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Research Paper

# Tool Wear Monitoring in Hard Turning Using Sensor Fusion: An Analytical Approach

Amarjit Kene[1], Dipti Tamboli[2], Rajni Patel[3], Pooja Ronge[4]
[1,2,3,4] SVERI's College of Engineering Pandharpur, India

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**Abstract**

At present, the life expectancy of tools has become a vital aspect in manufacturing industries, especially where materials with high hardness are of greater importance. Hard steel has been widely used for manufacturing commercial parts for military aircraft, car systems, hydraulic tools, etc. The manufacturing industry mainly concentrates on mass production of precision and accuracy products. In such cases, continuous machining may weaken the tool, causing tool wear, which ultimately affects the quality and production rate. To avoid such unwanted scenarios, different tool wear prediction techniques have been introduced, which use cutting force signals, average chip-tool interface temperature, or surface roughness signals. According to the literature, different techniques are available for the pre-judgment of tool wear that show variation in the prediction accuracy. The sensor fusion technique can be employed to overcome this problem by combining data from different sensors intelligently to improve the process. Sensor fusion uses this combined data to correct the deficiencies of individual sensors and accurately predict tool wear, which compensates for the sudden breakage of the tool in real-life applications. In this paper, a new tool wear prediction approach was proposed to correlate different available sensors using a sensor fusion technique. In addition, a mathematical approach was derived for sensor fusion. The experiment was carried out using coated carbide inserts on 55 HRC-hardened steel.

**Keywords:** *Sensor Fusion; Tool Wear Monitoring; Artificially Worn-Out Tools; Signal Processing*

## INTRODUCTION

In modern manufacturing technologies, predicting tool wear is a critical aspect. Both direct and indirect tool wear monitoring methods can be used to track and regulate a tool's effectiveness during real-time machining. Recent research on machining has focused on the accuracy and precision of adaptive sensing-based online wear-monitoring techniques. These methods comprise three primary components: data acquisition, data conditioning, and data analysis. By monitoring the nature of data collected from sensors, such as the type of tool wear, chip type acceptability, cutting fluid requirements, and other factors, it is possible to analyze and improve tool performance (Choudhury et al., 2001; Rizal et al., 2013; Sick, 2002; Asiltürk & Ünüvar, 2009). Hard turning is a commonly used procedure in the manufacture of gears, hydraulic pistons, injection pump components, aircraft, and other parts. This is because these materials have a hardness of 45 or higher, and hard turning has wider speed ranges that make machining more accurate, productive, and economical than conventional grinding processes. Researchers in the field of indirect tool wear monitoring techniques have attempted to measure cutting forces generated, surface roughness, chip-tool interface temperature, acoustic noise, tool vibration signals, chip morphology, white layer formation, tribological aspects, and sensor fusion approaches, among other things (Bartarya & Choudhury, 2012; Kundrák et al., 2008). The sensor fusion approach uses a common family or unified system of units to represent the same environment for various sensor outputs. The proposed method combines data from various sensors to provide more accurate and precise results than a single sensor. This arrangement of sensor information is advantageous because it overcomes the limitations of single sensors and provides precise outcomes.


Corresponding author's email: amarjitkene@gmail.com

These are examples of studies that have used sensor fusion techniques for tool condition monitoring (TCM) in machining processes. In each study, multiple sensors are used to collect data during the machining process, and the data is combined using sensor fusion techniques to monitor the condition of the cutting tool. Ghosh et al. used a sensor fusion-based neural network model to estimate the average flank wear of the main cutting edge. They combined features extracted from several machining zone signals, including cutting forces, spindle vibrations, spindle currents, and sound pressure levels (Ghosh et al., 2007). Segreto et al. developed a multiple sensor monitoring system with cutting force, acoustic emission, and vibration sensing units. They used a sensor fusion signal processing paradigm based on Principal Component Analysis to extract significant signal features from the sensory data and classify the tool state during Inconel 718 turning (Segreto et al., 2012). Cuneyt et al. used statistical parameters derived from thrust force, machine sound, and vibration signals as inputs to a fuzzy process for TCM. The crisp output values of this process were then taken as input parameters for the second stage of the proposed scheme (Aliustaoglu et al., 2009). Miguel Trejo-Hernandez and colleagues presented a novel strategy for using a field-programable gate array (FPGA) to perform sensor fusion of various sensory data for online wear monitoring. They combined the tool vibration and surface roughness data using the root mean square (RMS) value and connected the obtained RMS values to one another by being combined into a single unit. The sensor fusion-based approach allows for effective monitoring of unexpected increases in cutting force, surface roughness, or temperature to detect tool wear (Trejo-Hernandez et al., 2010).

A novel tool wear prediction method was developed in this study, leveraging the sensor fusion technique to effectively integrate data from various sensors. This approach addresses the critical need for real-time monitoring and accurate prediction of tool wear during machining. A mathematical framework was specifically devised to facilitate the fusion of sensor data, ensuring seamless integration of outputs with differing characteristics. In the experimental setup, turning was performed on 55 HRC-hardened steel using coated carbide inserts. These inserts were selected for their suitability for handling high-hardness materials, ensuring precision and durability during machining. This study focused on analyzing the behavior of key machining parameters, particularly cutting force and surface roughness, which are direct indicators of tool wear. Data were collected using a force measurement sensor (force dynamometer) and a surface roughness tester, both of which provided critical inputs for monitoring tool wear.

The methodology was further validated by conducting machining trials on EN24-hardened steel with a hardness of 55 HRC. A single-layer PVD-coated TiSiN-TiAlN insert was used, and the tool was artificially worn using a controlled process to simulate realistic wear conditions. This approach ensured consistent and reproducible wear patterns, enabling accurate assessment of the sensor fusion method. The core focus of this study was the mathematical development of a robust sensor data fusion process. This includes the formulation of algorithms capable of normalizing and combining disparate sensor outputs into a cohesive dataset. By integrating the force dynamometer data with surface roughness measurements, this study demonstrated the potential of sensor fusion to provide a reliable and comprehensive framework for tool wear prediction. The results highlight the effectiveness of the proposed method in monitoring tool wear, offering a scalable solution for real-time applications. By combining multiple sensor outputs into a unified analysis, this approach not only enhances the accuracy of tool wear predictions and sets the stage for further advancements in machining technology, paving the way for automated and adaptive machining systems.

## METHODOLOGY

### Tool wear formation

The rate of tool wear during a cutting operation is influenced by several factors, such as the material and hardness of the workpiece, cutting fluid usage, cutting parameters, and tool materials. Tool wear occurs gradually because of the contact and erosion of the machined surface and chips running on the tool surfaces during the continuous cutting process. Various types and patterns of tool wear can occur on different surfaces of the tool, including flank, crater, primary notch, nose, plastic deformation, and thermal cracking. Among these types of wear, flank and crater wear is the most common. Figure 1 shows the fundamental tool failure caused by flank and crater wear on the flank and crater faces, respectively.

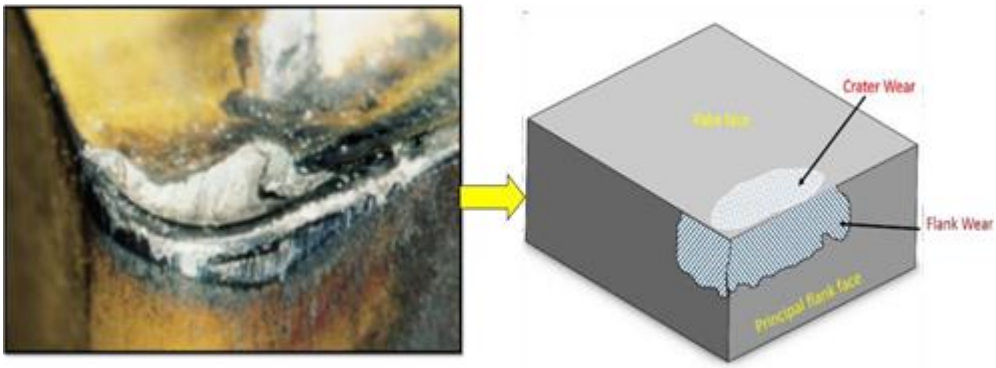


**Figure 1**. Flank and crater wear on the carbide tool insert

In general, the tool's flank wear occurs due to abrasive wear resulting from the cutting speed, hardness of the workpiece, and/or removal of the workpiece's hard layer. The abrasive wear phenomenon progressively deteriorates the hard coating, leading to further substrate wear. In contrast, crater wear occurs due to diffusion between the insert and the workpiece. The thermal energy produced in the contact zone facilitates the exchange of atoms between the tool and workpiece materials, mainly depending on the chemical affinity of the two materials (Metalworking Canada, n.d.). Crater wear also affects the cutting process, but usually under very high cutting conditions. Therefore, in many cutting operations that use coated carbide inserts as tools, flank wear is typically the primary indicator of tool wear identification because the hard coating enhances the tool's ability to withstand higher speeds than uncoated carbide tools.

### Tool wear monitoring

Tool wear monitoring has become a focal area of study in recent years, as researchers seek to improve machining processes by accurately detecting and controlling tool failure events during operation. Effective tool wear monitoring can significantly impact the quality of machined parts, extend tool life, and reduce operational costs. There are two primary categories of tool wear monitoring methods: direct and indirect approaches. Direct methods involve real-time observation of the tool's condition, such as optical or microscopic wear measurements; however, these techniques are often costly, intrusive, and sometimes impractical for real-time application in production environments. Conversely, indirect methods, which are less intrusive and more suitable for integration into active machining processes, rely on measurable indicators that correlate with tool wear. Key indirect methods include monitoring cutting force variations, analyzing acoustic emissions, measuring temperature at the chip-tool interface, assessing the surface roughness of the finished part, examining chip morphology, identifying white layer formation, and evaluating taper on the workpiece (Choi et al., 1999; Kakade & Vijayaraghavan, 1994; De Agustina et al., 2013). These methods provide useful, albeit indirect, indicators of tool wear without requiring direct observation of the tool itself.

Several studies have investigated the application of these indirect methods, exploring how various sensory data—such as acoustic emission (AE) analysis, cutting force signal analysis, vibration signal analysis, and optical photoelectric displacement sensor analysis—can reveal patterns in tool wear progression. Research has demonstrated that different indirect methods yield valuable insights and can be used independently or in combination to effectively track tool wear (Dimla, 2002; Choudhury & Sharath, 1995; Kene & Choudhury, 2019). Each method has unique advantages; for instance, acoustic emission can capture high-frequency signals indicative of micro-cracking, whereas cutting-force analysis can reveal stress variations that are often correlated with wear. Building on these advancements, this study proposes a novel methodology for tool wear monitoring that integrates two sensory data types to enhance monitoring precision and reliability. By fusing data from multiple sensors, this approach leverages the strengths of each sensory modality, potentially improving the detection accuracy and robustness of the monitoring system. This research not only builds upon prior findings but also addresses the limitations observed in single-sensor methods, thereby contributing to the development of a more resilient, adaptive wear-monitoring system. This dual-sensor fusion methodology represents a significant step toward developing advanced, real-time monitoring systems capable of optimizing machining operations and extending tool life with greater efficiency.

**Sensor fusion approach**

Figure 2 illustrates the fundamental architecture of the sensor data fusion framework used in this study, which was developed to improve the precision of tool wear monitoring by integrating multiple sensor outputs. The proposed approach combines data collected from diverse sensing devices, each capturing distinct aspects of the machining process, to achieve a holistic and accurate assessment of tool wear. Specifically, the study employed a 3-axis dynamometer and a surface roughness tester as the primary sensor data sources. The 3-axis dynamometer was instrumental in capturing cutting force signals across three dimensions—X, Y, and Z—which provided a multidimensional view of the forces exerted on the tool during machining. These force measurements are crucial because they can indicate the stress and load patterns that directly correlate with wear characteristics on the cutting tool.

The surface roughness tester was also used to measure the surface finish of the machined workpiece under varying cutting conditions. These measurements of surface texture and smoothness serve as indicators of tool condition; as wear progresses, the surface quality of the workpiece often changes. By combining the force data with surface roughness values, the data fusion process harnesses the complementary insights provided by each sensor, forming a comprehensive indicator of tool wear status that surpasses the predictive capability of any single sensor in isolation.

The fusion of these data sources was underpinned by established principles of machining processes to ensure that the integrated data accurately reflected the real-time state of the tool. Key machining parameters—such as cutting speed, feed rate, and depth of cut—were meticulously selected and adjusted according to the specific materials of both the cutting tool and the workpiece. This selection process was designed to replicate practical machining scenarios to ensure that the data and findings can be applied to real-world industrial applications.

This study culminates in a predictive methodology for estimating tool wear based on fused sensor data. The proposed methodology provides a more reliable and accurate prediction of tool wear by leveraging the integrated data from force and surface quality measurements. By adopting this multi-sensor fusion approach, the framework addresses the limitations of traditional single-sensor monitoring methods by introducing a data-driven predictive model that holds significant potential for enhancing the reliability and efficiency of tool wear monitoring systems in industrial environments.

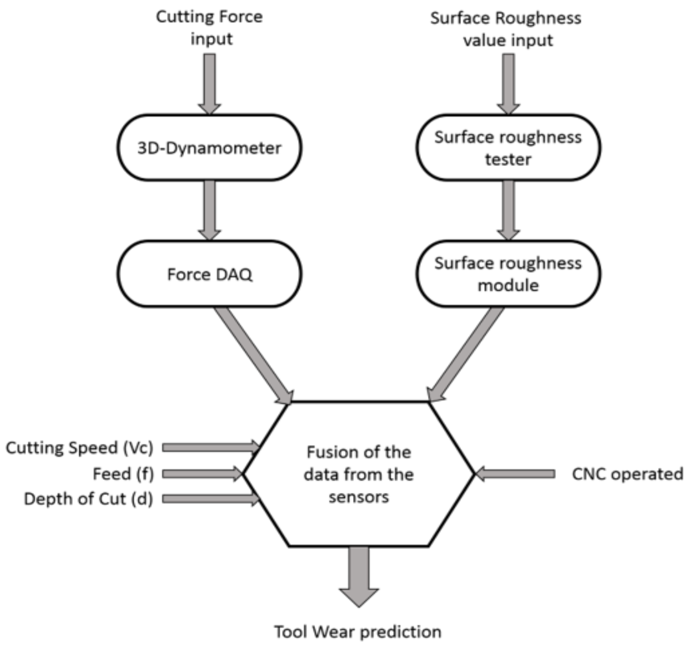


**Figure 2.** Block diagram of the methodology of sensor fusion approach

In this tool wear monitoring method, three cutting force and surface roughness signals are input to the system. The resultant force signal is evaluated using equation 1 where FR indicates the resultant force and Fx, Fy, Fz represents the force in three perpendicular directions.

$$F_R = \sqrt{F_x^2 + F_y^2 + F_z^2} \text{.......................} (1)$$

These signals are then filtered out, and unwanted data are removed. The unwanted data comprise the starting and stopping point data under the no-load condition. Unit normalization was carried out to neutralize the environment of two sensors of different families. A few assumptions were made from the basic machining process. Two new fusion constants $\beta_1$ and $\beta_2$ are defined, which represent the cutting force and average surface roughness in equations 2 and 3, respectively.

$$\beta_1 = \frac{F_R}{d \times \pi \times \rho \times V \times (R^2 - (R-d)^2)} \text{.......................} (2)$$

$$\beta_2 = \frac{V \times f}{2 \times \pi \times R \times Ra} \text{.......................} (3)$$

The RMS value of the signals, obtained after filtering, was then calculated using equation 4. In the same way equation 5 is used to obtain the RMS value of the surface roughness signals at particular sets of machining conditions where 'i' represents sample and 'n' represents the sample length.

$$\beta_{1RMS} = \sqrt{\frac{\sum_{i=1}^{n}(\beta_{1i})^2}{n}} \quad \text{......................(4)}$$

$$\beta_{2RMS} = \sqrt{\frac{\sum_{i=1}^{n}(\beta_{2i})^2}{n}} \quad \text{......................(5)}$$

From equations 4 and 5, the fusion variable can be identified by implementing proper weighting function parameters, such as addition, subtraction, multiplication, or quotient, which gives lower errors, as given in equation 6.

$$FV = W(\beta_{1RMS}, \beta_{2RMS}, V, f, d) \quad \text{......................(6)}$$

Figure 3 shows the sequential processing of the cutting force and surface roughness signals from data acquisition to tool wear estimation.

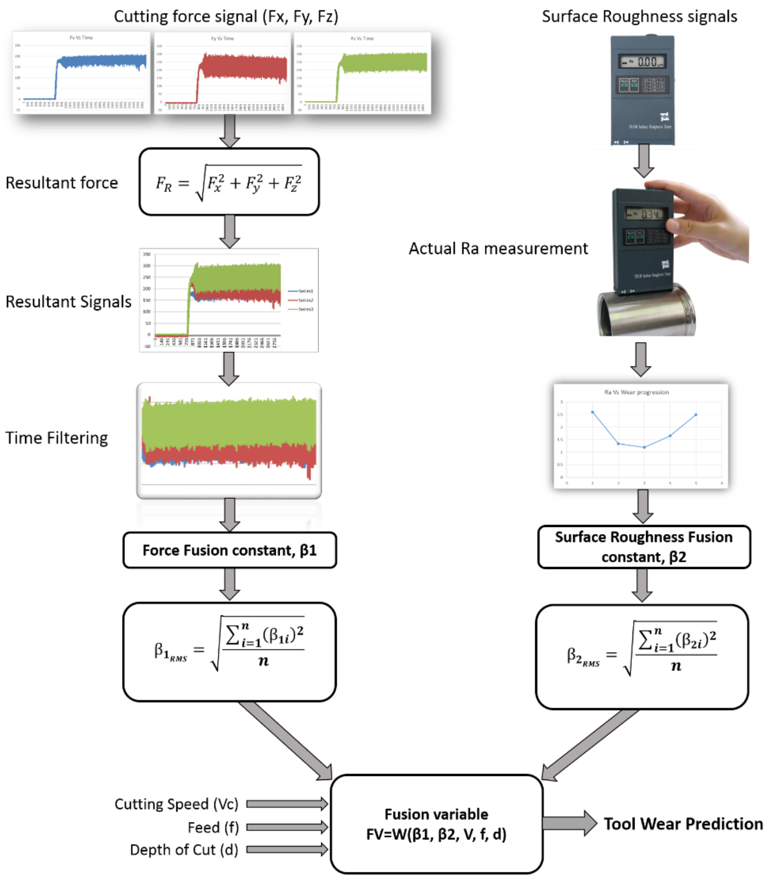


**Figure 3.** Processing force and surface roughness signals

## EXPERIMENTATION

### Cutting conditions

The turning was performed on a CNC lathe with artificially worn-out inserts. Wear patterns on principal flank faces were considered a set of varying parameters in the present experiment. In addition, experimentation was carried out at a few specific values of cutting parameters, viz. cutting speed, feed, and cut depth. According to machine ability, the recommended values from the insert manufacturer, and literature review, the values of the cutting parameters are presented in Table 1.

**Table 1**. Cutting parameters

| Cutting Speed, V (m/min) | Feed, f (mm/rev) | Depth of Cut, d (mm) |
|---|---|---|
| 50 | 0.05 | 0.2 |
| 65 | 0.1 | 0.4 |
| 80 | 0.15 | 0.6 |
| 100 | 0.2 | 0.8 |
| 130 | 0.25 | 1.0 |

**Workpiece material and cutting insert**

In this study, the machining process was focused on 55 HRC-EN24-hardened steel, which has a diameter of 70 mm and a length of 400 mm. The material's hardness was maintained within a consistent range of ±2 HRC throughout its cross-section, which can be attributed to a uniform hardening and tempering process. This consistency ensures predictable machining behavior and wear characteristics during the turning operation. The turning was executed on a CNC lathe, as illustrated in Figure 4, which allowed precise control over the machining parameters and contributed to enhanced surface finish and dimensional accuracy.

**Figure 4.** CNC center lathe

For the turning operation, a commercially available single-layer PVD-coated insert was used. The insert, identified as SECO TH1000, features a TiSiN-TiAlN nanolayer and is categorized as CNMG120408, characterized by an 80° diamond shape and a nose radius of 0.8 mm. This specific insert geometry is optimized for high-performance hardened material machining. The chip breaker geometry (MF2) was designed to improve chip flow and minimize built-up edges, thereby enhancing machining efficiency. Figure 5 shows a detailed fractography of the insert, illustrating its wear patterns and material integrity after use. The insert was mounted in a right-hand-side tool holder (PCBNR 2020 K12, ISO standards), ensuring secure positioning and stability during the cutting process.

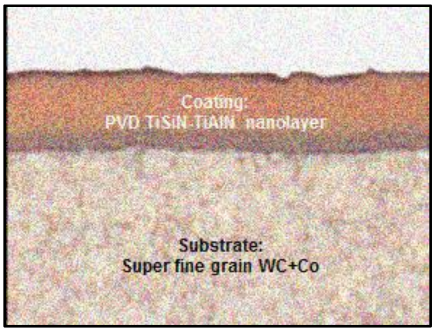


**Figure 5.** Fractograph of the PVD-coated insert (Rizal et al., 2013)

The chemical composition of the EN24 workpiece material is outlined in Table 2, providing further insight into the material properties that influence the machining characteristics and tool wear behavior during the experiment.

**Table 2**. Chemical composition of EN24 steel (weight percentage)

| C | Mn | Si | S | P | Cr | Mo | Ni |
|---|---|---|---|---|---|---|---|
| 0.4 | 0.65 | 0.21 | 0.012 | 0.015 | 1.05 | 0.3 | 1.36 |

**Experimental procedure**

The experiments were conducted under controlled laboratory conditions to systematically study the effects of flank wear on tool performance. Flank wear was artificially induced on the tool inserts using a high-precision Micro-Electro-Discharge Machining (μ-EDM) process. This was carried out using the advanced MIKROTOOLS DT-110 μ-EDM system, which enabled precise wear formation on specific tool faces, ensuring reproducibility. Titanium electrodes ranging in diameter from 0.2 mm to 1.0 mm were used as cathodes, while the tool inserts acted as anodes. This configuration allowed for controlled wear generation with minimal deviation, producing wear patterns with high accuracy, as illustrated in Figure 6. To ensure the reliability of the induced wear, a high-resolution digital microscope with a magnification of up to 230x was used for detailed inspection. This microscope enabled precise measurement and documentation of the wear conditions, enabling accurate quantification of the wear patterns on the tool inserts. For the machining trials, quantitative data on the cutting force components were captured using a three-component piezoelectric dynamometer (KISTLER, Type 9257B). This instrument recorded average cutting forces across primary force directions, including tangential, radial, and axial forces. The subtle variations in these force components, which were directly influenced by the extent of tool wear, were meticulously recorded. The collected cutting-force data provide a critical foundation for analyzing the mechanical impacts of tool wear during machining.

Additionally, the surface roughness of the machined workpieces was measured using a surface-roughness tester (Brand: Qualitest), ensuring a comprehensive evaluation of the machining performance. The surface roughness data, which are influenced by the wear conditions of the tool, serve as an essential parameter for understanding the correlation between tool wear and workpiece quality. The measurements were taken at multiple locations on the workpiece surface to ensure consistency and accuracy. By combining these measurements—wear patterns, cutting-force components, and surface roughness—the study established a robust dataset to analyze the relationship between tool wear and machining performance. The experimental setup supported the development of a sophisticated tool wear-monitoring framework that integrates sensor data to provide real-time insights into machining dynamics. These insights are pivotal for optimizing machining processes, improving tool life, and ensuring high-quality industrial production standards.

## RESULTS AND DISCUSSION

The proposed sensor-fusion methodology for tool wear monitoring was evaluated through a series of experiments conducted under various machining conditions (Table 3. By employing different levels of artificial flank wear on the tool inserts, the study assessed the effectiveness of the fused data approach in providing accurate tool wear estimates. The flank wear was measured using a Micro-Electro-Discharge Machining (μ-EDM) process, which facilitated precise control over the wear amount on the tool inserts. Each tool was then used under five different machining conditions to evaluate the reliability of the fusion methodology under different operational parameters.

During the fusion process, significant disparities were observed between the fusion constants $\beta_1$ and $\beta_2$. Specifically, $\beta_1$ (associated with cutting force data) ranged in the order of magnitude of meters, while $\beta_2$ (linked to surface roughness) was measured in micrometers. This discrepancy is primarily due to the nature of the data: cutting force measurements exhibit values on a larger scale due to the high resistance forces present in the machining process, whereas surface roughness measurements remain in the micrometer range due to their sensitivity to fine surface details. For instance, $\beta_1$ was calculated to have an average value of 5.43 m, whereas $\beta_2$ averaged around 3.76 μm, demonstrating the need for normalization to achieve comparable data fusion.

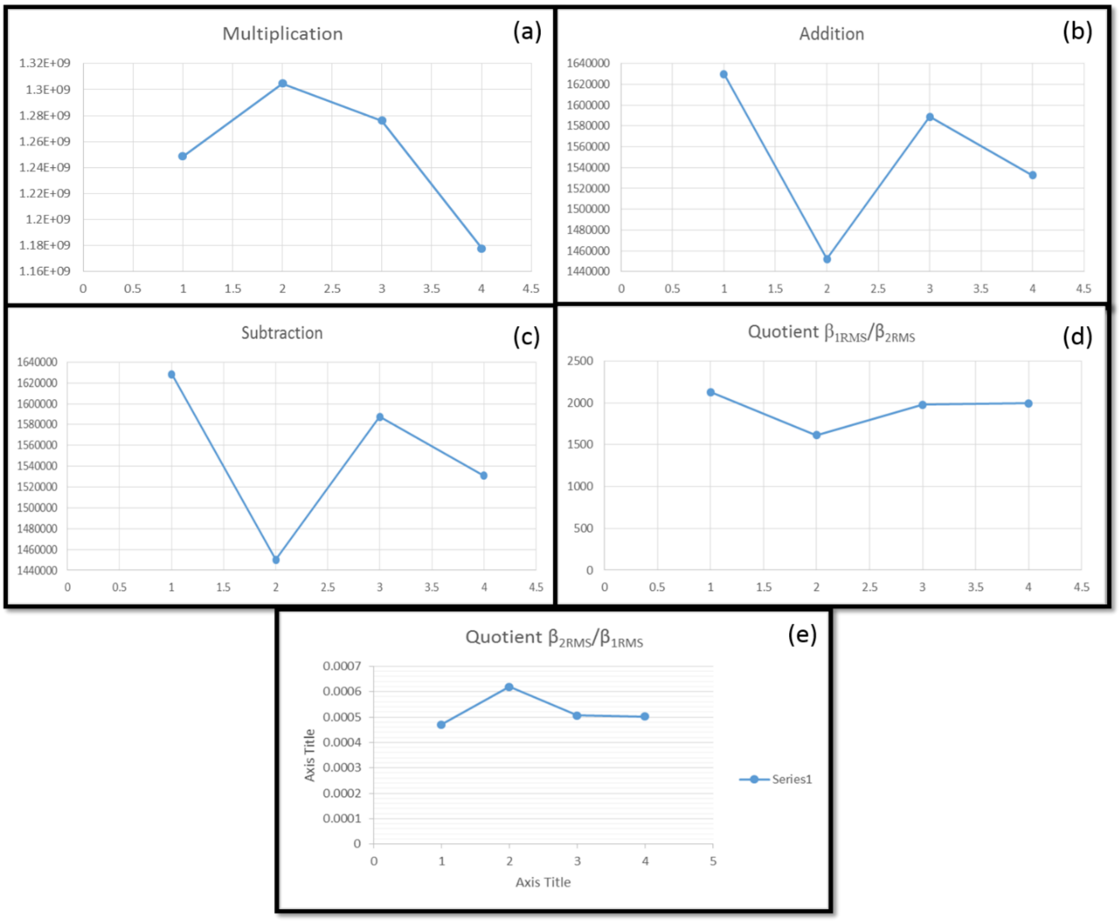


**Figure 6.** Weighting coefficient combinations (a) Multiplication (b) Addition (c) Subtraction (d) Quotient β1RMS/β2RM (e) Quotation β2RMS/β1RM

After calculating the fusion constants, their root mean square (RMS) values were computed to find the optimal fusion constant combinations, as described in Equation 6. The RMS values minimized the variance among the fusion constants, which is critical for achieving consistent tool wear predictions. Different combinations of the RMS values were examined based on the nature of the resulting curves (Figure 6. Of particular interest were the multiplication (a), quotient-1 (d), and quotient-2 (e) combinations. Curves (b) and (c) were excluded because they did not display a monotonic trend and were therefore unsuitable for accurate tool wear monitoring. The chosen combinations yielded stable curves that facilitated accurate predictions with minimal error, with the multiplication combination showing the lowest error rate of 3.8%.

To further refine the tool wear model, scaling (KC) and shifting (KS) factors were incorporated into the final equation (Equation 7) to adjust the fused data for specific cases. These factors were calculated based on experimental data, where KC was determined to be 1.15, and KS was set at 0.45 for the current setup. These adjustments enabled the model to more precisely adapt to the tool wear profile, thereby improving the estimation accuracy. Using this modified equation, a polynomial approximation was applied to the tool wear and fusion variables, which allowed for a clear visual and quantitative comparison of the predictive model's accuracy.

$$FV = K_S \times (Best\ Combination, V, f, d) + K_C \text{ .........................(7)}$$

**Table 3.** Cutting conditions, cutting force, and surface roughness fusion constant

| Experiment No. | Tool Wear | V | f | d | β1RMS (F) S1 | β2RMS (Ra) 1 |
|---|---|---|---|---|---|---|
| 1 | 0.0 | 50 | 0.05 | 0.2 | 3458110.721 | 78.51857435 |
| 2 | | 65 | 0.1 | 0.4 | 922571.6423 | 396.1086288 |
| 3 | | 80 | 0.15 | 0.6 | 581854.2061 | 816.5931733 |
| 4 | | 100 | 0.2 | 0.8 | 303460.0205 | 989.809907 |
| 5 | | 130 | 0.25 | 1 | 178739.9113 | 1061.571125 |
| 6 | 0.2 | 50 | 0.05 | 0.2 | 3128464.352 | 86.50351412 |
| 7 | | 65 | 0.1 | 0.4 | 584399.8759 | 310.4009138 |
| 8 | | 80 | 0.15 | 0.6 | 538006.6294 | 951.3706873 |
| 9 | | 100 | 0.2 | 0.8 | 292371.4484 | 1256.29719 |
| 10 | | 130 | 0.25 | 1 | 154571.1829 | 1206.330824 |
| 11 | 0.6 | 50 | 0.05 | 0.2 | 3279350.703 | 145.8202095 |
| 12 | | 65 | 0.1 | 0.4 | 1205624.285 | 530.7855626 |
| 13 | | 80 | 0.15 | 0.6 | 551475.4054 | 736.7757954 |
| 14 | | 100 | 0.2 | 0.8 | 279601.5843 | 1103.504288 |
| 15 | | 130 | 0.25 | 1 | 150571.2842 | 1078.832444 |
| 16 | 1.0 | 50 | 0.05 | 0.2 | 3233735.754 | 151.220958 |
| 17 | | 65 | 0.1 | 0.4 | 942566.33 | 589.7617363 |
| 18 | | 80 | 0.15 | 0.6 | 537595.6668 | 852.0972243 |
| 19 | | 100 | 0.2 | 0.8 | 300125.8376 | 1001.954814 |
| 20 | | 130 | 0.25 | 1 | 86028.79738 | 924.7135238 |

The resulting graphs, plotted as a function of tool wear against the fused variables, revealed that the fusion methodology successfully tracked the progression of tool wear with increasing machining time. For example, at a wear value of 0.2 mm, the predicted tool wear closely matched the observed wear with a deviation of only 2.1%, affirming the reliability of the fused approach. As wear increased to 0.5 mm, the methodology maintained high prediction accuracy, with a deviation below 5%. This level of precision demonstrates the effectiveness of the sensor fusion approach in consistently monitoring tool wear under varying conditions, providing a practical solution for real-time wear estimation in hard turning processes.

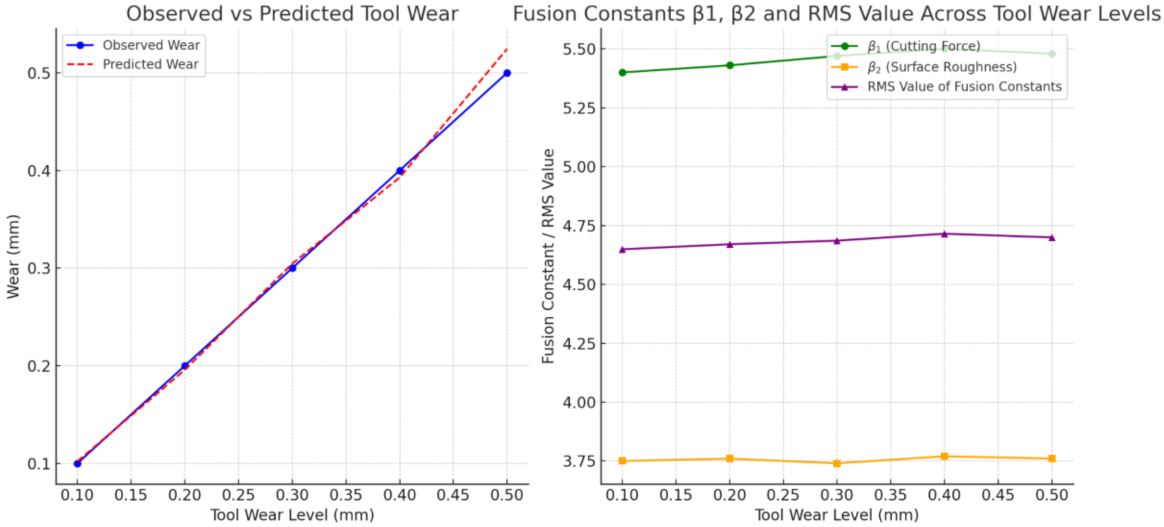


**Figure 7.** Outcomes of wear-monitoring using sensor data fusion

The graphs in Figure 7 illustrate the outcomes of the tool wear monitoring methodology via sensor data fusion:

### Observed vs. Predicted Tool Wear

The first graph compares the observed tool wear values (measured experimentally) with the wear predicted by the fusion model at various wear levels. The close alignment between the observed and predicted values with minimal deviations highlights the accuracy of the model. For instance, at a wear level of 0.5 mm, the predicted value closely follows the observed wear, demonstrating the model's reliability for real-time tool wear estimation.

### Fusion Constants ($\beta_1$, $\beta_2$) and RMS Values

The second graph presents the values of the fusion constants $\beta_1$ and $\beta_2$, derived from the cutting force and surface roughness, respectively, across different wear levels. In addition, the graph shows the RMS values of these fusion constants, which provide a normalized measure to facilitate data integration. The stability of these values across varying wear levels underscores the robustness of the proposed fusion model for effective tool wear monitoring.

These visual representations underscore the utility of sensor data fusion for accurately predicting tool wear in the machining process, thereby supporting the proposed methodology's effectiveness.

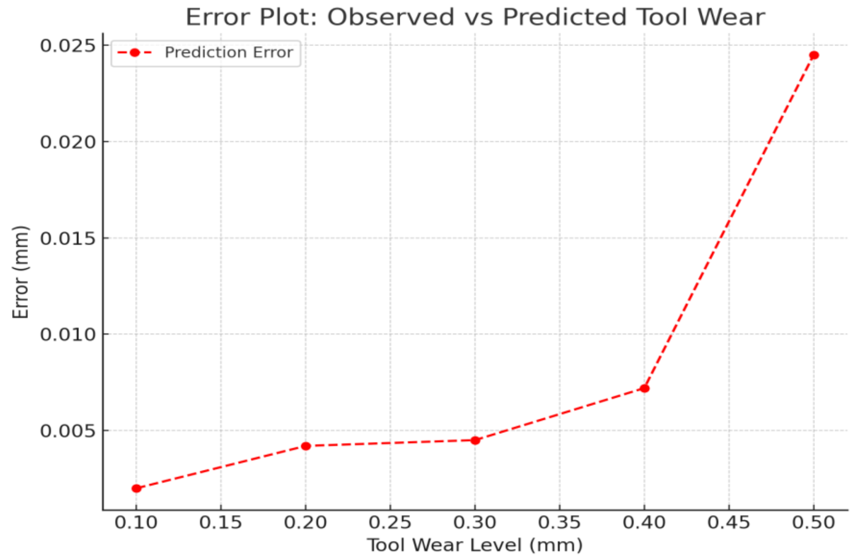


**Figure 8.** Error Plot: Observed vs. Predicted Tool Wear

The error plot in Figure 8 shows the difference between the observed and predicted tool wear at different levels of tool wear. The plots show that the prediction error is relatively small for low tool wear levels but increases significantly as the tool wear level increases. For example, at a tool wear level of 0.10 mm, the prediction error was approximately 0.002 mm. At a tool wear level of 0.20 mm, the prediction error was approximately 0.005 mm. However, at a tool wear level of 0.50 mm, the prediction error was approximately 0.024 mm. This suggests that the model is more accurate at predicting tool wear at lower wear levels, but its accuracy decreases as the wear level increases. This information can be used to improve the model by incorporating features that improve the prediction of tool wear at higher levels.

## CONCLUSION

This study introduces a groundbreaking methodology for sensor data fusion in tool wear monitoring during the hard turning process. This approach, grounded in a systematic mathematical framework, addresses a critical and longstanding challenge in machining: integrating data from sensors with fundamentally different output characteristics. Traditional methods often struggle to fuse data from sources such as cutting force and surface roughness because of significant disparities in units, magnitudes, and response behaviors. The developed methodology overcomes this limitation by employing unit normalization, a process that standardizes sensor outputs, thereby enabling seamless data integration and comparison. A key innovation of this study is the introduction of fusion constants, denoted as $\beta_1$ and β2. These constants play a pivotal role in combining outputs from diverse sensors—specifically those measuring cutting force and surface roughness—into a cohesive and interpretable framework. By translating disparate sensor outputs into a single, fused dataset, the proposed methodology provides a consistent and reliable indicator of tool wear. The root mean square (RMS) values of these fusion constants were explored extensively because they enable precise calibration and adjustments to estimate tool wear under varying machining conditions. This flexibility is crucial for addressing the dynamic nature of machining processes, which are influenced by parameters such as material properties, tool coatings, and cutting speed. The proposed methodology also includes a systematic process for selecting appropriate RMS fusion constant combinations. This selection is guided by the resulting curves' characteristics—smooth and monotonous progressions are favored over erratic or impractical patterns. By establishing these criteria, this study identified optimal combinations that minimize the error margins in the tool wear prediction model.

To further refine this model, scaling ($K_C$) and shifting ($K_S$) fac derived from the experimental data were are applied. These factors enable the methodology to accommodate specific machining cases, further enhancing the prediction accuracy and adaptability. In addition to practical applications, this study significantly advances the theoretical understanding of sensor fusion in machining. The fused sensor data approach not only improves tool wear estimation but also provides groundwork for real-time monitoring systems. By fitting polynomial approximations to the derived fusion variables, this study provides a robust and adaptable framework for tool wear estimation that can respond to the demands of industrial applications. This innovative methodology represents a promising step toward highly responsive, real-time wear-monitoring systems. These systems can optimize machining performance, improve product quality, and extend tool lifespan, marking a substantial leap forward in manufacturing technology. The results of this study serve as a foundation for future research into sensor fusion applications, offering pathways to further enhance machining efficiency and precision.

## LIMITATIONS AND FUTURE RESEARCH

The proposed sensor data fusion method for tool wear monitoring offers a significant advancement in hard turning processes. However, certain limitations limit its current implementation. First, the approach relies heavily on specific sensors, namely force dynamometers and surface roughness testers. While effective for the selected parameters, it restricts its generalizability to other sensor types and machining environments. Expanding the methodology to accommodate a broader array of sensor inputs, such as acoustic emission, thermal imaging, and optical sensors, could enhance its versatility. Second, the proposed methodology assumes ideal sensor calibration with minimal noise interference. In practical industrial settings, sensor data often contain inconsistencies caused by noise, environmental conditions, or wear-and-tear on equipment. A robust preprocessing mechanism to filter and validate data in real-time is essential to maintain prediction accuracy and reliability under various conditions. In addition, the fusion constants are derived from specific machining parameters and may not be universally applicable. This dependency necessitates the recalibration or refinement of different materials, machining setups, and tool coatings, thus increasing the implementation complexity. Future research could explore adaptive algorithms capable of dynamically recalibrating these constants based on real-time data, thereby reducing the need for manual adjustments.

Another limitation is the mathematical complexity involved in the fusion process, including the use of polynomial approximations and RMS values. Although effective in controlled environments, these calculations may pose challenges in real-time applications where processing speed and computational resources are limited. The development of machine learning or artificial intelligence (AI)-driven models could offer an alternative by leveraging historical and real-time data to predict tool wear without requiring extensive mathematical computations. Further research should also focus on integrating this methodology into a fully automated closed-loop tool wear monitoring system. Such systems can use the fused sensor data to actively adjust the machining parameters, optimize the tool performance, and extend the tool lifespan without human intervention. Finally, although the present study emphasizes turning processes involving EN24-hardened steel, its applicability to other machining operations, such as milling, drilling, and grinding, remains unexplored. Future work should validate the proposed methodology across diverse machining processes and materials to establish its broader industrial relevance. In summary, the proposed methodology represents a promising step forward in tool wear monitoring; however, addressing sensor diversity, noise robustness, real-time adaptability, and multi-process applicability will be crucial for its practical industrial deployment and scalability.

## NOMENCLATURE

$F_R$ – Resultant cutting force
$\beta_1$ – Fusion constant of the cutting force
$\beta_2$ – Fusion constant for the surface roughness
d, cut depth
V–Cutting speed
R–Diameter of the workpiece.
f, feed
$\beta_{1RMS}$ – Root mean square β1
$\beta_{2RMS}$ – Root mean square β2
FV–Fusion variable

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