

## Prediction of cutting force uncertainty characteristics through the integration of logical and numerical processing techniques

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### Abstract

This paper proposes a novel approach for predicting cutting force uncertainty characteristics by combining Large Language Models (LLMs) with traditional signal processing techniques. The methodology begins with signal filtering and residual noise extraction, followed by the development of uncertainty features using a Gaussian Mixture Model. System configuration, data format, and signal processing functions were encoded to create a fine-tuning dataset, which was used to adapt a locally quantised Llama3.2:3b model for the design of the uncertainty prediction framework. Final validation results indicate that predicting the residual uncertainty features of cutting force during the Partial Engagement stage is challenging, owing to numerous non-identical vibration components. In contrast, predictions for the Full Engagement stage demonstrate relatively greater accuracy. Overall, this study demonstrates the feasibility of integrating signal-processing-based logical reasoning with LLMs for uncertainty prediction.

**Keywords:** Large Language Model, LLM, signal processing, uncertainty prediction

### 1. Introduction

The studies focused on cutting force uncertainty are helpful for machine tool stability diagnostics and performance optimisation.

The traditional uncertainty analysis covers very wide range such as geometric uncertainty and vibration uncertainty. One of the important studies is cutting force uncertainty [1]. For example, in Axinte's work, the uncertainty factors related to calibration, acquisition, and process influences can significantly lower down the cutting force prediction accuracy [2]. And, by optimising the model and considering the uncertainty factors, the prediction of cutting force can be raised up to 95%.

Quantification of cutting force uncertainty is integral to improving machining process reliability and understanding variability in tool-workpiece interactions. Traditional uncertainty propagation techniques, such as first-order Taylor expansions and Monte Carlo simulations, have been widely used to estimate confidence intervals in predicted forces [3]. More recently, Gaussian Mixture Models (GMMs) have been introduced to better capture multi-modal distributions and non-Gaussian variability in cutting force residuals, providing richer statistical representations than single-Gaussian assumptions. For example, Xu employed GMMs to approximate non-Gaussian orbit uncertainty and demonstrated enhanced fidelity while managing computational costs [4]. Similarly, work by Muralikrishna integrated GMMs within a fuzzy logic framework to model error residuals in turning processes, showing improved uncertainty encoding in force prediction [5]. These developments indicate that GMM-based approaches offer a statistically robust foundation for uncertainty quantification, enhancing both interpretability and predictive accuracy in machining dynamics.

Modelling cutting force uncertainty using Gaussian Mixture Models (GMMs) provides a statistically principled approach to

representing the complex, non-Gaussian nature of machining variability. Traditional parametric models often assume unimodal Gaussian errors, which fail to capture the multi-modal or asymmetric distributions observed in experimental cutting force data [3]. GMMs address this limitation by expressing the probability density as a weighted sum of multiple Gaussian components, enabling flexible approximation of intricate residual noise structures. For instance, Xu demonstrated the use of adaptive GMMs for improved uncertainty propagation in manufacturing simulations, highlighting their ability to maintain fidelity with reduced computational cost [6]. Similarly, Muralikrishna integrated GMM-based error characterisation within fuzzy logic systems for turning force prediction, illustrating the benefits of hybrid modelling for uncertainty-aware process control [5]. Such approaches underscore the role of GMMs as versatile tools for uncertainty quantification in advanced manufacturing.

In summary, from previous works, there are two gaps:

- The uncertainty modelling only focus on cutting force signal rather than the residual noise in different engagement stages.
- The work of predicting uncertainty is still not sufficiently carried out.

This study will apply newest LLM and its related technologies together with traditional signal processing techniques provide the feasible solution for modelling residual noise of cutting force at different situations.

### 2. Experiment

#### 2.1 Experiment Platform

The milling experiments were carried out on a Cincinnati Arrow2 500 CNC, a three-axis milling machine with a 20-kW spindle operating from 0 to 10,000 RPM. The machine provides torque loads of 10 k Nm on the X and Y axes and 20 k Nm on the Z axis, with a maximum machining volume of 700 mm × 700 mm × 700 mm. After calibration, the slotting process consistently

achieved an average surface roughness below  $10\ \mu\text{m}$ . A Kistler Dynamometer (9255B) was installed as the working table (Fig. 1) and connected to a 5017 Amplifier and 5697A DAQ system. Cutting processes were monitored and visualised using Kistler's Dynaware software, supporting sampling frequencies up to approximately 70 kHz per channel.

### 2.2 Experiment Design

To ensure reproducibility, each machining parameter set was tested in four repeated trials, resulting in four test groups and a total of 16 cutting trials (Table 1). The applied mill tool details are listed in Table 2. Within each group, the assigned parameters remained consistent across all trials. Flood cooling was employed throughout to limit heat generation and reduce thermal deformation during milling of Al5083. Tool wear was measured at the start and end of each trial using an ALICONA optical system. After all, 4 tests, the recorded tool nose wear averaged 0.11 mm, well below the ISO 8688-2:1989 failure limit of 0.3 mm.



Figure 1. Cincinnati Arrow2 500 CNC.

Table 1 Machining parameters.

Trail NO.	RPM	DOC (mm)	Feed (mm/min)
1	3000	1	400
2	3000	1	750
3	5000	1	800
4	5000	1	1500

Table 2 Tool properties and geometric information.

Tool Type	2P170-1200-NA H10F	Applied Workpiece	Aluminium alloys <sup>a</sup>
Diameter	12 mm	Tool Material	Solid Carbide
Helix angle	$25^\circ$	Depth of cut maximum	48 mm
Radial rake angle	$17^\circ$		
Axis rake angle	$1^\circ$	Flute NO.	2
Corner radius	0.15 mm		
Tool length	99 mm		

## 3. Signal Feature Extraction

### 3.1 Define Engagement Stages

The different Cutter-Workpiece-Engagement stage can lead to variations of uncertainty due to different chip loads. This study will focus on Partial engagement and Full Engagement of face milling, which are defined as follow:

1. CWE Process Type I – Partial Engagement

For each tooth, the theoretical contact time per cycle is expected to be less than  $\pi/\omega$  seconds, where  $\omega$  is the tooth passing frequency.

2. CWE Process Type II – Full Engagement

This stage is characterised as "Full Engagement" when the theoretical contact time per cycle reaches  $\pi/\omega$  seconds. In practice, however, this duration varies over time due to residual uncertainties within the machine tool system.

### 3.2 Frequency features.

#### 3.2.1 Features of wide-band frequency distribution

For Partial Engagement stage and Full Engagement stage, the vibration due to machining processes is active only below 10000 Hz. As shown in Figure 2, the major components of the observed signal are located at the low frequency band between 0 Hz to 3000Hz. Most of the active frequencies are the tooth passing frequency and its high-order harmonics. The band between 3000 Hz and 6700 Hz contains high-order harmonics of tooth passing frequencies and non-identical frequencies which are also caused by the machining processes. Above 6700 Hz, the active frequencies are barely observed.

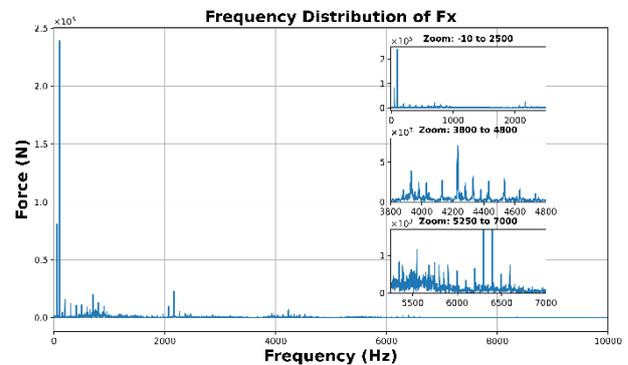


Figure 2. Frequency distribution of  $F_x$  from the measurement of Trial 1.

#### 3.2.2 Tooth passing frequency and harmonics

As mentioned in Section 3.2.1, the tooth passing frequency and its high-order harmonics are the major component to the measured cutting force signals. In Figure 3 (a), from the time domain analysis, the residual noise contribution to the target signal is very limited, which is less than 10 % of the cutting force peak value. By analysing the detection of the harmonics of tooth passing frequency, the Figure 3 (b) shows that the percentage of harmonics detection continuously drops with the increasing number of total frequencies ranked by their significance. This also evident that the tooth passing frequency and its harmonics are the major components to the cutting force signals.

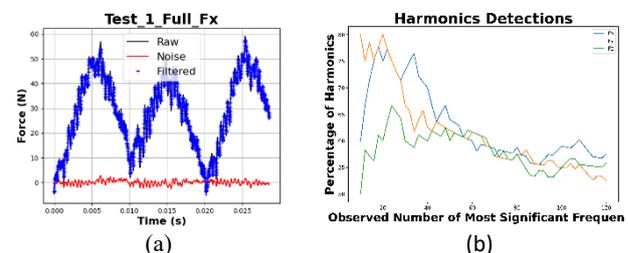


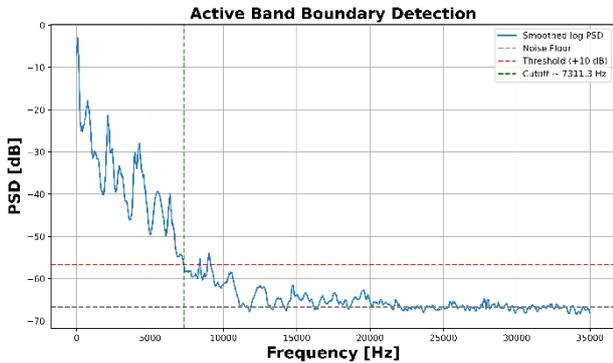
Figure 3. Analysis of tooth passing frequency and its harmonics.

### 3.3 Residual noise

#### 3.3.1 Cutoff frequency of gaussian band

The core task of this work is to study the uncertainty features, to develop the solution of extracting them and using the technology of fusing logic processing and numeric processing to predict the cutting force uncertainty. However, based on the analysis addressed in Section 3.2.1, at the lower frequency band, regardless of the tooth passing frequency and its harmonics, there are still a lot of non-identical frequencies caused by the

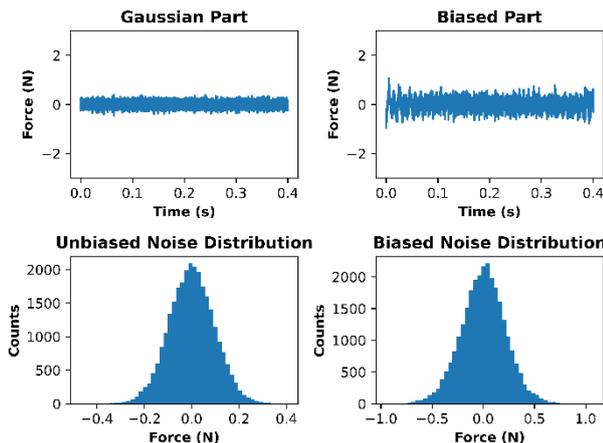
machining processes. But at the higher frequency band, the major noise might be gaussian noise. Therefore, it is necessary to determine a cutoff frequency which can effectively separate the residual noise. As **Figure 4** shows, by considering the time domain analysis and the analysis conducted in **Figure 2**, the **Power Spectrum Density (PSD)** threshold can be set to 10 db. With this threshold setting, the lower frequency band can contain full information of machining processes, while the higher frequency band will be close to Gaussian Noise with very limited influence by the machining processes.



**Figure 4.** Cutoff frequency between active band and gaussian band of  $F_x$  from the measurement of Trial 1.

### 3.3.2 Biased/Unbiased residual noise

For prediction of cutting force uncertainty, it is necessary to analyse the residual noise below the cutoff frequency and above the cutoff frequency due the influence of non-identical vibrations caused by machining process. And therefore, the residual noise located below cutoff frequency can be considered as biased noise, while the residual noise located above cutoff frequency can be considered as unbiased noise. **Figure 5** shows the comparisons of the residual noise distribution between these two frequency bands. The distribution of biased noise has the wider band of cutting force, even if it is close to the single peak Gaussian distribution. But by examining the biased noise distribution, the peak is slight leading to positive direction, which is caused by the non-identical vibration frequency.



**Figure 5.** Analysis of tooth passing frequency and its harmonics.

## 4. Uncertainty Prediction

For the present study, the prediction of the uncertainty model focuses exclusively on the distributional features of the residual noise. In order to ensure precision in fitting, these noise features are characterised using Gaussian Mixture Methods.

A wide range of industries stand to benefit substantially from advances in Large Language Models (LLMs) and related technologies. Integrated LLM capabilities can significantly enhance both productivity and the quality of task execution. In this work, a localised LLM and the Model Context Protocol are employed alongside traditional numerical signal processing

techniques to develop a solution for predicting cutting force uncertainty. The solution framework is designed using the quantised llama3.2:3b LLM, based on Llama3.2 (Meta), which is selected for its robust logical inference capabilities.

### 4.1 Chain-of-Thoughts from traditional method.

Based on feature analysis of the cutting force signals, the traditional approach to developing an uncertainty prediction framework can be described as follows:

Step 1: Data loading.

Step 2: Preprocessing of the loaded data to extract both biased and unbiased residual noise signals.

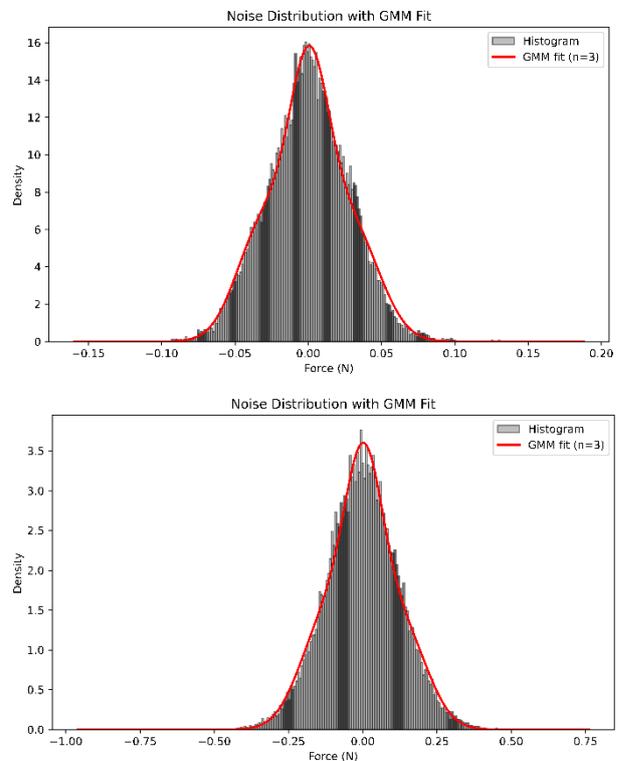
Step 3: Estimation of the weights, means, and variances of the Gaussian Mixture Model from the extracted residual noise signals.

Step 4: Construction of the training and validation datasets.

Step 5: Design of the predictive model.

Step 6: Training and validation.

Figure 6 illustrates examples of Gaussian Mixture Model fitting for both biased and unbiased noise. The analysis demonstrates that, even when the distribution appears as a single Gaussian peak, a mixture model with three components ( $n=3$ ) yields a superior fitting score.



**Figure 6.** Gaussian Mixture Model constants estimation for “Biased” and “Unbiased” residual noise.

### 4.2 CoTs with system information

Based on the tests, there are some essential elements to the application of LLM-driven signal processing: system configuration, data format, basic signal processing function and result validation.

For generic LLMs, the pre-trained knowledge does not include the details of specific system. Using LLMs to generate solutions for specific tasks will have risk of fail-to-implement or significant errors on generated results. This is considered as imprecise value alignment. Therefore, to overcome these issues, there are some steps need to be taken:

1 encoding system configuration, data format as fine-tuning dataset.

2 encoding basic function as fine-tuning dataset.

3 encoding Chain-of-Thoughts (CoTs) model into fine-tuning dataset.

4 implementing human-supervised fine-tuning tasks to ensure the fine-tuning quality.  
 5 implementing human-in-loop-validation (HILV).

### 4.3 Result & Discussion

#### 4.3.1 Validation of LLM-driven prediction

**Table 3** and **Table 4** list the results of the LLM-driven uncertainty prediction of the cutting force at Full Engagement stage and Partial Engagement stage. From the comparison, it can be clearly observed that the differences at the Partial Engagement stage are significantly larger than the differences of the Full Engagement stage.

**Table 3** Comparison of Gaussian Mixture – Full Engagement.

Source	Var 1	Var2	Var3	Constant Type
Original	0.46122	0.27277	0.266009	Weights
Predicted	0.48214	0.26885	0.24984	
Original	-0.00113	0.12981	-0.13118	Means
Predicted	-0.01316	0.14927	-0.12995	
Original	0.00425	0.00728	0.00728	Variances
Predicted	0.00329	0.00616	0.00621	

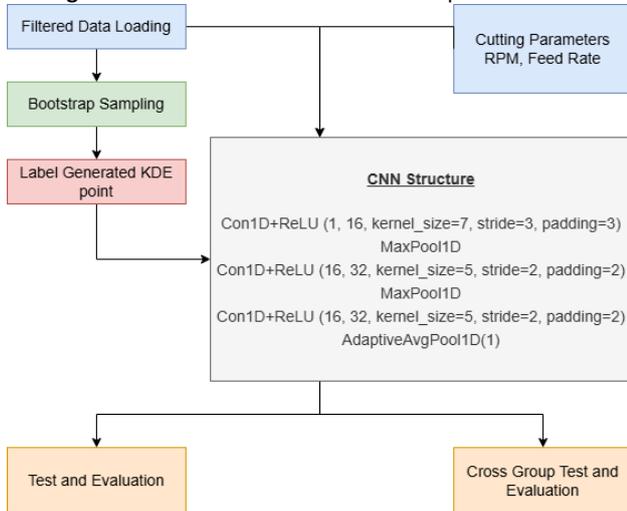
**Table 4** Comparison of Gaussian Mixture – Partial Engagement.

Source	Var 1	Var2	Var3	Constant Type
Original	0.27186	0.28074	0.44739	Weights
Predicted	0.20319	0.19131	0.61928	
Original	-0.03085	0.02991	0.00039	Means
Predicted	-0.01928	0.02133	-0.00645	
Original	0.00031	0.00036	0.00019	Variances
Predicted	0.00005	0.00006	0.0	

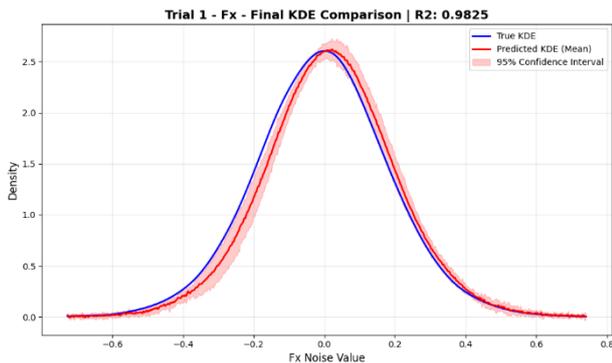
#### 4.3.2 Prediction on Kernel Density Estimation (KDE)

To furtherly check the framework feasibility, the same framework is also applied to KDE system.

The **Figure 7** shows the flowchart of the KDE prediction.



**Figure 7.** Flowchart of predicting KDE system of target signal residual noise.



**Figure 8.** Validation of the prediction of KDE system.

From **Figure 8**, The mean predicted KDE (solid red line), calculated as the average of predictions from all bootstraps, aligns closely with the true KDE (solid blue line), yielding an  $R^2$  of 0.9825. This high  $R^2$  value underscores the method's ability to capture the central tendency of the  $F_x$  force uncertainty distribution.

Additionally, the 95% confidence interval (shaded red region) quantifies the uncertainty associated with the predictions. The interval narrows around the peak of the distribution, where data density is highest and predictions are more confident, and widens in the tail regions, where sparser data introduces greater uncertainty. This behavior is statistically intuitive and demonstrates the methodology's capacity to provide not only accurate predictions but also a principled measure of reliability—critical for applications involving force uncertainty analysis.

### 5 Conclusion

This study employs Large Language Models (LLMs) and associated techniques to design and implement a signal processing task, which has been successfully validated through experimental evaluation. The findings suggest that this approach holds significant potential for further research, particularly in applying technology to uncertainty prediction across diverse systems and influencing factors.

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