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DEVELOPING A PREDICTIVE WEAR MODEL FOR INTELLIGENT TOOL CHANGE SYSTEMS

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Abstract: The article addresses the challenge of reducing machining errors under tight tolerances, which can negatively affect workpiece quality. It highlights the need for modelling and compensating individual error types, particularly those caused by tool wear. Traditionally, tool wear compensation relies on experimentally determined absolute wear values, but nonlinearity in wear introduces discrepancies between modelled and actual machining processes. To address this, the article introduces a novel tool wear model integrated into an Intelligent Tool Change System. The model represents changes in tool edge reduction over time, allowing for tool position correction relative to the workpiece and signalling alarm states. It incorporates a first-order inertial adaptive model, enabling accurate forecasting of tool wear. These predictions are based on real-time geometric measurements collected during cutting by an Automatic Measurement Unit. The measurements are analyzed in the time domain to provide current process corrections and determine the tool lifecycle. A key feature of the model is its self-tuning capability, which adjusts parameters dynamically to handle limited data availability, improving prediction accuracy and reducing the complexity of parameter settings. The model's predictions were validated by comparing predicted wear values against actual measurements. Additionally, the integrated model was compared with a linear prediction model, demonstrating superior accuracy. To evaluate the model's performance, the article uses the normalized root mean square error (NRMSE) as the assessment metric. Results confirm that the first-order inertial adaptive model not only enhances accuracy over adaptive linear model but also provides reliable wear predictions, supporting effective tool change strategies in machining processes. This innovative approach offers significant improvements in managing machining errors and optimizing tool usage.

Key words: tool wear; prediction model; Intelligent Tool Change System

1. INTRODUCTION

1.1. Tool wear and its symptoms

With the development of smart manufacturing technologies, managing materials, workforce, and equipment in machining processes has become crucial to ensure the reliability of key components. Tool wear, as the weakest and most damage-prone element in the OUPN system, affects both product quality and machining efficiency, and is unavoidable due to thermodynamic interactions during cutting [1]. Standards such as ISO 3685 [2] provide guidelines for tool performance at constant cutting speeds, while Taylor's equation is essential for predicting tool life and production costs, particularly for hard-to-machine materials [3]. Since variable cutting speeds are common in industrial settings, the study presented in [4] aimed to develop a method for predicting tool life under such conditions.

Predicting tool wear or damage, along with estimating its remaining useful life (RUL), is essential for effective monitoring of the machining process. This can be done by using reliability function models based on tool wear behavior, data-driven models utilizing signals from the process, workpiece, and tool, or hybrid models that combine both approaches [5].

In reliability function models, wear is described statistically by establishing a reliability function from empirical data. These models assume that tool degradation follows a specific probability distribution, with parameters estimated from the full wear dataset. Methods such as Gaussian process regression, hidden Markov models, Bayesian models, and adaptive hidden Markov models are commonly applied. A key step in these approaches is collecting accurate wear data and choosing a suitable distribution.

In evaluating tool surface degradation and reliability related to catastrophic failure, it is crucial to identify when a component of the machining system vector first exceeds a critical level. This is complex due to the system's multidimensional nature. The time to such failure is typically treated as a random variable, with its probabilistic characteristics derived from the system's statistical properties.

Many methods for tool wear assessment have been developed [6], with most focusing on identifying critical wear indicators, as summarized in Tab. 1. The data in Tab. 1 were obtained from research by D&H Innovations Ltd. and D&H Engineering Ltd. between 2021 and 2023. Certain wear types involve accelerated degradation of the cutting blade beyond technologically justified limits. However, such occurrences are rare, happening in less than 1% of all tool changes, a rate even lower than other operational events like retooling. This low incidence highlights the reliability of existing wear patterns and supports the feasibility of developing accurate tool wear models. These models can be confidently implemented in production to improve monitoring, optimize tool usage, and reduce unexpected downtime.

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Tab. 1. Critical value of tool wear symptoms

Tool wear symptom	Critical value
maximum width of flank wear VBB (ISO 3685 [4]); crater wear on the rake face	VBB = 0.6 mm in case the wear area is not regular; average wear width VBB = 0.3 mm for a regular wear surface in zone B of the cutting tool flank
intensive wear on the major or minor flank VBN	notch wear VBN exceeding 1 mm when it dominates other tool wear phenomena
chipping, flaking or cracking	excessive chipping, flaking or cracking of the cutting edge
sudden deterioration of the machined surface quality caused by destruction of the minor flank	Ra of the machined surface exceeds 0.4 μm, 0.8 μm, 1.6 μm, 3.2 μm, 6.3 μm, 12.5 μm (ISO 3685 [2]), other roughness or waviness parameters
cutting edge damage	catastrophic failure defined as sudden failure of the cutting edge under the influence of both load and increasing cutting temperature (ISO 3685 [2]).

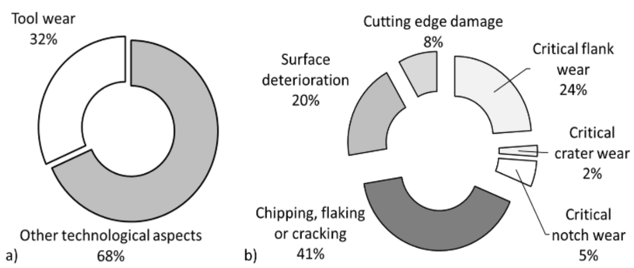

Fig. 1. a) Reasons for premature tool replacement, b) forms of tool wear

1.2. Tool wear prediction in Intelligent Tool Change System

Monitoring and prediction of tool wear has been the subject of many studies, where possible research methods have been indicated. In [7], a literature review is presented on tool wear, its description, monitoring, and RUL prediction in the context of big data. The authors proposed research directions in the area of tool wear. Most often, taking into account the critical value of tool wear, the reference value model was used, which is shown in Fig. 2.

Sensor data can refer to any measured quantity that shows a correlation with the amount of wear [8]. For example, in [9] the development of a wear measurement system based on the AE sensor was developed with an appropriate data processing system adapted to their properties. In works such as [10] and [11], the focus was mainly on developing signal processing for the tool wear inference system. In [12], methods for processing data to obtain the best RUL prediction are discussed in detail. In [13], the authors analyze changes in tool geometry, focusing on wear, design modifications, and operational factors, while presenting methods to describe these changes through measurements and descriptive metrics.

Abrasive wear depends on the physical properties of the interacting material pair – the tool material and the workpiece material, the stereometric features of the cutting edge, and the dynamic properties of the machining system. Changes in these factors over time lead to variations in the wear rate.

By understanding how the wear rate changes over time – that is, the tool wear intensity $I = dVB/dt$ – it is possible to determine the tool life at a given time as the inverse of the tool wear intensity

$$T = \int_0^{VB_{crit}} \frac{1}{I(VB)} dVB \tag{1}$$

VB – tool wear indicator,

VB_{crit} – critical value of the tool wear indicator.

The relationship between tool wear intensity and the actual tool life can be modelled using various functions. For constant tool wear intensity, the simplest and most commonly used approach is a linear model. It works well under stable cutting conditions with wider workpiece tolerance limits and effectively captures the linear portion of the wear curve, based on time or the number of workpieces processed. Tool replacement is then triggered after reaching the defined threshold.

Until the critical value of the tool wear indicator is reached, the tool position is continuously adjusted according to the progressive wear model. However, in cases of accelerated wear – after exceeding the critical value – even corrective measures may fail to keep up with rapid tool degradation. Therefore, to prevent sudden tool failure caused by cumulative cutting effects, the prediction range is intentionally limited to avoid accelerated wear.

The initiation of the tool change process can also occur in the case of a loss of stability in the manufacturing system. Process stability is determined based on measurement results and process stability data. The initiation of the tool change process carried out by the Intelligent Tool Change System, is based on information provided by the management computer, which monitor for any process trends in Statistical Process Control charts. The emergence of such trends signals a potential loss of process stability, leading to the application of artificial intelligence techniques to evaluate the state of the process and tools.

A review of AI integration into CNC systems is provided in [14], while [15] separates the tool wear process into monitoring and prediction phases. An advanced method using deep learning is described in [16].

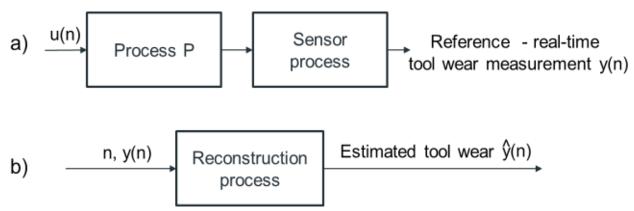

Fig. 2. a) Measuring reference data, b) off-line identification of reference value model

From the analysis conducted, the modelling of wear progression over time in modern systems takes the form of a recursive model, determined according to the scheme presented in Fig. 3. Wear values are predicted recursively based on previous values, considering the measurement data collected from the process.

In the application for tool wear prediction in the Intelligent Tool Change System, the model must be supplied with real-time data from the process. Under these conditions, the recursive model can predict the wear of a cutting tool over time, as tool wear is a gradual process that depends on the number of workpieces processed. Consequently, the model recalculates wear parameters with each new measurement.

The recursive model prediction relies on the quality of the acquired data, as the model update and tool wear prediction primarily depend on new data collected during the machining process. The model evolves with each additional measurement, adapting to real-

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time changes in the tool's wear state.

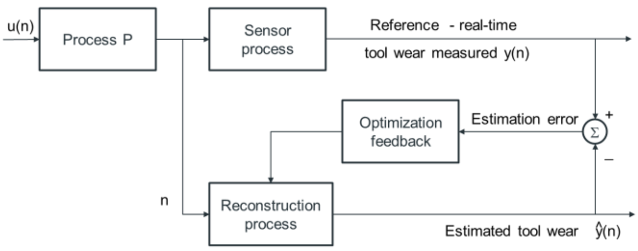

Fig. 3. Recursive model of tool wear

2. STRATEGY FOR DEVELOPING A TOOL WEAR MODEL

The technological problem in machining pertains to the change in the position of the tool tip. Considering the guidelines on the influence of cutting edge reduction on workpiece accuracy, it was found that when the actual reduction of the cutting edge reaches a critical value, the position of the cutting edge should be adjusted by introducing a correction into the CNC program. To implement the strategy and develop the appropriate model, it is essential to create an analytical structure for prediction, continuous data supplementation, and decision support systems. Fig. 4 presents a diagram illustrating the development of the integration prediction model.

The model developed within the intelligent tool change system is subject to integration within the production system. As shown in Fig. 4, for its operation, the system will require a production cell management system along with a database system, a communication and data exchange system, and a measurement system. In the integrated module with the CNC system, the system will collect measurement data and save it in the MES system.

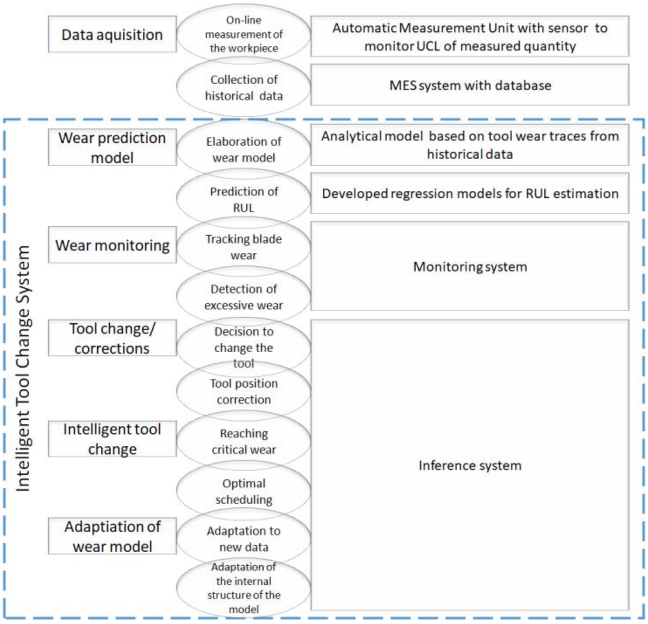

Fig. 4. The strategy for developing wear model useful in Intelligent Tool Change System

The MES data will then be used in the automatic process correction module to adjust the tool position and in the intelligent tool change system for tool change prediction. These actions will enable both the optimization of tool management and the maintenance of product quality at the level of specification compliance.

The model undergoes verification in production conditions. All points were validated by comparing predicted vs. actual tool wear. The strategy has been developed to accurately predict tool wear, optimize tool life, and enhance machining sustainability.

3. MATERIALS AND METHODS

The tests were carried out in industrial conditions, where the blade shortening during cutting was assessed. The maximum cutting time referred to the number of workpieces processed and amounted to 250 pieces. The experimental set-up with the measurement system is shown in Fig. 5

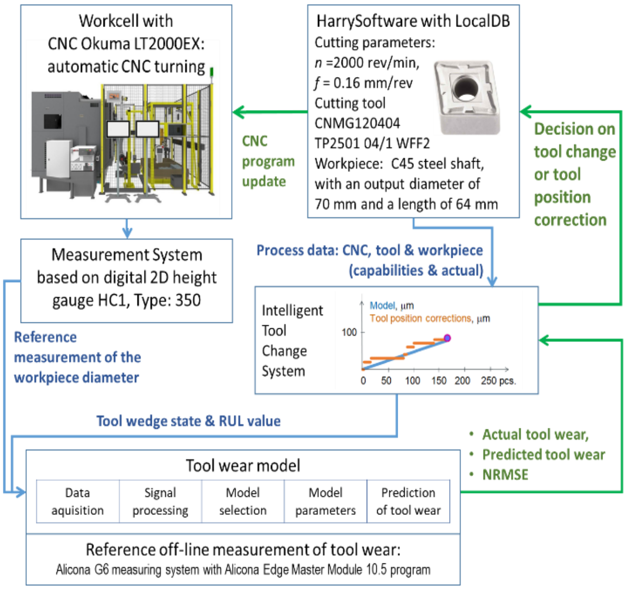

Fig. 5. Schematic diagrams of the cutting experiment and tool wear measurement setup

During cutting, reference measurements were taken and the tool position was corrected relative to the workpiece nominal and measured values. The measurement of the blade geometry in the worn state was verified by the Alicona G6 measuring system using the Advance Focus Variation method [17]. In the Alicona Edge Master Module 10.5 program, the $Ddmax$ parameter values (maximum wear depth along the profile determined on the cutting edge) were determined, which enabled the assessment of the blade shortening (Fig. 6). These values will be used to verify whether the measurements of the workpiece and the total corrections in the process define the tool wear, as determined by the parameter $Ddmax$.

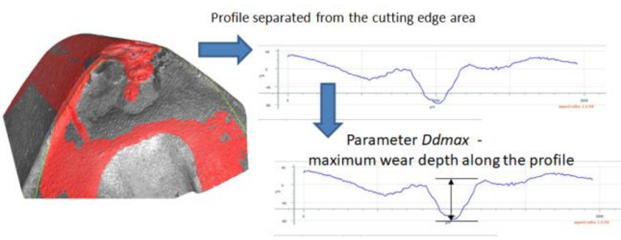

Fig.6. Determination of the blade shortening $KEmax$ using the $Ddmax$ parameter

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4. RESULTS AND DISCUSSION

4.1. Assumptions for developing the model

The cutting tool wear model occurs at various levels of the cyber-physical model. The basis for choosing the modelling method is the purpose for which the model is to be developed. The cutting tool wear model is a model of tool deterioration, which consists in the fact that the condition of a cutting tool becomes increasingly worse and gradually causes the tool to lose its ability to perform in line with expectations. However, the wear model is associated with the possibility of developing an inverse model and indicating the usefulness of a given tool, how useful it is in removing machining allowance. The definition of RUL is closely related to the wear model. On the other hand, the tool usefulness model is the possibility of introducing corrections to the process. It follows from the considerations that many basic assumptions should be taken into account when building the model. They are systematically listed in Tab. 2.

The development of models of blade wear over time and determination of RUL were carried out using monotonically changing values of wear indicators, which have a direct impact on the value of blade shortening and surface precision. Determination of the reference value of critical wear enabled the model to be adjusted to the actual values of blade wear in given cutting conditions. The biggest limitation in the use of models with a reference value is the problem of the dispersion of wear intensity and tool life. Studies show the randomness of factors that cause deterioration of cutting properties of tools, where, apart from abrasive wear, other wear mechanisms, such as diffusion or chemical wear, begin to dominate. Defining the tool life in the conditions of randomness of the tool wear process requires determining the time of its reliable operation until the blade blunting criterion (reference value) is achieved. Problems related to determining the time of the first exit of the process from the allowable area were considered in the theory of stochastic processes. Effective solutions can be obtained from the equation of the reliability function, which depends on the physicochemical and strength properties of the blade material. These in turn depend on the temperature and machinability of the processed material. Additionally, the wear of the blade depends on its load and the dynamics of the cutting process.

4.2. Development of the model

The linear wear model of the form as Eq. (2) was analysed

$$y(t) = y(t = 0) + At \tag{2}$$

where the parameter A refers to the intensity of tool shortening over time and the first-order inertial model as expressed in Eq. (2)

$$y(t) = y(t = 0)exp\left(\frac{-t}{T}\right) + K\left(1 - exp\left(\frac{-t}{T}\right)\right) + C_0 \tag{3}$$

The parameter T in equation (3) for T > 0 can be interpreted as the period where for t=T we reach 63% and for t=3T we reach 95% of the critical value of the wear. The parameter K can be interpreted as the gain, the maximum value in the steady state. Knowing the current value of y(t) and the value of y(t) for t=3T we can estimate the RUL.

Tab. 2. Summary of assumptions for building the cutting tool wear model

Assumptions	RUL	Tool position correction
The model should represent the change in tool edge reduction over time. The output of the model should be the tool edge reduction value KE, and the independent variable should be cutting time.	The edge reduction value over time allows for summing values and comparing them with the critical value.	The edge reduction value over time allows for determining current corrections in the process and predicting corrections for subsequent time units.
The model should enable the determination of the tool infeed, taking into account the tool edge reduction. The infeed value determined on the basis of the model should enable the correction of the position due to the assumed accuracy of the workpiece.	The infeed value determined on the basis of the model enables comparison with the critical infeed value, above which it is not possible to achieve the assumed dimensional and shape accuracy and surface roughness.	The infeed value determined on the basis of the model makes it possible to achieve the assumed accuracy of the workpiece.
The model should reflect the progression of tool wear over time, i.e. a typical S-shaped profile, with rapid initial growth, an almost flat middle region, and a final rapid growth. The model is nonlinear and it should be taken into account that the wear pattern changes with time tA.	The gradient of the S-shaped function determines three areas of wear changes over time: the first area with a decreasing value, the second area of a constant value and the third area of accelerated wear, the value of which increases over time and which allows for the estimation of the RUL.	The gradient of the W-shaped function determines three areas of wear changes over time and thus allows for estimating the correction values for each of the areas.
The model should take into account tool wear mechanisms. Model parameters must be interpretable in terms of tool edge reduction over time. Parameters must enable assessment of the intensity of wear mechanisms over time for different cutting conditions.	Model parameters resulting from the intensity of elementary wear processes can be used to estimate the RUL value.	Model parameters resulting from the intensity of elementary wear processes enable the determination of corrections to tool life based on them.
The model should take into account the constant cutting process load as an input signal. In principle, the undeformed chip thickness for each tool feed has a constant value, which at a constant cutting speed allows the assumption of a constant load (material removal rate), described by a unit stroke function.	The model taking into account the constant cutting load makes it possible to predict RUL.	Assuming a constant cutting load allows the influence of other factors influencing the wear process to be limited and thus the error in predicting corrections in the process to be limited.

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The goodness of fit of the models was assessed using the NRMSE index. The goodness of fit values are within the range $\langle -\infty;\ 1\rangle$, where “0” – perfect fit to the reference data (zero errors) $"-\infty"$ – poor fit, “1” – the model values do not fit better than the fit of the reference value with a linear model. Tab. 3 presents the results for the average NRMSE values for the goodness of fit of the reference data for the linear and first-order inertial models for all experiment points. The results indicate the advantage of the first-order inertial model over the linear model. The fit was significantly better, and the average NRMSE value was half as small.

Tab. 3. Summary of assumptions for building the tool wear model

Cutting edge reduction KE	$NRMSE$	
	Linear model	First order inertial model
10%	1.2	0.17
50%	0.86	0.47
75%	0.75	0.39
100%	0.33	0.43

Fig. 7 shows an example of a single cutting process, in which the collected reference data of the tool wear for 75% of the critical value. The reference data were modelled with a linear model and a first-order inertial model. For this specific cutting case, the linear model seems to be a better fit than the first-order inertial model. The fit was similar for the linear model and the first-order inertial model. However, statistically for the entire experiment, the results for the first-order inertial model indicated its advantage over the linear model.

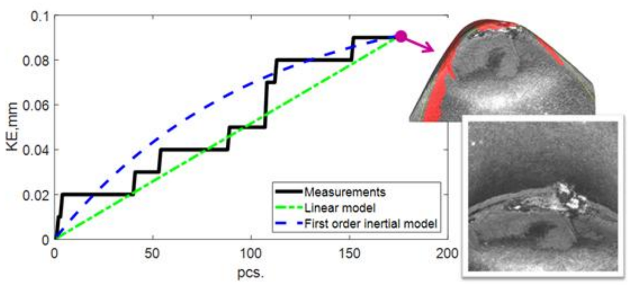


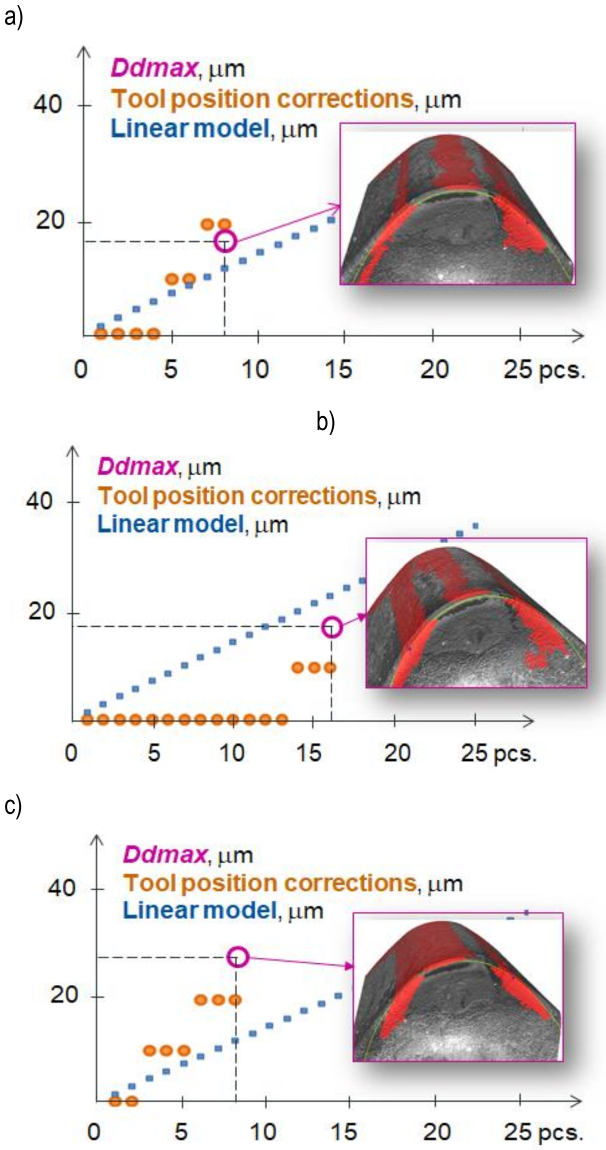
Fig. 7. Example of application of linear and first-order inertial models in the estimation of tool wear

Despite the good fit of the models, it can be observed that the measured values and the values estimated by the models, when compared to the reference value under narrow tolerance conditions, do not ensure complete compliance of the items with the specification. To perform a more comprehensive analysis, Fig. 7 presents the measured value of $Ddmax$ for selected experimental points (10% of the critical wear value) along with the cumulative value of tool position corrections. The value of $Ddmax$ and the cumulative value of the tool position correction, adjusted for the current measurement value, remain in high agreement, which was confirmed by a statistical test for equality of means. The plots in Fig. 8 have been supplemented with estimated cutting edge reduction values for the linear model. The linear model was determined using the least squares method based on all the measured data.

The chart in Fig. 8a indicates that a tool position correction was made for the fifth and seventh workpieces. The corrections were significant, amounting to 10 μm each. Introducing the correction based on the measured dimension values of the workpiece enabled the production of subsequent workpieces in compliance with the specification. Similarly, the situation unfolded in the remaining cutting trials, as shown in Fig. 8b-8d.

In this particular case, all workpieces were measured, and the correction was made in the subsequent step. This is an ideal situation, as statistical process control is used in production, and corrections are applied with a certain delay relative to the current measured value. Therefore, there is a need to predict the tool position correction values for the production of subsequent workpieces.

If the linear model identified based on multiple repetitions of the experiment were applied, it would be evident that its use in production would not guarantee an accurate reflection of the wear progression. The corrections calculated from this model might not ensure the production of workpieces within the specified dimensional tolerance. For example, the intensity of tool wear, according to Fig. 8a and 8c, is much greater than in the case of the experiments shown in Fig. 8b, where tool position corrections were made only for the 14th workpiece. The linear model suggested an earlier correction; however, despite the delay, the intensity of tool wear was small enough that the workpieces remained within the accepted tolerance range.



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d)

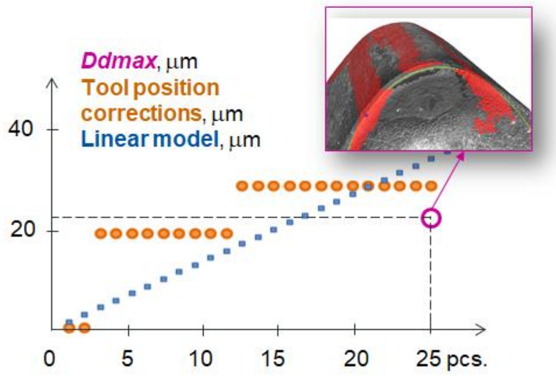


Fig. 8. Tool wear cases as a function of the number of workpieces, highlighting the $Ddmax$ values

The analysis of cases involving tool position corrections and wear progression indicates the need to train the models with reference values during the machining process in order to predict wear values. This, in turn, would enable the effective application of tool position corrections.

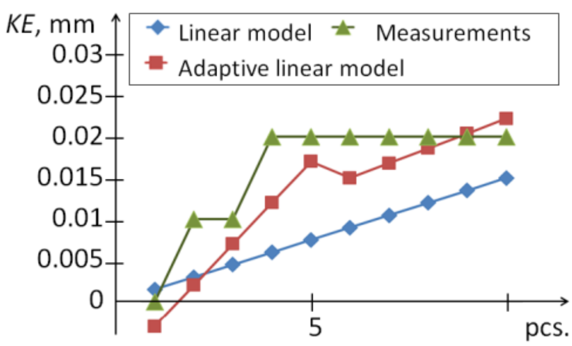
4.3. The recursive model with reference value

In the case of the Intelligent Tool Change System, the model is developed based on historical data of the process trace and tool wear. The maximum cutting edge reduction and the number of workpieces machined with the given tool are determined. As indicated in section 4.2, these values do not guarantee achieving the required workpiece accuracy due to the cutting edge reduction but serve as baseline data for developing the appropriate model selection strategy.

The adaptive linear model and first-order inertial adaptive model were developed in two versions, the results of which are shown in Fig. 9 and Fig. 10.

The adaptive linear model (Fig. 9a) and first-order inertial adaptive model (Fig. 9b) more accurately represent the tool position corrections than the linear model. The smoothing of the curves by averaging predictive tool position data from the current and previous models allowed for the model to be smoothed. The use of measured values for model fine-tuning means that the developed recursive model could be applied to predict wear values for subsequent workpieces.

a)



b)

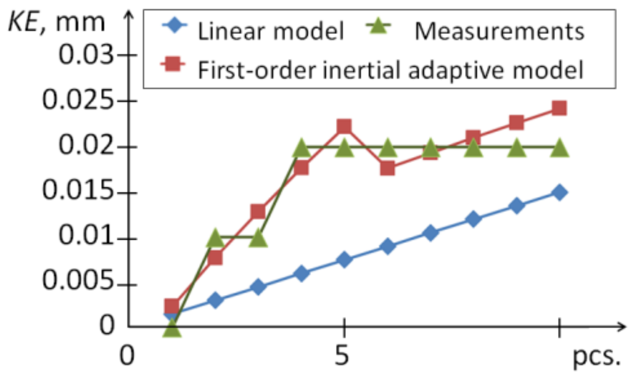
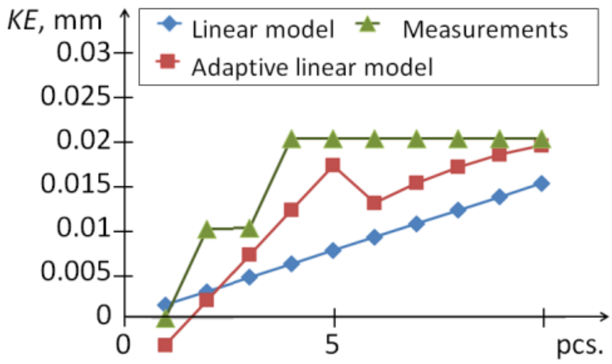


Fig. 9. A comparison of tool wear measurements and data generated using the linear model, as well as the adaptive linear model (a) and first-order inertial adaptive model (b), as reference data for tool position correction for the first 10 pieces

a)



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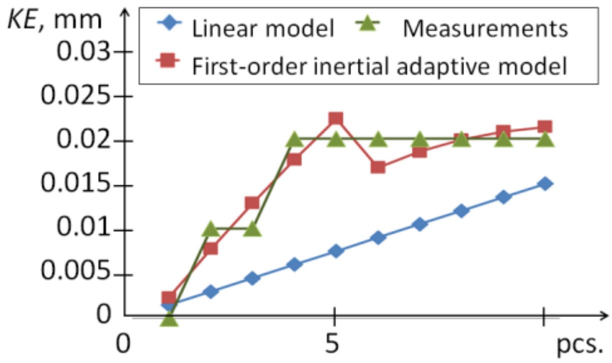

Fig. 10. A comparison of tool wear measurements and data generated using the linear model and the adaptive linear model (a) and first-order inertial adaptive model (b), as reference data for tool position correction, considering a smoothing window for the first 10 pieces

The strategy for determining and fine-tuning the models was verified using experimental data from a real production process in the Intelligent Tool Change System. For the manufacturing process being carried out, based on workpiece measurements taken every 5 pieces, corrections were made using the adaptive linear model. The model was fine-tuned as new measurements were received and predicted the cutting edge reduction values based on a monotonic function model with an increment of 5 μm. The prediction and

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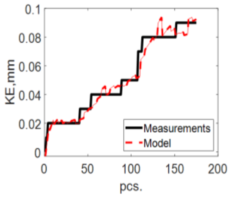
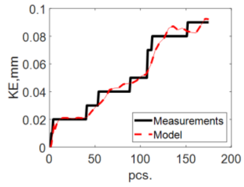
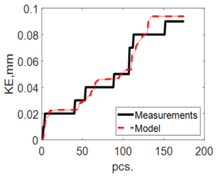
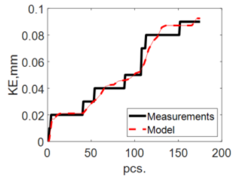
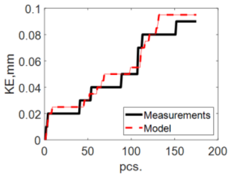
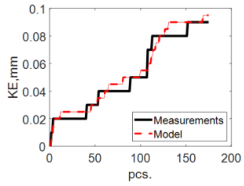
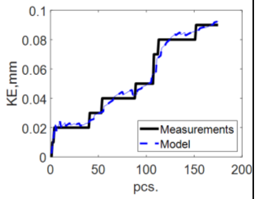
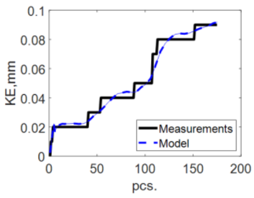
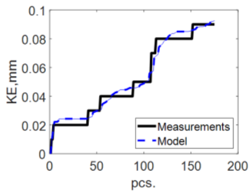
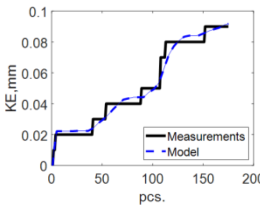
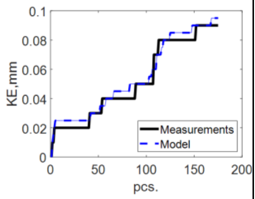
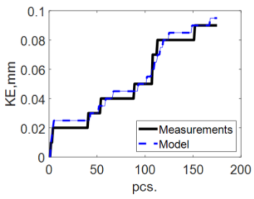
actual measurements were in high agreement. For the sample data from Figure 7, the goodness of fit index $NRMSE$ for the model was 0.2674, and after averaging, it was 0.2187 (Tab. 4).

Tab. 4. Adaptive linear function models with a 50-piece FIFO buffer

	Recursive model with parameter estimation every 5 pieces	Averaging recursive model
Adaptive linear model	 $NRMSE\ = 0.2087$	 $NRMSE\ = 0.1964$
Model of the monotonic function	 $NRMSE\ = 0.2350$	 $NRMSE\ = 0.1884$
Model with a constant increment of 5 µm	 $NRMSE\ = 0.2674$	 $NRMSE\ = 0.2187$

Tab. 5. First order inertial adaptive model with a 50-piece FIFO buffer

	Recursive model with parameter estimation every 5 pieces	Averaging recursive model
First order inertial adaptive model	 $NRMSE\ = 0.1515$	 $NRMSE\ = 0.1527$
Model of the monotonic function	 $NRMSE\ = 0.1685$	 $NRMSE\ = 0.1543$
Model with a constant increment of 5 µm	 $NRMSE\ = 0.1890$	 $NRMSE\ = 0.1783$

The use of the first-order inertial adaptive model for all experiment points yielded better results than the adaptive linear model. For the sample data from Fig. 7, the goodness of fit index NRMSE for the first-order inertial adaptive model was 0.1890, and after averaging, it was 0.1783 (Tab. 5). The prediction allowed for real-time tool position correction, ensuring that all workpieces were produced within the specified dimensional tolerance.

5. CONCLUSIONS

Tool wear during machining negatively affects the dimensional accuracy of the workpiece. In practice, the shortening of the cutting edge is compensated for by applying tool position corrections relative to the workpiece, typically integrated into the production program. These correction values are often based on reference measurements or predefined benchmarks. However, models relying solely on offline-determined parameters often fail to deliver accurate predictions, especially when the tool undergoes rapid wear or when tight dimensional tolerances must be maintained.

To address this limitation, a wear prediction strategy was developed using reference values dynamically adjusted during the machining process. This approach was tested using two model types: an adaptive linear model and a first-order inertial adaptive model. The latter demonstrated superior performance in terms of predictive accuracy and process stability. By fine-tuning model parameters based on real-time tool wear, inferred from measurements of the machined workpieces, it was possible to achieve reliable tool wear prediction. This enabled timely corrections that ensured dimensional compliance across all manufactured parts in a system equipped with the Intelligent Tool Change System.

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