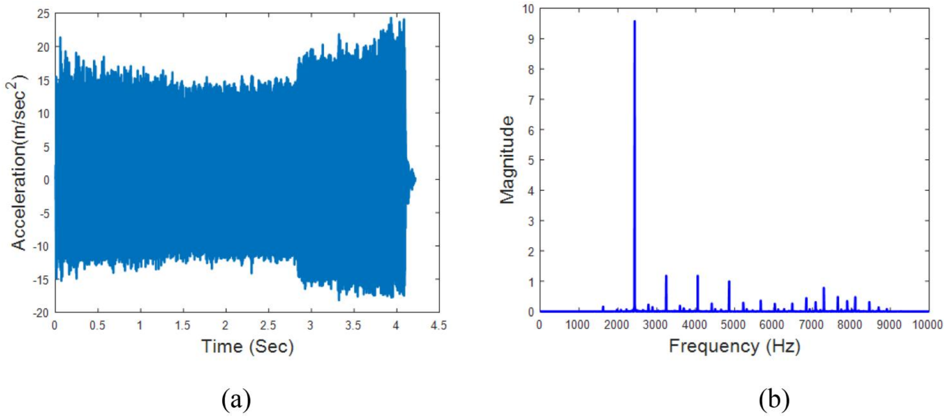


Figure 9. (a) Acceleration signal; (b) acceleration spectrum for micromilling at 50,000 rpm, 130 µm radial depth of cut and a feed of 3 µm/flute.

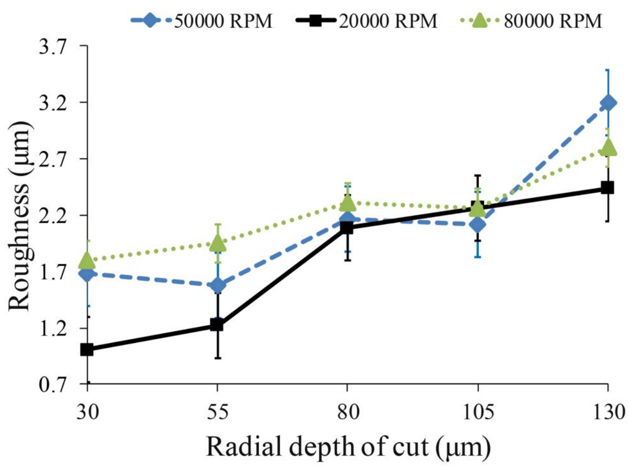


Figure 10. Surface roughness at different radial depth of cuts and cutting speeds.

machining process (Chiou et al., 1995; Chiou and Liang, 2000). An increase in area of the cutting edge due to tool wear acts as a damper and hence reduces the chatter amplitude (Figure 8a). However, the bluntness of the cutting tool due to wear starts rubbing the surface instead of shearing it, which leds to deterioration in surface finish.

The critical wear where there is severe deviation in surface topography from the required surface finish is said to be exciting the chatter in place of dampening the effect of it (Cook, 1959). Hence, a change in depth of cut from 80 µm radial depth of cut to 105 µm has led to decrease in the amplitude of the dominant mode of the workpiece and severity of chatter decreases as the value of roughness decreases by 2.25% at 105 µm compared to 80 µm radial depth of cut (Figure 10). Furthermore, an increase in radial depth of cut to 130 µm has increased the amplitude of acceleration with increase in time (Figure 9a). A dominant magnitude of acceleration has been obtained at 2429 Hz, which is near to the first mode frequency of the workpiece (Figure 9b). The magnitude of the peak at 2429 Hz for machining at 130 μm radial depth of cut is approximately two times the dominant magnitude at 80 μm radial depth of cut. A presence of dominant magnitude in acceleration spectrum for 130 μm indicates the presence of chatter. Hence, the chatter onset, which occurred at 80 μm radial depth of cut, has become severe at 130 μm radial depth of cut. Consequently, it is important to analyze the vibration signal during micromilling to identify the chatter onset, which occurred at 80 μm radial depth of cut. The analysis of the vibration spectrum in offline mode can indicate chatter post-machining and hence, the produced component will not have the desired surface finish and accuracy if chatter has occurred during the machining process. The analyses need to be projected to a screen in real-time to identify the chatter onset in smart manufacturing.

The analysis of micromilling of thin-walled Ti6Al4V has also been carried out at cutting speeds of 20,000 rpm and 80,000 rpm. An analysis of acceleration spectra at radial depths of cuts of 30, 55, 80, 105 and 180 μm also showed onset of dominant magnitude near the workpiece natural frequency for machining at 80 μm radial depth of cut and hence, chatter onset occurs at 80 μm radial depth of cut for all the cutting speeds. The measured surface roughness also shows almost similar pattern for all cutting speeds at different radial depth of cuts (Figure 10). The presence of stable and chatter-dominant machining conditions has also been confirmed from the machined surface images. The surface roughness before machining has been obtained as 2.106 μm (Figure 11a). However, the machined surface is stable at 30 μm radial depth of cut and 50,000 rpm, as shown in Figure 11b. An increase in depth of cut to 80 μm has led to uneven surface and hence, chatter onset is observed (Figure 11c). The machined surface at 130 μm radial depth of cut has produced an abrupt change in the feed marks (Figure 11d), which led to rough surface with higher roughness (Figure 10).

Displacement signal analysis

The acceleration spectrum has detected the chatter onset at 80 μm radial depth of cut, attributed to the presence of a dominant magnitude near the thin-walled workpiece's natural mode (Figure 7b). The presence of chatter has grown further and severe chatter has occurred at 130 μm radial depth of cut due to presence of high value of dominant magnitude at natural mode of workpiece in acceleration spectrum (Figure 9b). However, chatter onset at 80 μm has to be studied in-depth as the machinist has to check the

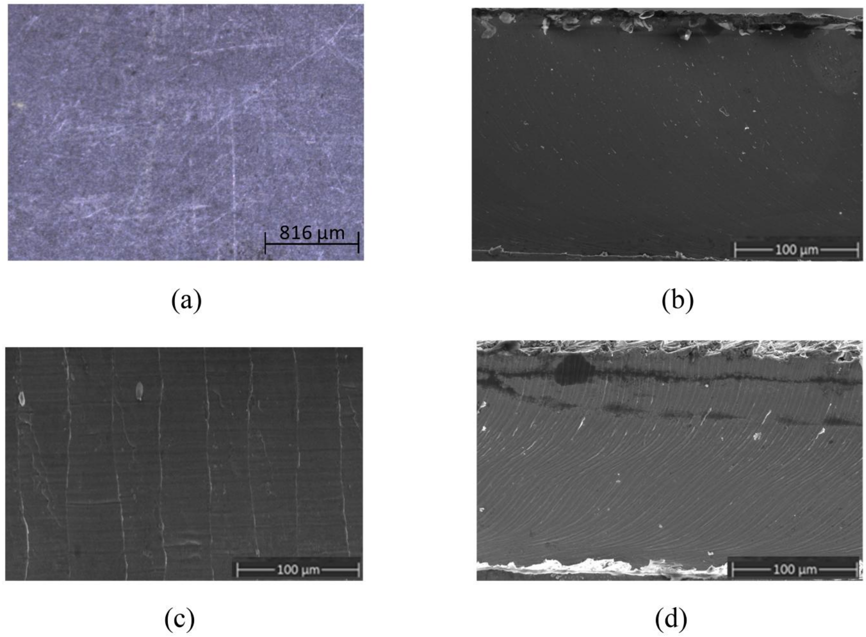


Figure 11. Thin-walled Ti6Al4V images: (a) surface image before machining; (b) machined surface image at 50,000 rpm and 30 µm radial depth of cut; (c) machined surface image at 50,000 rpm and 80 µm radial depth of cut; (d) machined surface image at 50,000 rpm and 130 µm radial depth of cut.

condition of the cutting tool or alter the micromilling process parameters. The decision to change the cutting tool can be taken by analyzing the shape of the machined workpiece. Hence, displacement of the thin-walled workpiece in the normal feed direction has been analyzed to estimate the deflection of the thin wall. The measured displacement of the thin wall consists of both forced vibration and permanent deformation, tha is, both elastic and plastic deformation. Hence, the displacement signal has also been filtered at tooth passing frequency (1666.67 Hz) with second-order high-pass Butterworth filter to remove the effect of forced vibration and estimate the permanent deflection of the thin-walled workpiece.

A maximum permanent deformation of 3.2 µm has been obtained at 30 µm radial depth of cut (Figure 12a), which has been determined after filtering the tooth passing frequency from the measured displacement. This permanent deformation has reached 51.97 µm at 80 µm radial depth of cut (Figure 12b). An increase in the radial depth of the cut to 130 µm leads to a maximum deformation of 197.43 µm (Figure 12c). The chatter-onset machining condition, as obtained from the acceleration spectrum, is for an 80 µm radial depth of cut (Figure 7b), which leads to a permanent deflection of 51.97 µm. Hence, the machinist has to make decision about changing the cutting tool if the deflection of 51.97 µm is not acceptable.

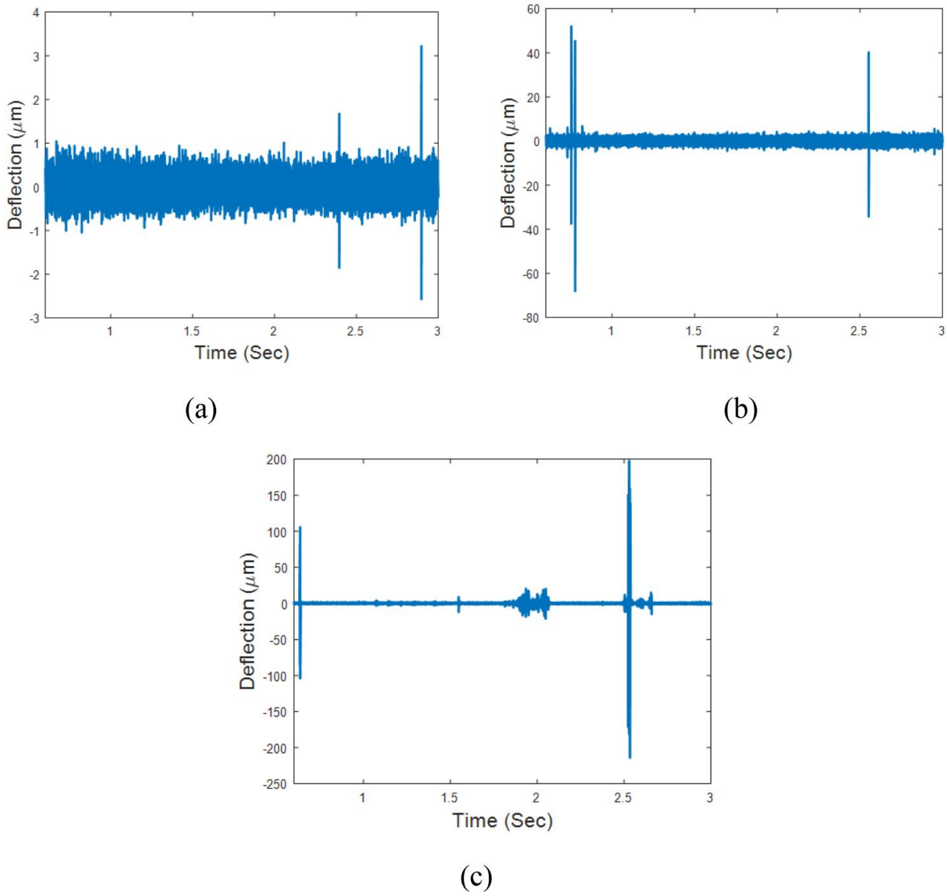


Figure 12. Filtered displacement of thin-wall at machining conditions of (a) 50,000 rpm and 30 µm radial depth of cut; (b) 50,000 rpm and 80 µm radial depth of cut; (c) 50,000 rpm and 130 µm radial depth of cut.

Furthermore, if the machining is continued without changing the cutting tool or altering the machining process parameters, it leads to severe deflection of 197.43 µm, which is on higher side. The real-time information of this change in deflection with progress of machining will be highly useful for the machinist to produce the component with permissible tolerances.

Dash app development for web application

A dash app is powerful tool for analytical and interactive design of a web interface for any business. Dash app can be used for deploying a web version for all activities required to monitor the manufacturing process. The acceleration and permanent deformation for monitoring the thin-wall

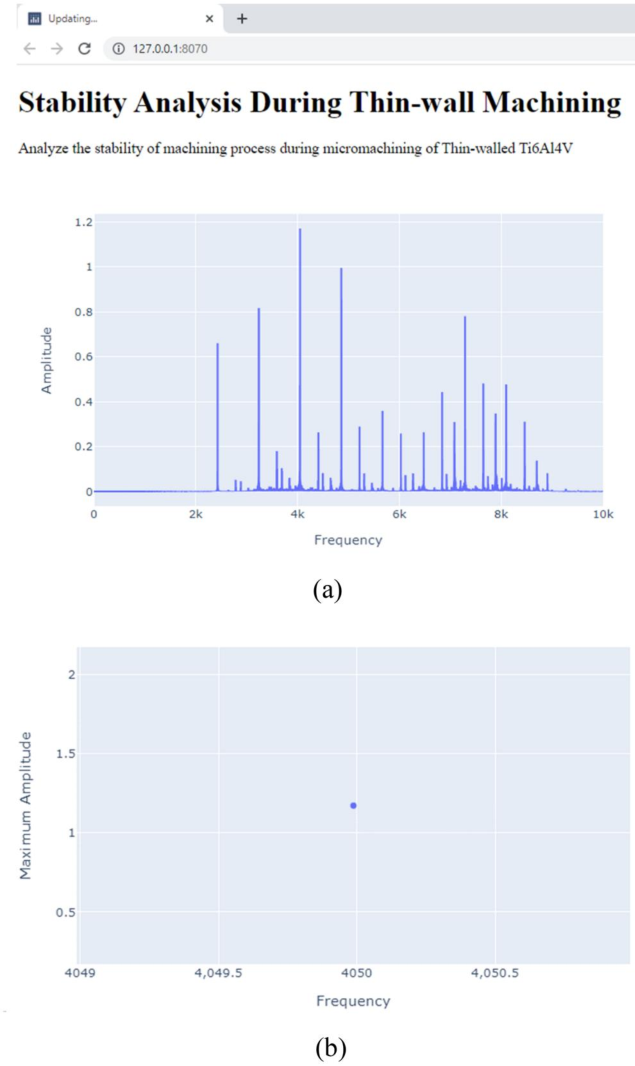


Figure 13. Projection of data on web with HTML address of 127.0.0.1:8070 (a) acceleration spectrum; (b) maximum amplitude of acceleration spectrum.

machining can be projected on web in real-time by developing the dash app.

Changes occurring in shape of thin-walled workpiece due to the progress of machining can be captured in real-time through the developed web version of the analyzed signals. Note that the web version of monitoring the machining can also be accessed by different people on the shop floor. The acceleration and deflection analysis have been carried out in Matlab and the analysis results have been interfaced to Python to project the real-time information on the developed web interface. A projection of the acceleration spectrum for micromilling at 50,000 rpm and at 30 µm radial depth of cut on the web interface shows a change in amplitude of all the frequency components present in the spectrum (Figure 13a). The frequency at which maximum amplitude occurs has been projected as an interactive feature on the web and the frequency at which maximum amplitude occurs is 4050 Hz (Figure 13b). This frequency 4050 Hz is near the fifth harmonics of the spindle rotational frequency and hence, the process is stable. The projection of the acceleration spectrum and deflection of a thin-walled workpiece at 50,000 rpm and at 30 μm radial depth of cut on the web leverages the machinist with the option of visualizing the machining in real-time (Figure 13).

A web version of acceleration spectrum shows the magnitude and frequency of acceleration and hence, the real-time information about the stability or abnormalities of machining can be extracted. The inclusion of all analyzed results in a drop-down fashion will help the machinist quickly monitor the process as per his requirements. Hence, a drop-down list for different figures has been developed in a web application to access the desired information by operators or machinists. The drop-down list of figures includes both acceleration spectrum and deflection results (Figure 14). A quick access to the acceleration spectrum may indicate the presence of harmonics of tooth passing frequency and the natural modes of the thin-walled workpiece (Figure 14a). This quick access of information directs the machinists to think about the appropriate action to be taken to carry out machining with the desired surface finish. Information about real-time may also be accessed from the drop-down list to quickly estimate the permanent deflection in the machined components (Figure 14b).

The deflection can be determined at any instantaneous machining time by toggling the cursor through the deflection signal (Figure 15b). Moreover, if all the real-time analyzed signals overlap with each other with the progress of machining, it may help in visualizing the change in machining response at a certain interval of material removal rate. An overlapping of instantaneous signals indicates the frequency that leads to dominant magnitude (Figure 15a). The identified frequency can be checked for the presence of workpiece's natural frequency or cutting tool's natural frequency and corrective action may be taken to eliminate the excitation of natural frequency to carry out the machining without chatter. Furthermore, the overlapping of deflection with progress of machining indicates the time and machining length where the maximum permanent deformation has occurred (Figure 15b). The presence of a high value of permanent deformation will be highly useful for the operator to check the condition of the cutting tool before changing it or to continue the machining until the deflection of the workpiece crosses the allowable limit of deflection.

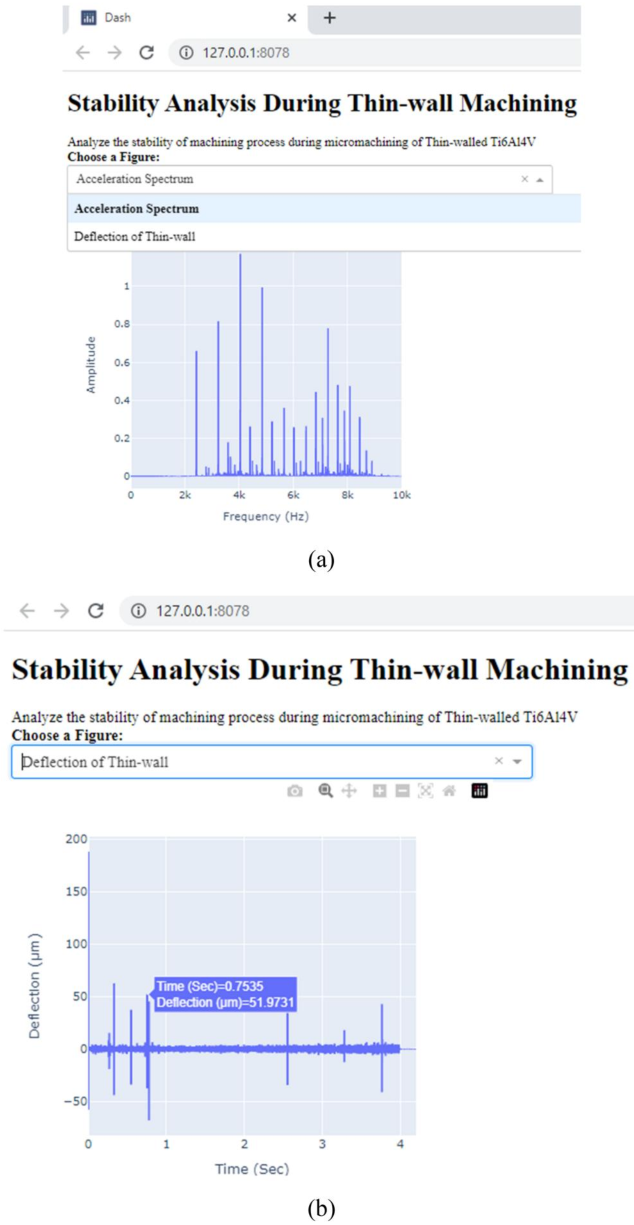


Figure 14. Web version for both acceleration spectrum and deflection of thin-wall in dropdown style: (a) selection of the acceleration spectrum; (b) selection pf deflection.

Overall deflection analysis

The maximum deflection can be estimated for incoming displacement signal from the laser displacement sensor and it can be projected on web interface. All the filtering of the incoming displacement and estimation of permanent deformation have been carried out in Matlab, and the analyzed results have also been interfaced with Python to visualize the deflection on

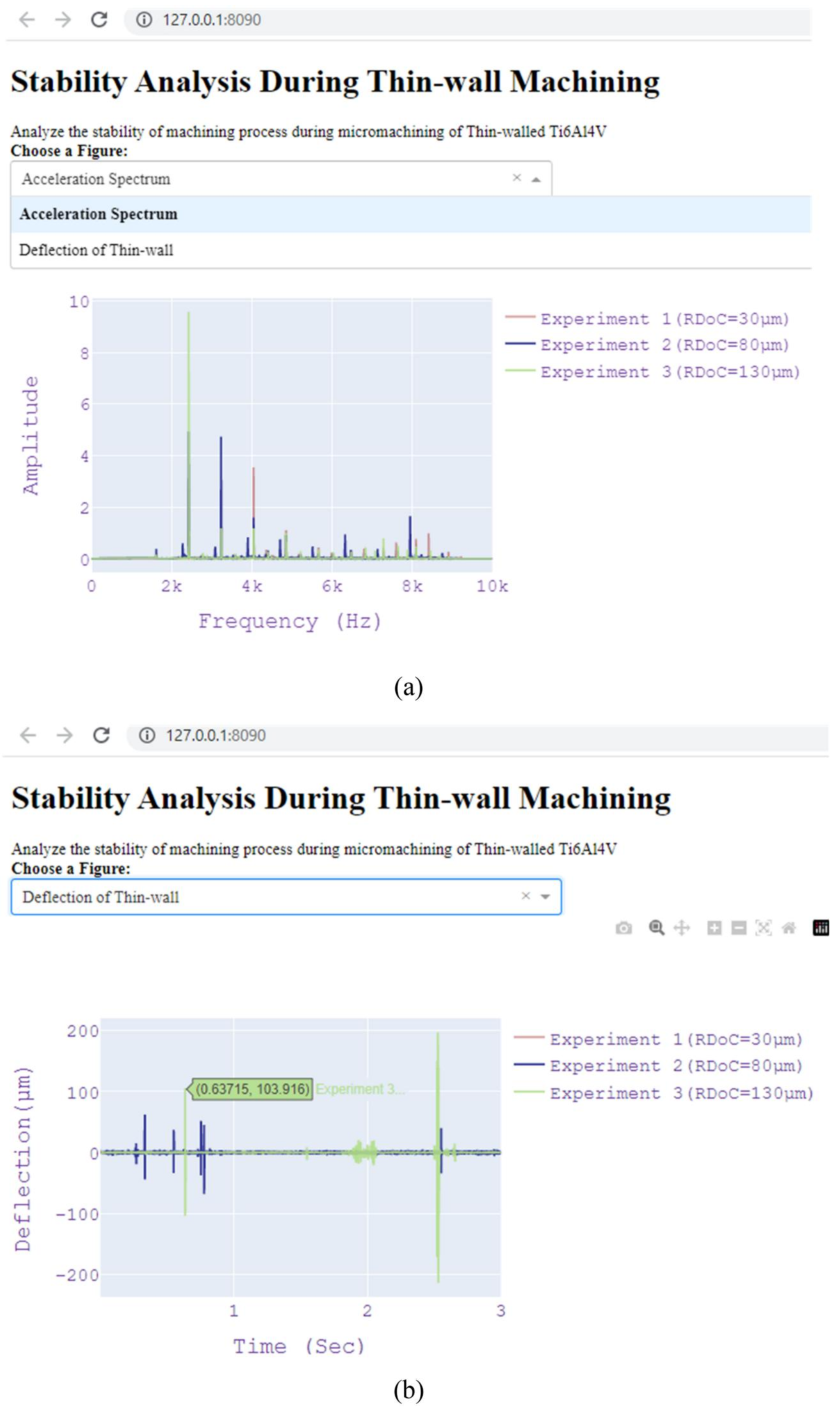


Figure 15. Web interface for (a) overlapping of acceleration spectrum for incoming signal for each machining pass; (b) overlapping of deflection of thin-wall for incoming signal for each machining pass.

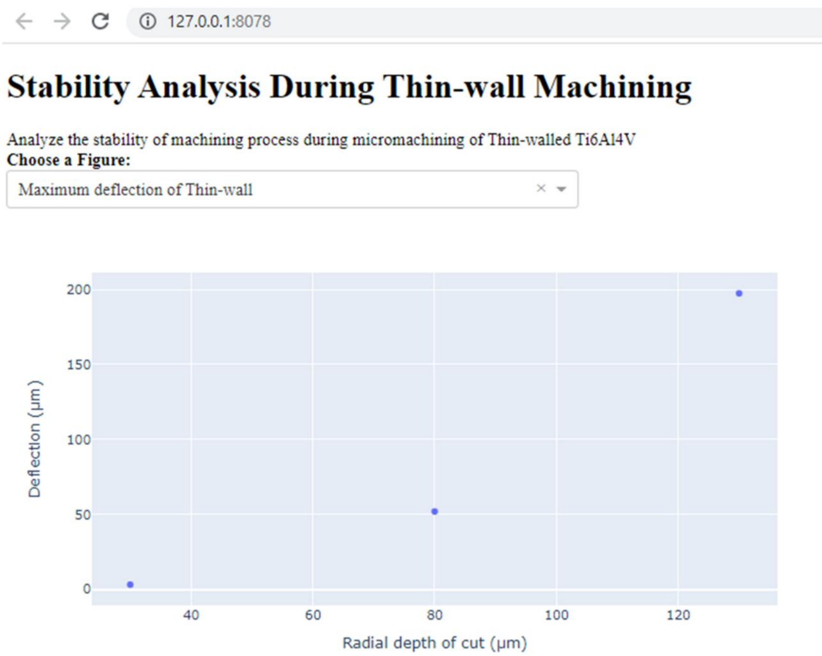


Figure 16. Maximum deformation projection on web browser.

the web browser. The deflection on web browser shows that there is an increase in deflection with an increase of radial depth of cut and hence, necessary action must be taken to reduce the deflection (Figure 16).

Machine learning approach for stability classification

The micromilling of thin-walled Ti6Al4V has been carried out at different radial depth of cuts and cutting speeds. Furthermore, the maximum deflection and surface roughness have also been estimated for each machining conditions. A critical radial depth of cut has been obtained as 80 µm above which the micromilling is unstable for all the cutting speeds and it has been discussed in the section of acceleration signal analysis. A support vector machine (SVM)-based machine learning approach has been applied in the present work to draw a hyperplane between the stable and chatter-dominant micromilling process conditions. Hence, SVM has been adopted to classify the machining process into stable and unstable classes after training the input data. The input data are maximum deflection and surface roughness obtained from the machining conditions, and it have been trained for classification using SVM (Figure 17). 80% of data has been used for training and 20% has been used for testing. 92% of accuracy in classification has been obtained using linear kernel. The trained model can be used for predicting stable and chatter machining conditions based on the real-time data recorded during the experiments.

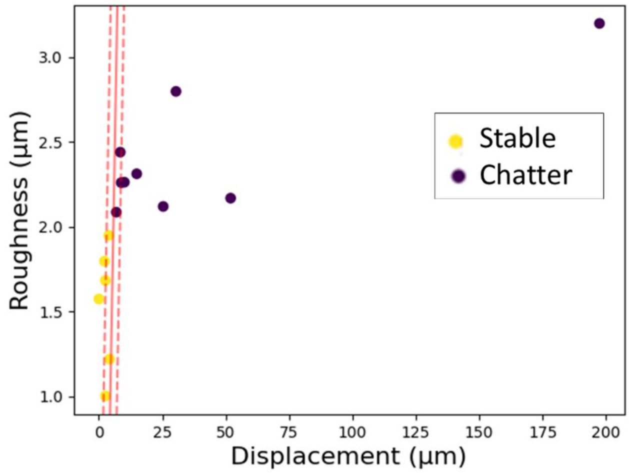
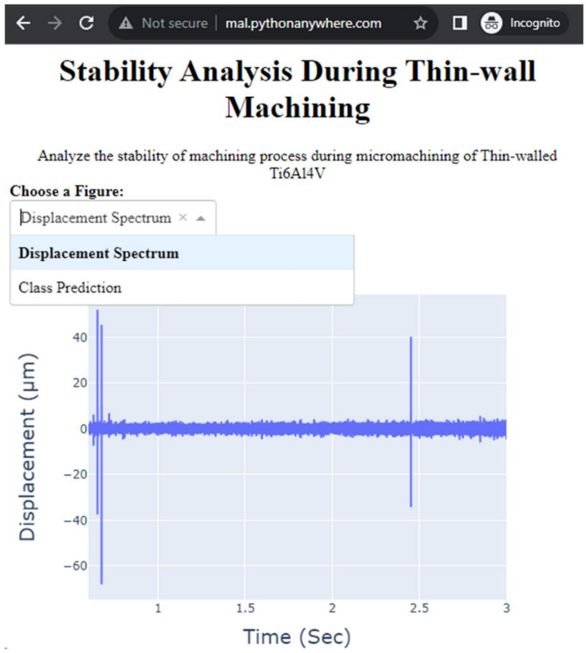


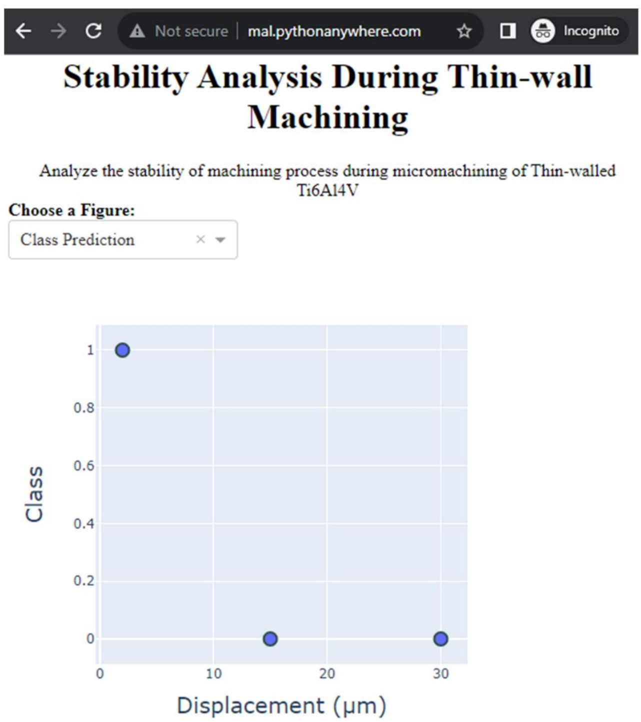
Figure 17. SVM classification.

Deploying a DASH app in cloud

All the interactive features developed in the dash app can be accessed easily on the local server. However, it is imperative to monitor the process in the cloud by updating the in-process captured data. Hence, the developed dash app has also been forecasted in the cloud. Forecasting the dash app in the cloud has been carried out with the pythonanywhere interface. PythonAnywhere is an effective tool to host the website and deploy the Python code without the need for any other software. The data from the sensors is captured and updated in the backend, and it is further converted into the frequency domain to identify the stable and chatter-dominant machining conditions. The time-series displacement of thin-walled parts during micromilling can be used to determine the maximum displacement, which can be fed to the developed SVM-based machine learning approach to classify the machining process into stable and chatter machining conditions. The predicted class can also be verified by the presence of dominant workpiece natural frequencies in the acceleration spectrum. The developed dash app has been hosted in the cloud, which shows the monitoring of displacement can easily be done away from the local server, as shown in Figure 18a. Furthermore, the developed machine learning approach based on SVM for the identification of stable and chatter machining conditions has also been included in the cloud *via* the dash app (Figure 18b). The maximum deflection measured from the in-process displacement signal (Figure 18a) is directly taken to the SVM algorithm, which predicts the stable machining conditions (Class 1) and chatter dominant machining conditions (Class 0), as shown in Figure 18b. The dash app developed in the present work can also be utilized to add any additional feature into it and it can be accessed *via* cloud.



(a)



(b)

Figure 18. In the cloud projection of the dash app for process analysis; (a) in-process displacement: (b) class prediction using SVM.

Concluding remarks

A framework for smart manufacturing to monitor and detect abnormalities during high-speed micromilling of thin-walled workpiece of Ti6Al4V has been developed in the present work. The necessary criteria to identify the instability during micromilling of the thin-walled workpiece has been analyzed first, which is also responsible for form deviation in the machined thin-walled structure. Furthermore, a dash app has been developed for interactive web applications to visualize the real-time analysis of the signal captured during the micromilling process. The developed dash app has also been augmented with a support vector machine (SVM)-based machine learning approach to predict stable and chatter-dominant machining conditions. The developed SVM takes the data from the captured signal in the dash app to predict stable and unstable machining conditions. Different features for monitoring the micromilling process developed in the dash app have also been forecasted in the cloud. Hence, online monitoring of the micromilling process in real-time is possible with a developed cloud-based web interface with different interactive features. Moreover, the identified stable and chatter-dominant machining conditions can also be further verified by the excitation of thin-walled natural frequencies in the acceleration spectrum in real-time. This online monitoring of the micromilling process is highly desirable, attributed to the use of a low-flexural cutting tool, which can fail catastrophically if the chatter is not detected on time and destroys the dimensional and geometrical accuracy of the machined thin wall.

Following conclusions can be drawn from the present work:

- The analysis of acceleration spectrum indicates the chatter onset at 80 μm radial depth of cut due to presence of dominant thin-walled workpiece natural frequency.
- An increase in depth of cut to 130 μm radial depth of cut at 50000 rpm and at 3 μm/flute feed rate increases the magnitude of excited thin-wall natural frequency to two-times the magnitude obtained at 80 μm radial depth of cut. Hence, severe chatter is observed at 130 μm radial depth of cut.
- An increase in the radial depth of cut from 80 to 130 μm at a cutting speed of 50,000 rpm and a feed rate of 3 μm/flute increases the deflection by 279.89%.
- The change in magnitude at different frequencies can be visualized on the developed web browser and the dominant frequency can be identified in real-time during machining process.
- All acceleration spectrums during the machining process can be updated automatically in real-time on the developed web browser, and all spectra

can also be overlapped to visualize the shift in frequency as machining progresses.

- The forecasting interactive feature developed in the Dash app in the cloud can be used to monitor and predict the stable and chatter dominant machining conditions from any location, and hence, it makes the monitoring of the micromilling process highly flexible.
- The visualization of change in maximum deflection on the web browser is highly useful for the machinist to take corrective action if the deflection goes beyond the allowable limit.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Funding

The authors declare that no financial assistance has been received for the work carried out in the present paper.

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