



Development of scientific foundations for an intelligent cutting tool wear assessment system and adaptive control of cutting parameters

Ravshanov Jamshid Ravshanovich

PhD, Associate Professor, Head of the Department of Mechanical Engineering Technology,
Navoi State University of Mining and Technologies. Navoi city. Uzbekistan.

ORCID: 0009-0009-5649-0022

E-mail: ravshanov.zhamshid@mail.ru

Qodirov Bektosh Sherquvat ugli

Independent Researcher, Navoi State University of Mining and Technologies
Navoi city. Uzbekistan. ORCID: 0009-0004-8009-4330

E-mail: bektoshqodirov8@gmail.com

Oripov Dostonjon Rustamjon ugli

Assistant Lecturer, Department of Mechanical Engineering Technology,
Navoi State University of Mining and Technologies. Navoi city. Uzbekistan.

ORCID: 0009-0005-3957-5965

E-mail: orrudos@mail.ru

ABSTRACT

This study develops a methodological framework for intelligent cutting tool wear assessment and adaptive adjustment of cutting parameters in CNC machining. The framework integrates machine-vision measurements, tool-state estimation, wear-dependent cutting-load prediction, and supervisory feed correction. The methodology combines analytical modeling with a structured synthesis of research materials. Sequential tool images are geometrically registered and segmented to determine local, mean, and maximum flank-wear widths. Calibration and boundary-localization uncertainties are considered when assessing measurement reliability. A multirate estimation architecture combines intermittent visual observations with more frequently acquired process signals, accounting for the corresponding machining conditions. The estimated wear state is incorporated into the cutting-load model, and its uncertainty is propagated into the predicted cutting force. The analytical relationship shows that the contribution of wear-estimation uncertainty depends on the sensitivity of the load model to wear. Both measurement reliability and model uncertainty therefore influence the confidence associated with load predictions. The framework provides a basis for bounded supervisory feed correction using predicted loading and its uncertainty. The findings establish methodological relationships between measurement, estimation, prediction, and control rather than demonstrating new experimental improvements in machining performance. Independent CNC experiments are required to calibrate the models, evaluate prediction accuracy, and assess practical control benefits under changing machining conditions.

Keywords:

cutting tool wear, machine vision, intelligent wear assessment, physics-informed modeling, measurement uncertainty, cutting-load prediction, adaptive control, feed-rate correction, CNC machining.

Kesuvchi asbob yeyilishini intellektual baholash tizimi va kesish rejimlarini adaptiv boshqarishning ilmiy asoslarini ishlab chiqish



ANNOTATSIIYA

Mazkur tadqiqotda CNC stanoklarida kesuvchi asbob yeyilishini intellektual baholash va kesish rejimlarini adaptiv korreksiyalashning ilmiy-uslubiy tizimi ishlab chiqiladi. Tizim mashinaviy ko'rish orqali o'lchash, asbob holatini baholash, yeyilishga bog'liq kesish yuklamalarini prognozlash va surishni yuqori darajadagi boshqaruv orqali korreksiyalashni birlashtiradi. Metodologiya analitik modellastirish va ilmiy materiallarning tizimli tahliliga asoslanadi. Asbobning ketma-ket tasvirlari geometrik moslashtiriladi va segmentatsiyalanadi; ular orqali orqa yuzadagi mahalliy, o'rtacha va maksimal yeyilish kengliklari aniqlanadi. O'lchash ishonchliligini baholashda kalibrlash va chegaralarni aniqlash noaniqliklari hisobga olinadi. Ko'p chastotali baholash arxitekturasini davriy vizual kuzatuvlarni tez-tez olinadigan jarayon signallari bilan birlashtirib, tegishli ishlov berish sharoitlarini hisobga oladi. Baholangan yeyilish holati kesish yuklamasi modeliga kiritiladi va uning noaniqligi prognoz qilinayotgan kesish kuchiga tarqatiladi. Analitik bog'lanish yeyilishni baholash noaniqligining hissasi yuklama modelining yeyilishga sezgirligiga bog'liqligini ko'rsatadi. Shu sababli o'lchash ishonchliligi va model noaniqligi yuklama prognozlariga bo'lgan ishonch darajasiga birgalikda ta'sir qiladi. Tizim prognoz yuklamasi va uning noaniqligi asosida surishni belgilangan chegaralarda korreksiyalash uchun uslubiy asos yaratadi. Natijalar ishlov berish samaradorligining yangi tajribaviy yaxshilanishlarini tasdiqlamaydi, balki o'lchash, baholash, prognozlash va boshqarish o'rtasidagi uslubiy bog'lanishlarni asoslaydi. Modellarni kalibrlash, prognoz aniqligini baholash va o'zgaruvchan ishlov berish sharoitlarida boshqaruvning amaliy samaradorligini aniqlash uchun mustaqil CNC tajribalari talab etiladi.

Kalit so'zlar:

kesuvchi asbob yeyilishi, mashinaviy ko'rish, yeyilishni intellektual baholash, fizik qonuniyatlarga asoslangan modellastirish, o'lchash noaniqligi, kesish yuklamalarini prognozlash, adaptiv boshqaruv, surishni korreksiyalash, CNC stanoklarida ishlov berish.

Разработка научных основ системы интеллектуальной оценки износа режущего инструмента и адаптивного управления режимами резания

АННОТАЦИЯ

В исследовании разрабатывается методологическая структура интеллектуальной оценки износа режущего инструмента и адаптивной коррекции режимов резания на станках с ЧПУ. Структура объединяет измерения средствами машинного зрения, оценивание состояния инструмента, прогнозирование нагрузок резания с учётом износа и коррекцию подачи на уровне супервизорного управления. Методология сочетает аналитическое моделирование и систематизированный анализ научных материалов. Последовательные изображения инструмента геометрически совмещаются и сегментируются для определения локальной, средней и максимальной ширины износа по задней поверхности. При оценке достоверности измерений учитываются неопределённости калибровки и определения границ. Многочастотная структура оценивания объединяет периодические визуальные наблюдения с более часто регистрируемыми сигналами

Ключевые слова:

износ режущего инструмента, машинное зрение, интеллектуальная оценка износа, моделирование с учётом физических закономерностей, неопределённость измерений, прогнозирование нагрузок резания, адаптивное управление, коррекция подачи,



процесса, учитывая соответствующие условия обработки. Оценённое состояние износа включается в модель нагрузки резания, а его неопределённость распространяется на прогнозируемую силу резания. Аналитическая зависимость показывает, что вклад неопределённости оценки износа определяется чувствительностью модели нагрузки к износу. Таким образом, достоверность измерений и неопределённость модели совместно влияют на степень доверия к прогнозам нагрузки. Структура создаёт основу для коррекции подачи в установленных пределах с учётом прогнозируемой нагрузки и её неопределённости. Полученные результаты устанавливают методологические связи между измерением, оцениванием, прогнозированием и управлением, а не подтверждают новые экспериментальные улучшения показателей обработки. Для калибровки моделей, оценки точности прогнозирования и практической эффективности управления в изменяющихся условиях обработки необходимы независимые испытания на станках с ЧПУ.

обработка на станках с ЧПУ.

1. Introduction

Cutting tool wear is a major source of time-dependent variation in CNC machining. As machining progresses, changes in cutting-edge geometry and tool-workpiece contact conditions influence friction, cutting forces, spindle torque, and power demand. These changes may also affect dimensional accuracy, surface quality, and process stability. Consequently, cutting parameters selected for a new tool may become less suitable as wear develops. Reliable assessment of tool condition is therefore necessary for determining when operating parameters should be adjusted and when the cutting tool should be replaced.

Tool condition monitoring approaches generally employ direct measurements, indirect process signals, or a combination of both. Direct methods, including optical microscopy, machine vision, and surface profilometry, provide information about the geometry of the worn region. Indirect methods infer tool condition from cutting forces, vibration, spindle current, power consumption, or other process-related signals. These approaches provide complementary information. Visual measurements can establish geometrically interpretable wear indicators, whereas indirect signals can support more frequent monitoring between successive inspections. Combining them requires consistent identification of the tool, synchronization of measurements, and explicit consideration of the machining conditions associated with each observation [1].

Machine vision offers a practical basis for quantitative wear assessment because tool images can be processed to determine mean flank-wear width, maximum flank-wear width, and worn area. However, obtaining a segmented wear region does not, by itself, establish measurement accuracy. Image displacement, rotation, scale variation, uneven illumination, reflections, coolant contamination, and built-up edge can influence the detected boundaries. Errors in image calibration or reference-edge reconstruction may subsequently propagate into the calculated wear parameters. Image registration is therefore an important step in making sequential tool images geometrically comparable before wear measurement. Segmentation performance must also be assessed alongside errors in the resulting physical wear measurements [2].

The interpretation of indirect signals presents a different challenge. A change in cutting force or spindle power may result from tool wear, but it may also arise from changes in feed, cutting depth, radial engagement, workpiece properties, or machine operating conditions. Accordingly, an estimator that attributes every load variation to wear can produce misleading tool-state estimates. Mechanistic cutting models provide a means of relating process loading to machining geometry and operating parameters. Nevertheless, their coefficients and assumptions require identification and validation for the particular tool, workpiece material, and operation under consideration.



Physics-informed and hybrid learning approaches provide a basis for combining these mechanistic relationships with information extracted from measured data. Physical models can supply an interpretable baseline, while a trainable component can represent systematic discrepancies between predicted and observed behavior. Their relevance to adaptive machining lies in the possibility of estimating tool condition while maintaining consistency with known process relationships. Such consistency, however, does not eliminate measurement uncertainty or guarantee reliable performance outside the validated operating range.

Integrating wear assessment with adaptive control introduces further requirements. The controller must consider both the estimated wear state and the reliability of that estimate. It must also account for the interval between image acquisition and the execution of a corrective command. A practical architecture can therefore combine a relatively fast force or power regulation loop with a slower machine-vision loop that updates wear-dependent model parameters and operating limits. Feed correction should remain compatible with machine capabilities, tool limits, and workpiece quality requirements.

The research problem addressed in this study is the coordination of these measurement, estimation, prediction, and control functions within a unified methodological framework. The supplied research materials and previously published computational studies address individual aspects of this problem. The present work synthesizes those contributions and formulates their relationships explicitly, with particular attention to the transfer of wear-measurement uncertainty into cutting-load prediction and admissible feed correction [3].

The objective is to develop scientific foundations for an intelligent cutting tool wear assessment system and adaptive control of cutting parameters. The framework combines geometrically consistent visual measurements, physics-informed state estimation, wear-dependent load prediction, confidence-sensitive control decisions, and delay-aware supervisory integration with CNC. Previously reported computational findings are examined as supporting evidence, with their original scope retained. The resulting framework establishes a basis for subsequent experimental validation rather than claiming that its industrial performance has already been demonstrated.

2. Literature Review

2.1. Direct Measurement and Machine-Vision-Based Wear Assessment

Direct tool-wear measurement provides geometrically interpretable information about the condition of the cutting edge. Optical inspection can be used to determine mean flank-wear width, maximum flank-wear width, and the dimensions of localized damage. Surface profilometry provides additional information about wear depth and material loss, while scanning electron microscopy supports the investigation of damage morphology. These methods serve different purposes: detailed characterization of wear mechanisms and frequent assessment for process control do not necessarily require the same instrumentation.

Machine vision extends optical inspection by automating image acquisition, wear-region identification, and geometric measurement. However, repeated images of the same tool may differ because of positioning errors, rotation, illumination changes, and temporary surface contamination [4].

Registration and segmentation address distinct parts of the measurement problem. Registration improves geometric comparability, whereas segmentation identifies the worn region. Neither operation independently guarantees an accurate physical measurement. Calibration, reference-edge reconstruction, and comparison with an independent measurement method remain necessary. Consequently, segmentation metrics such as Intersection over Union and Dice should be supplemented by errors in measured wear width.

2.2. Physical Modeling of Wear and Cutting Loads

Mechanistic cutting models relate machining loads to chip geometry, tool engagement, and cutting coefficients. Cutting-force components can be represented through contributions associated with material removal and cutting-edge contact. This structure provides a basis for introducing wear-



dependent coefficients and evaluating how changes in tool condition influence force, torque, and power.

Wear evolution requires an additional description of the underlying degradation process. Wear prediction requires appropriate parameter identification and a defined operating range. A model calibrated for one tool–material combination cannot be assumed to remain accurate for another combination without verification.

The supplied load-modeling studies incorporate wear into cutting-force prediction and describe the evolution of tool condition between visual inspections [5]. Their methodological value lies in treating wear as a changing state rather than a fixed characteristic. Nevertheless, variations in engagement and operating parameters must be distinguished from wear-induced load changes.

2.3. Physics-Informed and Hybrid Monitoring

Data-driven models can represent relationships between measured process signals and tool condition. Their reliability depends on the operating conditions represented in the training data. Physical relationships can complement these models by introducing constraints and interpretable dependencies. The proposed estimation framework combines physical process relationships with measured data. Its predictive performance requires independent validation.

A distinction is required between correcting a model and evaluating its adequacy. A small training error does not establish reliable extrapolation, and an internally calculated confidence indicator may fail to reveal a factor omitted from the model. Independent wear measurements, residual checks, and validation under changed operating conditions are therefore important.

Table 1.

Comparison of approaches relevant to intelligent wear assessment and adaptive machining

Approach	Main information provided	Principal limitation	Role in the proposed framework
Direct optical measurement	Wear geometry and reference measurements	Sensitivity to calibration, positioning, and visibility	Establishing and updating the measured wear state
Image registration	Geometric alignment of sequential images	Dependence on stable features and valid transformations	Improving measurement comparability
Mechanistic load modeling	Relationship between cutting conditions and mechanical loading	Dependence on identified coefficients and engagement information	Predicting wear-dependent force, torque, and power
Physical wear modeling	Relationship between wear progression and contact conditions	Parameter uncertainty and restricted applicability	Providing a baseline wear-evolution model
Physics-guided learning	Data-based prediction with physical consistency	Dependence on training coverage and constraint suitability	Correcting and constraining wear estimates
Hybrid residual monitoring	Discrepancies between expected and observed process behavior	Sensitivity to unmodeled changes and residual thresholds	Supporting model adequacy checks

2.4. Research Gap and Position of the Present Study

The reviewed approaches address complementary functions, but their integration requires a consistent relationship between measurement reliability and control action. Accurate image processing alone does not determine an admissible feed correction. Similarly, a wear-dependent force model does not establish whether the wear estimate is sufficiently reliable for adaptation.



The present study addresses this coordination problem by linking visual wear measurement, uncertainty propagation, state prediction, and constrained supervisory control. Its methodological focus is the use of both the estimated wear state and its uncertainty when determining allowable process loading. Diagnostic delays and changes in machining engagement are also considered. This integrated formulation is developed as a basis for experimental assessment; quantitative industrial benefits must be established through independent validation.

3. Research Methodology

3.1. Research Design and System Architecture

The methodology combines analytical modeling and a structured synthesis of the supplied research materials. It integrates visual wear measurement, tool-state estimation, cutting-load prediction, and supervisory adjustment of machining parameters.

The proposed architecture contains two interacting feedback paths. A relatively slow machine-vision path supplies direct wear measurements and their uncertainty. A faster process-monitoring path supplies cutting-force, spindle-power, or current measurements together with the corresponding machining parameters. The state estimator combines these inputs, and the load predictor translates the estimated tool condition into expected mechanical loading. A supervisory controller determines admissible feed correction while retaining the native CNC control functions.

3.2. Image Processing and Quantitative Wear Measurement

Sequential images are first registered to a reference image using stable features outside the developing wear region where possible. Registration compensates for acquisition-related displacement and rotation while preserving actual changes in tool geometry. Image-quality checks identify excessive blur, saturation, or contamination before the measurement is accepted [5].

Following segmentation, local flank-wear width is calculated from the perpendicular distance between the reconstructed reference edge and the wear boundary:

$$VB_i = s |(x_{w,i} - x_{r,i})n_{x,i} + (y_{w,i} - y_{r,i})n_{y,i}| \quad (1)$$

where VB_i is the local flank-wear width at sampling position i , expressed in millimetres; s is the calibrated image scale in millimetres per pixel; and $(x_{r,i}, y_{r,i})$ denotes the corresponding point on the reconstructed reference edge. The coordinates $(x_{w,i}, y_{w,i})$ identify the intersection of the local edge normal with the segmented wear boundary. The components $(n_{x,i})$ and $(n_{y,i})$ define the unit normal to the reference edge at position i . This formulation measures the wear width perpendicular to the reference edge.

The image scale is determined using a calibration target or a reference feature with a known physical dimension:

$$s = \frac{L_{cal}}{P_{cal}} \quad (2)$$

where L_{cal} is the known reference length in millimetres and P_{cal} is its corresponding length in pixels. Calibration and wear measurement must use the same imaging configuration. If perspective distortion is significant, the image is rectified before physical distances are calculated.

For N valid, equally spaced sampling positions along the evaluated cutting-edge segment, the mean flank-wear width is calculated as:

$$VB_{mean} = \frac{1}{N} \sum_{i=1}^N VB_i \quad (3)$$

The maximum flank-wear width is determined as:

$$VB_{max} = \max(VB_1, VB_2, \dots, VB_N) \quad (4)$$

The mean value characterizes the overall wear condition within the evaluated segment, whereas the maximum value identifies localized wear concentration. Both indicators are retained because similar mean wear values can correspond to different spatial wear distributions. The evaluated segment and sampling procedure remain consistent across sequential images.

Measurement uncertainty is assessed by considering image calibration and the estimation of the perpendicular distance. Defining d_i as the measured local distance in pixels gives:

$$VB_i = s d_i \quad (5)$$



Assuming independent calibration and distance-estimation errors, first-order uncertainty propagation yields:

$$u(VB_i) = \sqrt{(d_i u_s)^2 + (s u_{d,i})^2} \quad (6)$$

where $u(VB_i)$ is the standard uncertainty of the local wear measurement, u_s is the standard uncertainty of the image scale, and $u_{d,i}$ is the standard uncertainty of the measured distance in pixels. The distance uncertainty includes contributions from image registration, reference-edge reconstruction, and wear-boundary localization. These contributions should be estimated from repeated measurements or comparison with independent reference measurements.

Uncertainty in the mean wear width must account for correlations between sampling positions. In particular, a shared calibration error affects all local measurements and cannot be assumed to decrease simply by increasing the number of sampled points [5].

Images that fail the quality checks are excluded from the measurement update. Accepted wear measurements, their acquisition time, and the associated uncertainty information are passed to the tool-state estimator. This allows subsequent cutting-load prediction and supervisory feed correction to consider both the estimated wear condition and the reliability of the visual measurement.

3.3. Tool-State Estimation and Multirate Sensor Fusion

The tool-state estimator combines intermittent machine-vision measurements with more frequently acquired process signals. The estimated state represents the underlying wear condition, while its uncertainty describes the confidence associated with that estimate. This distinction is necessary because image quality, sensor noise, and variations in machining conditions can affect the observed measurements.

Before fusion, sensor observations are synchronized using their acquisition timestamps. Cutting-force, spindle-power, or current measurements are associated with the feed rate, spindle speed, and depth of cut recorded during the same interval. Signals collected during tool engagement, disengagement, or rapid operating-condition changes are treated separately because transient loading may not represent the steady cutting condition.

Between accepted image measurements, the estimator predicts wear evolution using a non-negative wear-growth model. Process-monitoring signals provide additional information about deviations from the expected tool condition. However, an increase in cutting force or spindle power is not interpreted directly as increased wear: the corresponding machining parameters must first be considered. Consequently, process observations are compared with the loading predicted for the current operating conditions.

When a valid visual measurement becomes available, the predicted wear state is corrected according to the relative uncertainty of the prediction and the measurement. A measurement with lower uncertainty receives greater influence, whereas a less reliable observation produces a smaller correction. This uncertainty-weighted update prevents an individual low-quality image from causing an excessive change in the estimated tool condition.

The predicted wear state is constrained to remain non-negative. Gradual wear growth is distinguished from abrupt tool damage, such as edge chipping or fracture, which may require a separate diagnostic response. Small decreases in measured wear are treated as possible measurement variability and assessed against the associated uncertainty rather than interpreted automatically as physical recovery.

If a visual measurement is rejected or temporarily unavailable, the estimator continues to propagate the tool state, with increasing uncertainty as the interval since the last accepted observation grows. Supervisory feed correction is restricted when this uncertainty exceeds a predefined admissible level. The threshold must be selected using validation data for the relevant tool, workpiece material, and machining conditions.

The estimator outputs the current wear estimate, its uncertainty, and a diagnostic validity indicator. These outputs are supplied to the cutting-load prediction module, allowing subsequent control decisions to reflect both the inferred tool condition and the confidence in that inference.

3.4. Cutting-Load Prediction and Uncertainty Propagation

The cutting-load prediction module estimates the cutting force from the machining parameters and the estimated tool-wear condition:

$$\hat{F}_c = g(v_c, f, a_p, \hat{VB}; \theta) \quad (7)$$

where $\hat{F}_c$ is the predicted cutting force; v_c , f , and a_p denote cutting speed, feed, and depth of cut, respectively; $\hat{VB}$ is the estimated flank-wear width; and θ represents the model parameters. The model accounts for operating conditions so that load changes caused by machining-parameter adjustments are distinguished from those associated with wear.

For known machining parameters and independent wear-estimation and model errors, prediction uncertainty is approximated as:

$$u_F^2 \approx \left(\frac{\partial g}{\partial VB} \right)^2 u_{VB}^2 + u_{model}^2 \quad (8)$$

where u_F is the standard uncertainty of the predicted force, u_{VB} is the wear-estimation uncertainty, and u_{model} accounts for the remaining model uncertainty. The partial derivative describes the sensitivity of cutting force to wear.

Model coefficients adopted from the supplied materials are used within their original applicability conditions. The predicted force and its uncertainty are passed to the supervisory controller to support feed correction against an admissible load limit.

4. Results and Discussion

The analytical synthesis establishes a connection between visual tool-wear measurement, tool-state estimation, and uncertainty-aware cutting-load prediction. The results concern the relationships defined by the proposed framework; they do not represent newly obtained experimental measurements. The main findings are discussed in terms of wear characterization, uncertainty propagation, and their implications for machining supervision.

The image-processing formulation provides complementary measures of tool condition. Local flank-wear width describes the spatial development of wear along the evaluated cutting edge. Mean flank-wear width summarizes the overall condition of this segment, while maximum flank-wear width identifies localized wear concentration. Using both indicators avoids relying exclusively on an average value that may conceal a narrow region of substantial wear. Consistent selection of the evaluated edge segment is essential because changes in the measurement region can alter these indicators independently of actual wear progression.

Calibration directly affects the physical wear values obtained from images. Equation (6) separates the contributions of image-scale uncertainty and boundary-distance uncertainty. This distinction helps identify whether measurement improvement should focus on calibration or on image registration and segmentation. Repeated measurements can reduce some random contributions, but a shared calibration error remains correlated across sampling positions. Consequently, increasing the number of sampled points does not automatically eliminate uncertainty in the mean wear estimate.

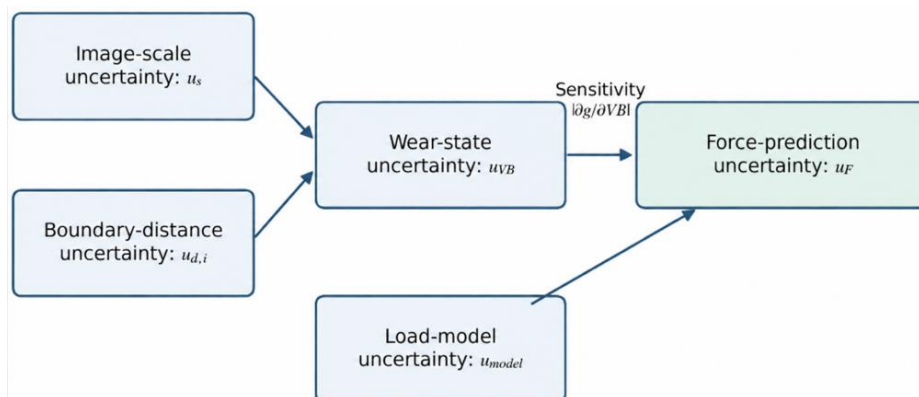


Figure 1. Principal uncertainty pathways from visual wear measurement to cutting-force prediction.

Table 2.

Analytical findings and their implications for the proposed system.

Analytical finding	Interpretation	Practical implication
Mean and maximum wear describe different aspects of tool condition.	Average wear can conceal localized deterioration.	Retain both indicators during tool-condition assessment.
Calibration uncertainty affects all sampled wear values.	Local measurements may share a common error contribution.	Account for correlated uncertainty when calculating aggregate indicators.
Force uncertainty depends on sensitivity to wear.	Equal wear uncertainties can produce different force uncertainties.	Evaluate sensitivity at the current operating conditions.
Process signals depend on machining parameters as well as wear.	Increased loading does not uniquely indicate tool deterioration.	Associate sensor observations with feed, speed, and depth of cut.
Prediction uncertainty can increase between valid images.	Confidence depends on measurement availability and model reliability.	Restrict feed adjustments when the state estimate becomes insufficiently reliable.

The multirate estimation approach combines observations with different information content and acquisition rates. Machine-vision measurements provide direct geometric information about wear, whereas force, power, or current signals describe the response of the machining process. Their combination can support tool-condition assessment between image acquisitions. However, this benefit depends on synchronization and on the ability of the process model to account for changing operating conditions. Without these provisions, a feed increase or a transient engagement event could be incorrectly interpreted as wear growth.

The cutting-load formulation explicitly includes cutting speed, feed, depth of cut, and estimated wear. It therefore provides a basis for evaluating wear-related loading at specified operating conditions. Its quantitative accuracy depends on the selected model and its coefficients. Parameters obtained for one tool–material combination cannot be assumed to describe another combination without verification. Similarly, extrapolation beyond the original calibration range introduces additional uncertainty that must be considered before the prediction is used for control.

Equation (8) provides the principal uncertainty-related finding. The contribution of wear uncertainty to force uncertainty is scaled by the squared sensitivity of the load model to wear. When this sensitivity is high, improving wear measurement can substantially reduce that contribution. When model uncertainty dominates, better images alone may produce only a limited reduction in overall prediction uncertainty. The framework thus helps identify whether further improvement should prioritize visual measurement or cutting-load model calibration.

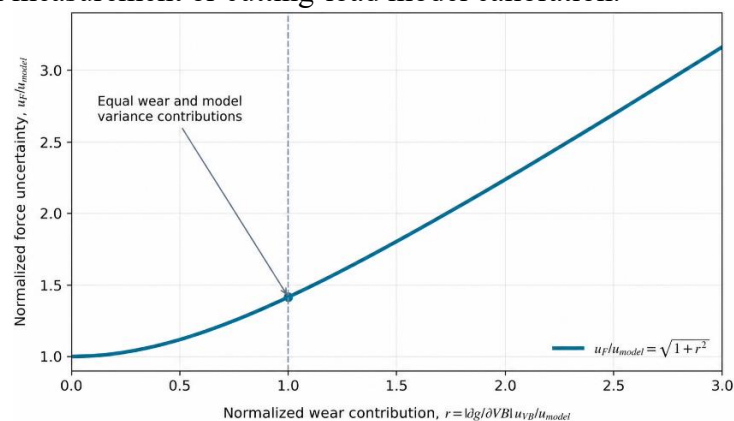


Figure 2. Relationship between wear-estimation uncertainty and cutting-force prediction uncertainty.



For supervisory machining control, the predicted force and its uncertainty provide more information than a point estimate alone. A force prediction below the admissible limit may still warrant conservative operation if its uncertainty is large. Conversely, a sufficiently reliable prediction can support bounded feed adjustment within validated operating conditions. The selection of uncertainty margins, load limits, and feed bounds remains specific to the machining operation.

The present analysis supports the methodological consistency of the integrated architecture. Demonstrating improvements in prediction accuracy, tool life, productivity, or surface quality requires independent experimental validation. Such validation should compare wear-aware predictions with a baseline model that excludes wear and assess whether the estimated uncertainty corresponds to observed prediction errors. Previously reported computational examples may support individual model relationships, but they do not by themselves establish the performance of the complete integrated system.

5. Conclusion

This study presents an analytical framework integrating machine-vision wear measurement, tool-state estimation, cutting-load prediction, and supervisory feed correction in CNC machining. Mean and maximum flank-wear widths describe overall and localized wear, while uncertainty estimates indicate the reliability of the visual measurements.

The uncertainty-propagation model shows that the contribution of wear-estimation uncertainty to force-prediction uncertainty depends on the sensitivity of the cutting-load model to wear. Considering both predicted force and its uncertainty provides a basis for selecting conservative feed adjustments.

The framework establishes a methodological basis for uncertainty-aware machining supervision. Its quantitative performance remains to be validated through synchronized wear and cutting-force measurements. Future work should calibrate the model for specific tool–material combinations and evaluate prediction accuracy and control behaviour under practical machining conditions.

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