

Artificial neural network and particle swarm optimization approach to enhance productivity of CNC lathe

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Abstract. This paper suggests a way of increasing productivity and reducing chatter in CNC turning processes. Vibration signals recorded through a microphone were decomposed using a combined Wavelet Denoising and Local Mean Decomposition (WDLMD) method and dominant Product Functions related to the chatter were recreated to be analysed. Different backpropagation algorithms were tested to enhance ANN-based prediction, and the Levenberg-Marquardt algorithm illustrated the lowest average absolute percentage error in predicting Chatter Index and Material Removal Rate. Multi-objective particle swarm optimization was further refined to obtain optimal process parameters including depth of cut (0.32-0.38 mm), spindle speed (1480-1680 rpm), and feed rate (35.5-40 mm/min) that will be used to achieve high quality surface. The strength of the suggested framework was confirmed by further experiments.

Introduction

Regenerative chatter is a significant obstacle in machining, which restricts automation and stability of the process. Though stability lobe diagrams are very popular in defining stable cutting zones, they do not consider crucial parameters like feed rate, and hence to accurately select the parameters is not easy [1,2]. Therefore, efficient chatter detection by acquiring and processing signals is crucial. Microphone-based sensing has been considered to capture vibration signals, but these signals are usually polluted by ambient noise [3,4]. Conventional denoising techniques such as time, frequency, and time-frequency domains necessitate effective denoising of the data [5,6,7]. Other advanced methods such as the wavelet packet decomposition, empirical mode decomposition and Hilbert-Huang transform have shown promise but they have problems such as modal aliasing and end effects [8,9]. Local mean decomposition has better performance, but the shortcomings remain [10,11]. In order to overcome these limitations, the current work proposes a hybrid WDLMD method which combines the wavelet denoising and the local mean decomposition to improve signal clarity and the extraction of chatter features. Moreover, it is noticed that simultaneous enhancement of surface quality and removal rate of the material is required and thus a multi-objective optimization framework is used to identify optimal turning parameters to achieve a stable and productive machining.

Methodology

The MTAB XL-TURN, CNC lathe, cutting tool, carbide insert TTS04, and workpiece Al-6061-T6 were utilised to validate the suggested WDLMD process. The signal was measured with AHUJA AGN-480 dynamic unidirectional microphone at a sample time of 0.125 milliseconds on a full factorial basis. Chatter Index (CI) and Threshold using Nakagami distribution is shown in Fig.1.



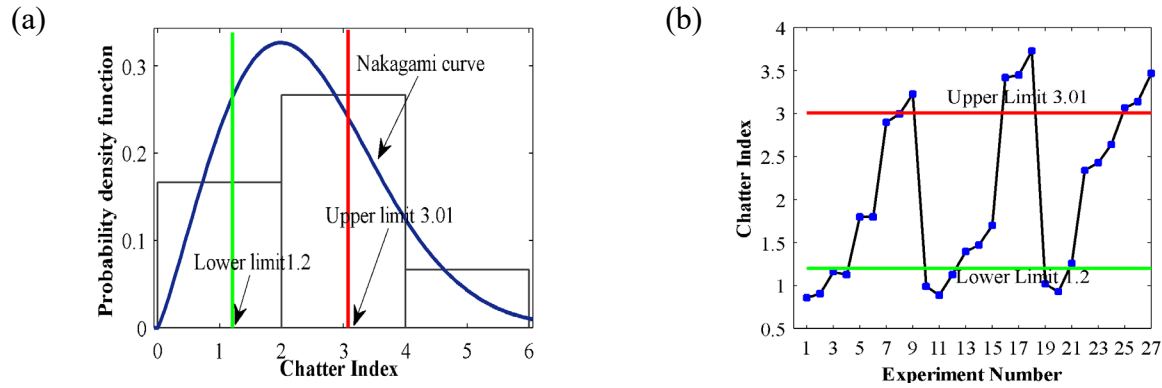


Fig. 1 (a) PDF vs. CI (b) CI vs. Experiment number

Metal removal rate (MRR)

$$MRR = \frac{W_i - W_f}{t}$$

Estimated MRR for all 27 experiments has been calculated using this equation.

Prediction model of responses using ANN.

This section will give the evolution of ANN-based models to predict Chatter Index (CI) and Material Removal Rate (MRR) which have nonlinear dependence on machining parameters [12,13]. Two models were developed based on three-layer architectures, optimized hidden neurons, and respective outputs (CI or MRR). Hidden layer configuration, training algorithms, and activation functions influence model performance, therefore, these factors were systematically optimized in order to reduce prediction error. The assessment was performed on five backpropagation algorithms: BFG, CGB, GDX, LM and RP.

The mean squared error (MSE) was used as a performance measure to determine the optimal number of hidden neurons to avoid overfitting and underfitting. To train the models, the dataset was split into train and validation sets in the ratio 70:30, and by adjusting the hidden neurons of each algorithms 1 to 20, the models were trained. Results indicate that optimal neuron counts vary with the training function. The best neurons in predicting CI were 5 (BFG), 6 (CGB), 11 (GDX), 9 (LM) and 7 (RP) respectively as shown in Figs 2 and 3. These optimized settings were then employed in training the models.

Predictability

In this section, the effects of various training functions on the accuracy of prediction of CI and MRR are considered. Three-layer ANN models, including input (n, f, d), optimized hidden layer, and output (CI or MRR) were trained with five variants of backpropagation namely: BFG, CGB, GDX, LM, and RP. The dataset was split into training, validation, and testing subsets and the performance of the model was assessed by the use of absolute percentage deviation (APD).

The average absolute percentage deviation (AAPD) for CI prediction was 9.08 (BFG), 15.62 (CGB), 16.01 (GDX), 8.70 (LM), and 14.31 (RP), while for MRR prediction it was 10.67, 13.09, 14.39, 9.74, and 11.12, respectively. Of all these algorithms, Levenberg Marquardt (LM) algorithm had the lowest AAPD of both responses, which means that it predicts better. Therefore, LM was chosen as the best training functionality towards the ultimate prediction models.

Optimization using Multi-Objective Particle Swarm Optimization (MOPSO) method

The multi-objective optimization strategy will be needed to reduce CI and maximize MRR considering the models obtained by ANN. Through experimentation, it has been observed that there is a trade-off, such that as cutting parameters are increased, MRR rises, but chatter also rises, and vice versa. Multi-Objective Particle Swarm Optimization (MOPSO) was used to overcome this conflict, to identify optimal combinations of machining parameters. MOPSO has been proven

to perform better than other optimization methods in the same application [14,15]. The algorithm in Fig.4, works by searching optimal solutions until a termination criteria is reached, resulting in a final set of non-dominated (Pareto-optimal) solutions.

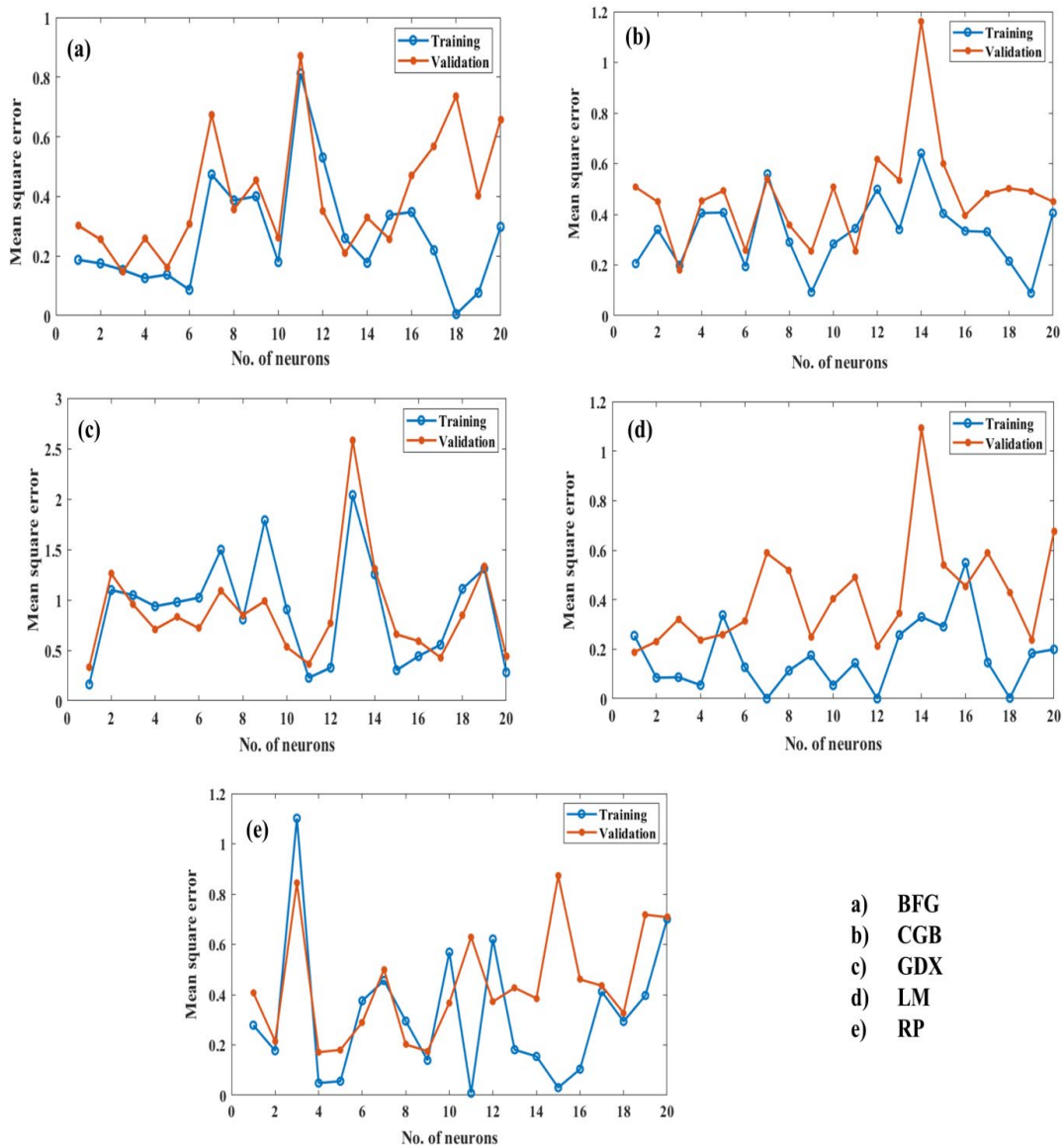


Fig. 2 MSE for CI data sets for all five training function

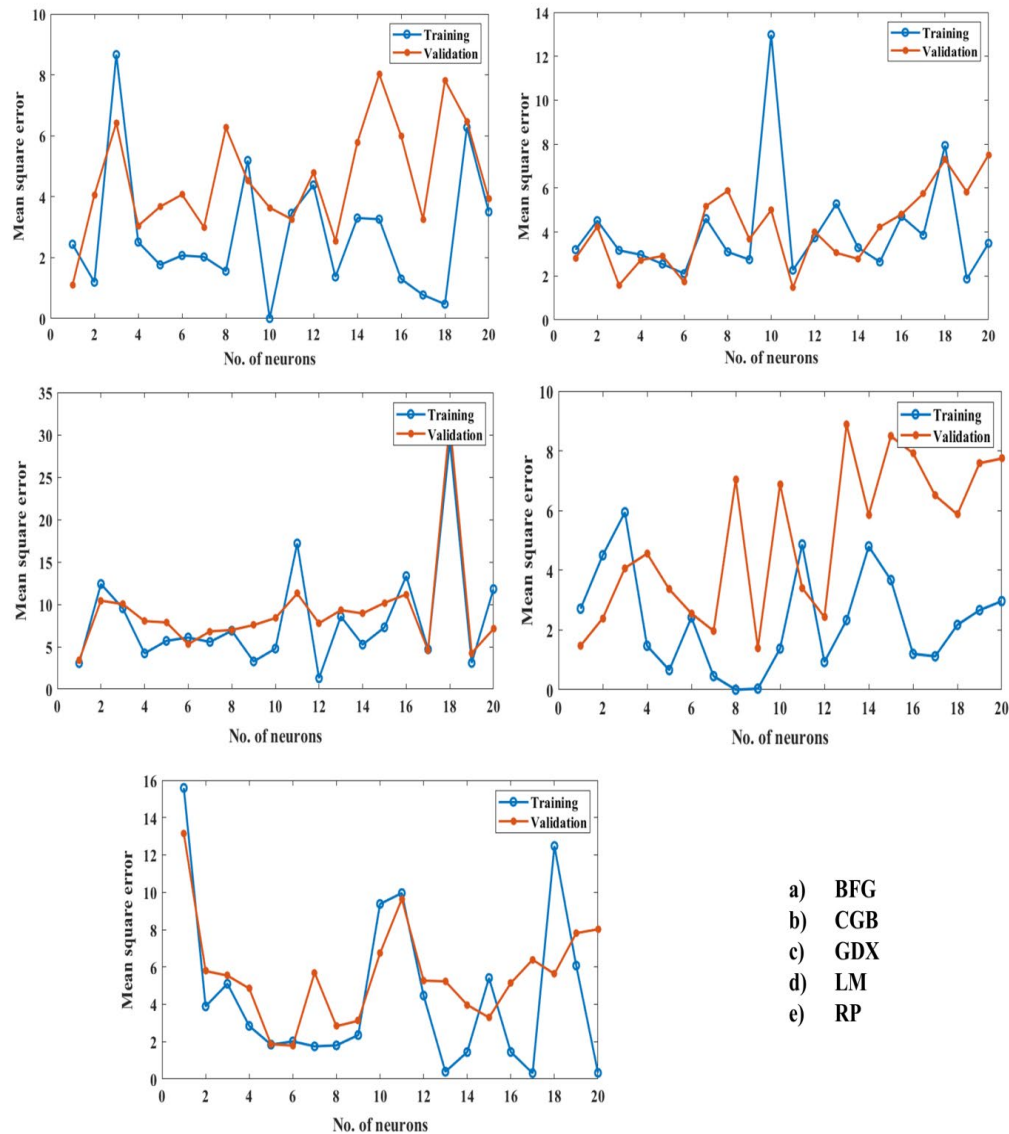


Fig. 3 MSE for MRR data sets for all five training function

Results and discussion

The WDLMD method was able to filter noise and isolate true chatter frequencies as seen through the distinguishable FFT peaks of the reconstructed signal that have shown little noise interference, and mode mixing. Additionally, MOPSO was used to optimize CI and MRR and contour plots were plotted to study machining behavior. The contour analysis indicates that cutting parameters have a significant impact on both responses. There is an increase in machining stability with increased spindle speed, and a decrease in machining stability with increased feed rate and depth of cut. In contrast to previous research, the results show that the feed rate has a smaller impact on chatter than spindle speed and depth of cut. MRR rises when the parameter values are high as shown in the contour plots on Fig.5. These observations led to safe machining zones to attain high productivity with less chatter. Higher values of depth of cut and feed rate are associated with higher spindle speeds and moderate values of the latter, whereas excessive values of the latter result in severe chatter. Detailed contour analysis was carried out to give optimal parameter ranges to minimize CI and maximize MRR.

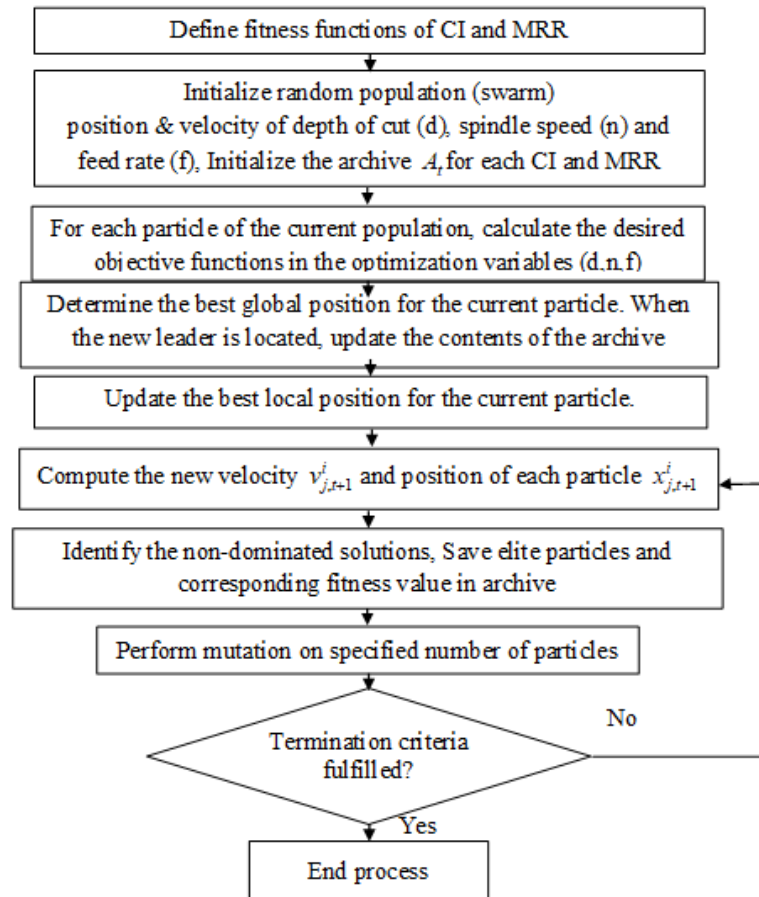
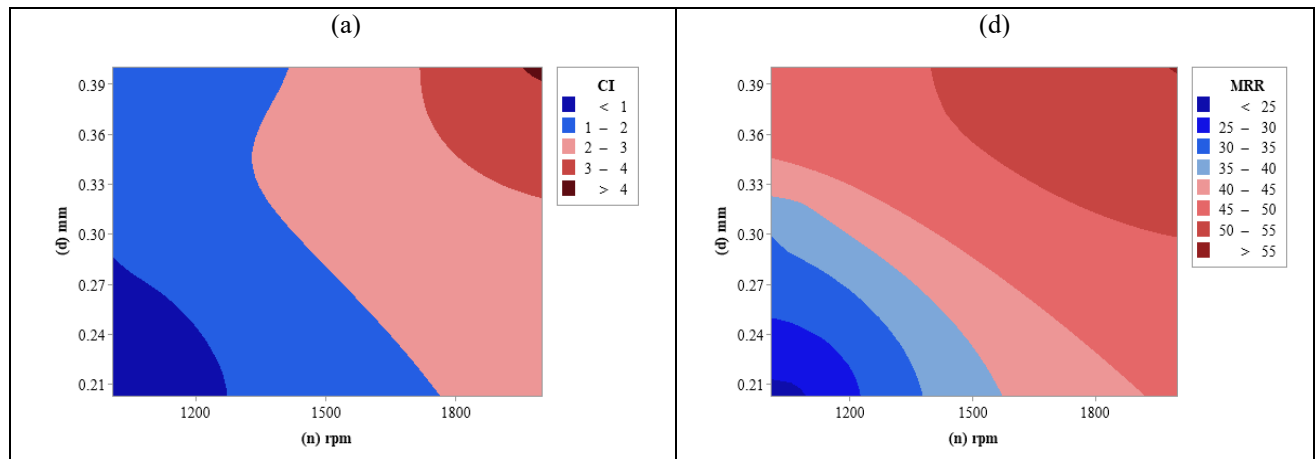


Fig. 4 Flowchart of MOPSO



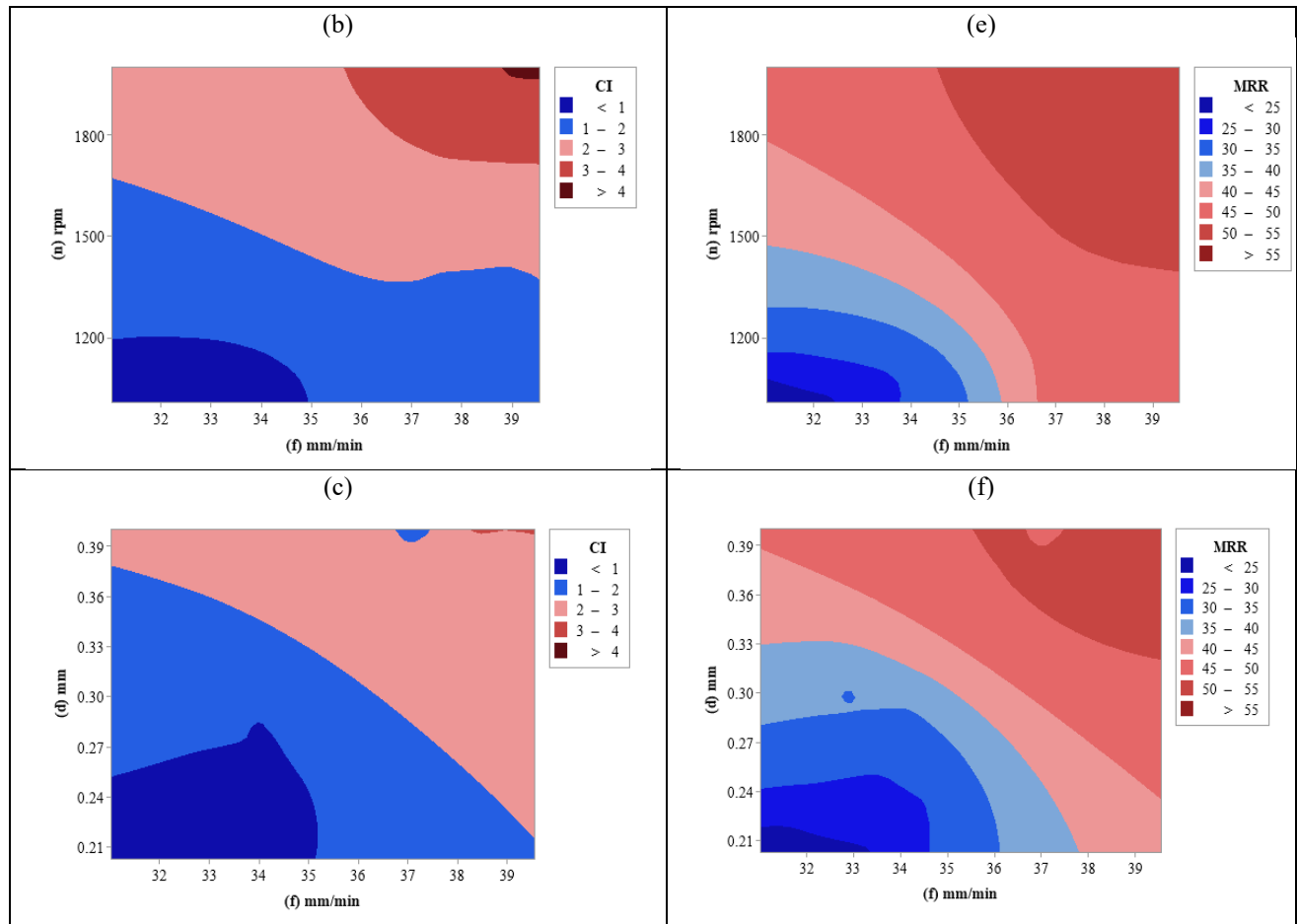


Fig. 5 CI and MRR variation w.r.t. d , n and f

The paper will seek to find the best machining parameters that can provide high MRR with limited chatter. By overlapping the personal parameters limits of CI and MRR, a single set of optimal parameters was formed. Findings show that Nakagami distribution is a good representation of machining stability. CI threshold limits were found to be 1.2 (lower) and 3.01 (upper). The samples with CI lower than the lower limit appeared smooth with negligible chatter marks, whereas samples with CI higher than the upper limit had severe chatter marks. Samples of the range of the threshold had mild chatter. These observations verify the validity of the proposed thresholds and also reveal the effectiveness of the methodology in determining stable machining conditions.

Conclusions

In this paper, a stable range in the cutting of CNC turning is identified in order to obtain a better quality surface and productivity. The suggested WDLMD method is effective in extracting chatter features and suppressing noise, and FFT analysis can accurately identify the chatter frequencies. The Chatter Index (CI) is a trusted measure of chatter severity, distinguishing between stable, moderate and unstable regimes based on threshold limits calculated using the Nakagami distribution. The higher the spindle speed, the greater the stability and the greater the depth of cut and the feed rate, the worse the chatter. ANN models that had been developed with optimized training functions and neuron configurations were further optimized with MOPSO to come up with optimal machining conditions. The recommended parameter ranges such as depth of cut (0.32-0.38 mm), spindle speed (1480-1680 rpm) and feed rate (35.5-40 mm/min) are considered to

provide stable machining with increased MRR. The suggested framework presents a viable guideline to consider machining parameters when applied in industries

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