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Development of Digital Twin for production**

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The prediction method of tool life on small lot turning process – Development of Digital Twin for production

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Abstract

Saving resources is one of the most significant factors in the manufacturing industry. There are in the factory, several different products under processing at the same time, therefore the handling of production conditions could be hard every now and then. Changing tools during operation might cause interruption and prolong production time. Estimation of a tool life during turning process is one of the key factors to avoid unnecessary unfinished parts and waste of resources. Overall research aiming to develop a machine learning method to predict tool life for any work-piece or tool material in the general turning process. The addressed method is important in modern small lot production when parts and materials changed constantly. The Purpose of this particular paper is to find out suitable machine learning method or several methods to evaluate tool-life in different turning conditions and circumstances. As a hypothesis of this research, we assume machine learning combine mathematical modelling is a proper method to estimate tool life in small-lot production with reasonable cost and operation time.

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Keywords: Tool life; turning process; artificial intelligence; mathematical modelling; digital twin.

1. Introduction

According to a recent report on energy consumption by Nordregio, an international research centre for regional development and planning, the Nordic countries have a similar level of emission greenhouse gases generation when compared to other, similarly sized countries [1]. Factories represent a significant share of these emissions. For example, in 2017, manufacturing basic metal and fabrication metal product produces 3,380,660 greenhouse gases in Finland [2]. Manufacturers in this region focus on flexible facilities that support the fast production of individualized products. Industry 4.0 provides digital facilities to design, develop, and optimize the production process in advance.

In the future, it is expected that a digital twin will save resources by optimizing the process performance and parameters before starting the actual production process,

avoiding the need for costly trial and error. Small lot production consumes a lot of energy and time per unit, yielding a small run of products at a high cost.

The concept of a digital twin has made considerable progress in last decades. Digital frameworks are now able to mirror some physical manufacturing processes in virtual space, allowing real-time decision-making [3]. One necessary element for applying this methodology to small lot production is being able to estimate tool life in a production environment where the product being manufactured changes constantly based on the evolving needs of customers, that is to save without any predetermined patterns.

At the highest level, a tool life function yields a tool's remaining useful life over time. Tool life can be measured using different metrics including the cumulative cutting time from the beginning of the process to tool failure, the number of parts produced before that failure, or the cumulative volume of the

metal removed prior to failure [4]. Several parameters can be significant factors in determining a tool's life, include the surface roughness of the part being machined, the specific geometry of wear on the tool, chip formation, accuracy, and built-up edge [5].

During the cutting procedure, tool wear happens as inevitable phenomena consequence of load factors on the cutting edge. Different types of wear affect the integrity of the tool because of the load factors. Process, material and environment affect wear formation on the cutting tool.

There are also ancillary parameters whose relative importance changes in different environmental conditions or during specific turning processes. These include cutting conditions, cutting force, feed force, cutting temperature, tool geometry, tool material, workpiece material, tool coating material and vibration behavior of the tool system and piece.

When estimating tool life, it is important to have a specification for the required surface quality on the final product as the surface quality changes as the tool wears. The specification can be used to determine when the tool's useful life has ended. The alternative would be to wait until the tool breaks while machining a part, increasing waste both in terms of time and material costs.

There are several approaches for tool condition monitoring using mathematical modeling. These approaches estimate both the total tool life as well as the remaining life for a particular tool. However, these traditional formulas have trouble modeling real world situations, as the relationship between tool life and machining conditions is complex, non-linear and time-variant.

Another significant approach involves using experimental data to achieve a reliable prediction of tool wear and estimate the tool life. On the other hand, data from sensors contains noise and disturbances for several reasons such as outbreaks at cutting edges, variances of the tool geometry or of the properties of the work material, sensor non-linearity, noise of digitizers, and chatters. Artificial intelligence and machine learning methods have been used in last decades to predict the tool wear behavior in academic research.

The rest of the paper is organised as follows. The "Research problems" sections explain goals of this study, assumptions, and research restrictions. The "Research methods" section describes the literature review of the methods to estimate tool life in turning and similar processes. The "Results and Discussion" section introduces the author's proposed methods for defined research problem. The conclusion of the outcomes of the research is presented in the "Conclusions" section.

2. Research problem

The goal of this research is to propose machine learning methods to predict the tool life in small lot production in variable condition of turning process.

In this article, we have studied methods to estimate the tool life in the turning process. Despite the numerous amounts of prior work in estimating tool life, very little attention has been placed on the optimizing the small lot production plan based on the estimation of tool life. On the other hand, this study is not restricted by specific environment and workpiece properties.

The intent of the present effort is to propose suitable methods to suggest the sequence of fabrication different products by turning process, according to the longest tool life estimation.

The authors propose a method to find an algorithm to estimate the tool life when machining small lots. This algorithm will be used when manufacturing some work pieces with a variation in both geometry and material using a new tool. Figure 1 depicts the scope of the research problem. The research is studying the intelligent method to estimate the tool life for the following scenario. A new tool is installed on the turning machine to produce, for example, 5 parts with specific material and geometry, then fabricate, for example, 3 workpieces with another specific material and geometry and after that produce, for example, 3 of the other part with different material and properties. It needs to mention that all materials are metal based and cutting parameters are the only factors which need to change during the process.

the aim of this study is to find a most suitable algorithm to estimate a tool life in turning process of manufacturing less than 10 workpieces with variable turning conditions. The algorithm predicts the tool life for the demand production plan and optimize the order of manufacturing to consume optimum amount of resources. A digital twin of the production process will use this algorithm to model the process with optimized parameters to minimize materials cost and time. Digital twin results help manufacturers and engineers make a production plan for ordered small lot products.

Manufacturing costs are the expenses incurred when producing a product. Usually, manufacturers compute overall expenses in terms of the cost of production per part. Manufacturing costs are thus sensitive to changes in production volume.

The manufacturing cost calculation also includes overheads such as set up cost and inventory cost. Inventory cost means the cost of preparation, storage, and management of inventory, which includes the ordering cost of inventory, the carrying cost of inventory and cost of storage and replenishment.

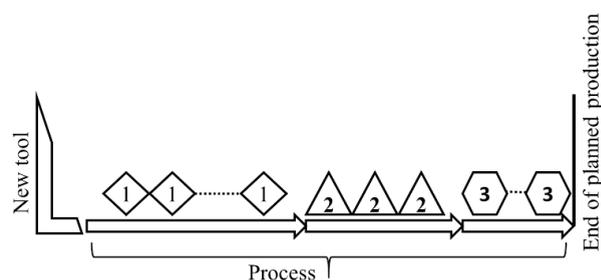


Fig 1. Research restriction – Starting the production with a new tool and continued until end of the proposed production plan without changing the tool, number 1, 2, and 3 dedicate the different workpieces

Sophisticated manufacturers aim to reduce their overall manufacturing costs, a concept known as economic lot size. The optimal order quantity, or lot size, is defined by considering the ordering cost of inventory and carrying cost of inventory. These two elements are often in opposition to each other: A manufacturer can often reduce ordering costs by placing a larger order, but that then increases the inventory carrying and storage costs. Equation 1 and figure 2 represent

the economic lot size relation to expenses. As the figure 2 presents the larger the lot size is, the higher the average inventory level is and its inventory carrying cost also increase by a certain ratio [6].

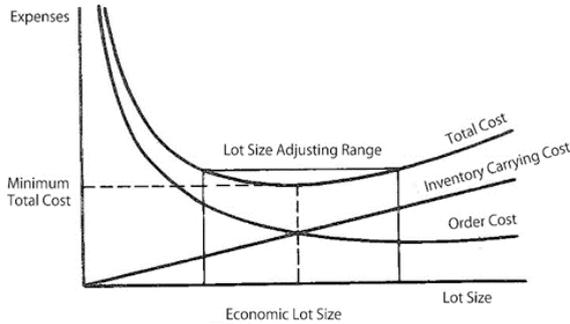


Fig 2. Expenses vs. lot size [6]

Usually the manufacturing cost per product in small lot production is high because of relatively high set up costs.

Furthermore, production lead-time is the time from customer order to the end of the production. Production lead-time consists of setup time, run time, material-handling time, and queuing time. Equation 2 defines the relationship between production lead-time and lot size. In the formula L is a production lead-time, θ is a setup time, p is a run time per unit, Q is a lot size, and δ is a shop floor queuing factor. The setup time and run time are the factors that determine actual processing time [7].

$$L = \frac{2 \times \text{Forecast annual usage} \times \text{set-up cost of the part}}{\text{Annual inventory carrying cost}} \quad (1)$$

$$L = (\theta + pQ)\delta \quad (2)$$

Generally, in the manufacturing industry, the lot size determines a process plan. As figure 3 determines, if the set up time is smaller than the process time, the lot size is called “big lot” and if the setup time is larger than process time the lot size is considered a “small lot.”

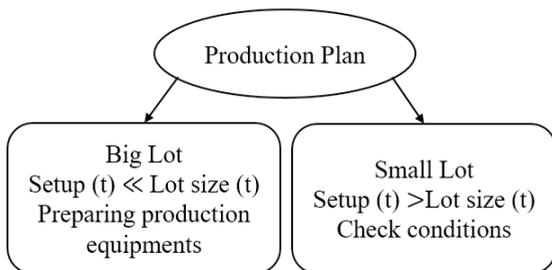


Fig 3. Determining lot size based on setup time

Small lot size production has remarkable demand in Nordic countries. A method that can save energy, materials and time can have a significant impact on the price of a small lot production run because these are major cost elements. Knowing a tool life and the parameters that affect the tool during the manufacturing of small lot production runs helps

save time by reducing the need to pause production and swap out a tool that still has useful life remaining. The same methods can save energy and reduce materials costs because, without a digital twin, the insight into when to swap out a tool is the result of trial and error which means scrapped parts due to tool breakage.

In 2019, we proposed an extensive digital twin framework for manufacturing processes. The framework is able to make a decision automatically [5]. To reach this aim, machine learning methods need to extract features, discover the relationships between data, and then make a decision in different situations. As it is presented in [5], in creating a digital twin of a process or production line, each part has its own digital twin that means it is possible to use different methods in analyzing.

4. Research method

Monitoring tool condition is an old and important topic in manufacturing study because of its significant role in product quality, cost, and energy saving. Many methods have been developed to calculate or estimate the tool wear and tool life in past decades. Some of these methods are explained in the next section. Methods categories in various ways such as direct and in-direct group, model-based and data-driven methods (Mathematical modeling and artificial intelligence). Indirect methods use sensor signals related to tool wear like acoustic emission, cutting force, vibration, current, or power signals. The data is then analysed using mathematical or machine learning methods. Direct methods use images of the tool statuses during machining to predict the condition in future and remaining tool life.

In this paper we investigated recent articles regarding tool wear identification and tool life prediction in milling and turning. The aim is studying the conditions and data requirements for each applied tool life prediction method.

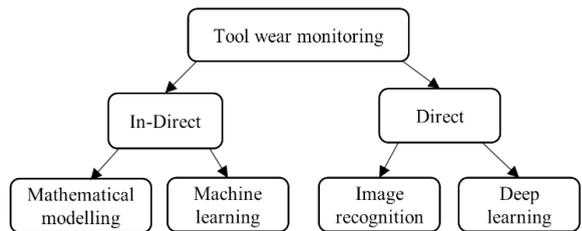


Fig 4. Tool wear monitoring method

1.1 Mathematical modelling (physics-based study)

Several studies have been done in recent decades about estimation or prediction of tool life. Taylor defined a relationship between tool life and cutting speed as in formula 1 where C and n are constants that should be defined for work and tool material and machining conditions. In this formula V is the cutting speed in a one-minute tool life [8].

$$VT^n = C \quad (3)$$

In [9], the first and second order model of developed Taylor equation have been estimated by response surface methodology combined with the factorial design of an experiment for turning high strength steel. In the experimental tests, flank wear was considered as a failure criterion. The results gave tool life contours to determine the optimum cutting conditions for a known tool life. On the other hand, formula 4 shows the contours could be used to find the maximum tool life for a given metal removal rate as a function of cutting variables (feed, cutting velocity, and depth of cut).

$$T = C(V^l f^m d^n)\epsilon \quad (4)$$

In [10], the first and second order model of tool life were developed for micromilling hardened steel by Central Composite design method. The second order model has more accurate prediction with interaction of all factors. Article [11] found optimum process parameters: cutting force, cutting speed and material removal rate for better tool life during aluminum turning operation. Reference [12] used the central composite design of experiment in turning process of dry cutting of hardened steel. Flank wear is the considered criteria to determine the tool life. Regression analysis was used to present relationship between tool life and machining variables which are independents. The results show all parameters have significant impact on tool life, however cutting speed has the maximum effect and depth of cut has minimum effect in this experiment. In [4], authors used experimental data to develop a mathematical model to estimate flank wear and cutting force in various conditions. Genetic algorithm technique was applied to optimize cutting conditions to predict optimized tool life. Crossover probability and the mutation probability were used to control the genetic algorithm.

1.2 Machine learning (data-driven study)

In recent years, researchers have been studying how artificial intelligence can predict tool life because the mathematical models are non-linear and there are complex relationships between parameters like process conditions and tool conditions [4]. Hence, finding this relationship is the aim of using AI methods. In mathematical models, there is inherent uncertainty in the empirical constants [13].

Tool wear monitoring is a method to predict the tool wear during a manufacturing process. Generally, machine learning and neural networks methods are applied on the collected sensor signals to identify the correlation between actual tool wear and extracted features from sensor data. The raw signal data contain noises and disturbances so pre-processing techniques are required. The first step is choosing suitable signals which collect data during the process. A proper feature extraction technique plays an important role in finding relationship between sensory signals and tool wear or tool life [14]. Ordinary feature extraction techniques such as mean value and standard deviation are suitable to extract features from single sensory signal. Reference [15], used the shop-floor production data to model tool wear and predict tool life. In this case, tool life is a classification problem that means the model

can predict tool wear at the time of changing the tool. Then a comparative study had done on two machine learning methods (Support Vector Machines (SVM), and logistic) for tool wear classification.

Article [16] investigated a method of tool condition monitoring that eliminates the need to pre-processing data. Gramian Angular Summation fields used to image sensor signals and convolutional neural network used for classification. In [17], tool wear tests have done in turning to predict tool life with probability density function in Bayesian inference. Moreover, Metropolis-Hastings algorithm of the Markov Chain Monte Carlo was applied to estimate the constants in Taylor equation. Moreover, paper [17] used Bayesian inference to estimate constants in implemented Taylor tool life equations. In this research the Bayesian inference used the Metropolis-Hastings algorithm of the Markov Chain Monte Carlo (MCMC) approach to estimate the constants related to feed, cutting speed, and tool-workpiece combination properties factors. This method investigated in results of the experimental tests of turning operation with a carbide tool and MS309 steel work material.

Paper [18] used Convolutional neural network in dry milling process with a non-coated ball endmill on a stainless steel workpiece to predict tool wear. This approach used cutting force signals as input. After training the network, the adaptive controller adjusted feed rate and spindle speed to gain the command force. The novelty of this approach is the combination of the self-learning and self-adaptive components operating simultaneously online as one body to produce an in-process smart tool wear detection and prediction system. In addition, another paper predicted tool breakage by convolutional neural networks and back propagation neural network in milling process with cemented carbide milling tools. Inputs were spindle current signals. Results show CNN has better accuracy than BP [19]. Paper [20] used Convolutional neural network method to monitor tool wear in milling process. Both researches applied back propagation algorithm for pre-processing collected data by sensors. In [20], they improved the BP algorithm by combined with stochastic gradient descent algorithm. Images were taken during milling process and use as datasets. Wear characteristics are the required features, which extracted adaptively. Softmax classifier training identified the wear types after CNN was trained.

In [21], authors applied artificial neural network on turning process of SiCp/Al to analysis the machining parameters impact tool wear and tool life. In this survey studied the effect of material properties of metal matrix composite on choosing the proper cutting tools to save resources. Cutting speed, feed, and depth of cut are the inputs of the feed forward back-propagation multi-layer neural network. In the experiment, 16 dry cutting operations were tested and wear progression on non-coated carbide was measured after each operation. It can be seen from the experimental results that in the processing of particle reinforced aluminum matrix composites, the tool wear phenomenon varies with different component materials due to the difference in internal particle size and particle content. Another method is continuous hybrid tool wear estimator that contains two modules for classification and estimation.

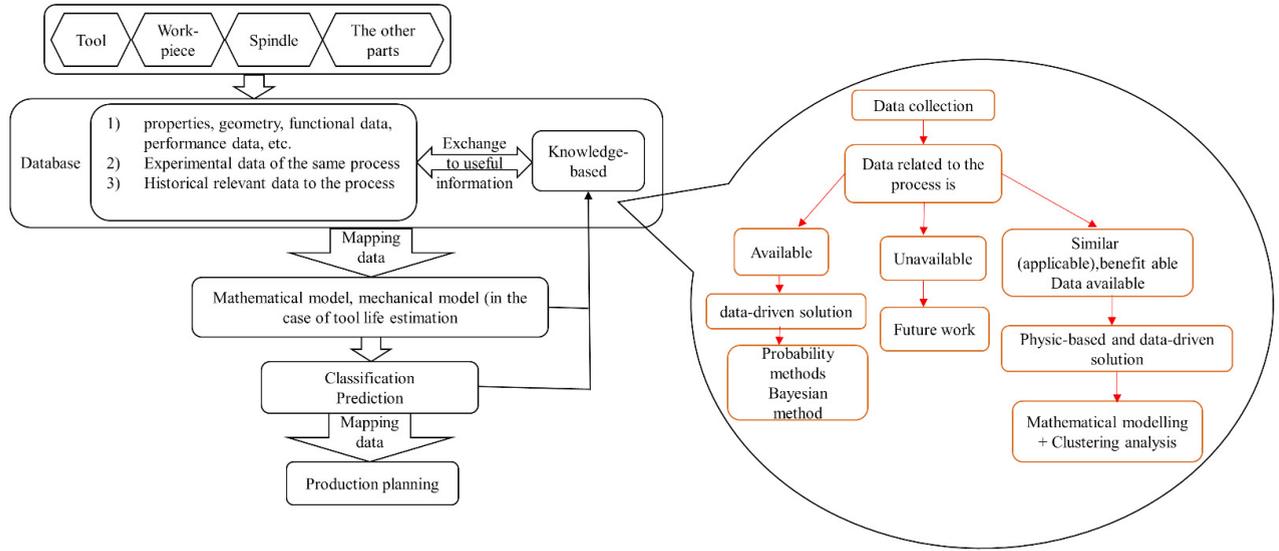


Fig 5. Digital twin framework to estimate tool life based on article [5].

Table 1. Advantages and disadvantages of machine learning methods

Name	type	Advantages	Disadvantages
SVM	Supervised Learning, Kernel methods-based	No probability Good for high dimensional data Less risk of over-fitting	Difficult to choose a proper kernel function Long training time Difficult to understand and interpret the final model, variable weights and individual impact does not perform very well, when the data set has more noise
Logic regression Regression	Supervised Learning	Easy to understand and explain provide feature importance Outputs a probabilistic interpretation Has a small number of hyperparameters	Overfitting in large numbers of features only learn linear hypothesis functions so are less suitable to complex relationships between features and target Input data might need scaling May not handle irrelevant features well A complex hypothesis function is really difficult to fit
CNN	Supervised Learning Deep Learning	accuracy in image recognition problems very good feature extractors	High computational cost. Need many training data. comparatively slow
Bayesian learning	Statistical	the training and classification of the project is only a mathematical operation of the feature probability works well for small-scale data, can handle multi-category tasks, and is suitable for incremental training (that is, it can train new samples in real time) Less sensitive to missing data explains the results easily	Need to calculate the prior probability There is an error rate in the classification decision Very sensitive to the form of input data
Mont-Carlo	Reinforcement learning solution		Only can be used in episodic problems has high variance only learn from complete sequences

An example of using this method represented in [22]. Reference [22] used neuro-fuzzy hybridization to monitor and estimate tool wear on turning operation of cast iron and alloy steel with uncoated carbide tools. Inputs are time, cutting forces, vibrations and acoustic emissions signals to three neuro-fuzzy approaches such as inductive, transductive and evolving to compare the performance of each approach. Training algorithm for Adaptive-network-based fuzzy inference system (ANFIS) was back propagation and least squares method, for Dynamic evolving neural-fuzzy inference system (DENFIS) was least squares method, and for Transductive-weighted neuro-fuzzy inference system (TWNFIS) was back propagation. The results demonstrated the TWNFIS had smaller error and better performance than the other methods. Reference [23] studied learning the relation between tool life and cutting conditions in turning medical grade cobalt chromium molybdenum alloy (ASTM F75) by a Bayesian hierarchical Gaussian process model. Twenty-one experimental tests have done for different cutting speed and feed rate. A Bayesian hierarchical model helps to analyze tool wear rate in any force direction. This simulation is a linear regression of force vs length of cut. Gaussian process modelled the slopes. The advantage of this method is optimizing tool life and cost of manufacturing process.

Bayesian methods could estimate the future probabilities based on historic available data and background knowledge. Assume there are training data D , hypothesis h is defined as a pattern of training data distribution before we observed D . The prior probability of h shows any background knowledge about the chance that h is correct. Post probability shows that how much the hypothesis was accurate based on the training data. The mentioned Bayes theory makes the Bayesian method more flexible than the other learning algorithms and its ability to give enough accurate probability of the future data [24].

A comparative study has been done in [25], to predict tool life in high speed turning processes. The result shows artificial neural network has better results than support vector regression and polynomial regression.

Because of huge amount of data include complex features, it is trying to skip the pre-processing step and use raw data. In the recent years, researchers focused on deep learning and image recognition to estimate the remaining useful life during the process. In [26], time series image (summation of angular fields, Gramian Angular Summation Fields (GASF)) was used to feature classification. In [14], tool wear prediction is studied on different coated tools in four cutting speeds. Three-dimensional tool wear progression and flank wear progress were used to estimate tool life in finishing cutting of an aerospace component machining. In this method 3D image was taken after each cutting pass to compare with previous image of the shape of the tool surface. Then parameters extracted with Measure Suite software to study the effect of cutting speed and coating in turning process. Cutting speed, material removal rate, index of performance, TWR and feed rate, and built-up edge are the parameters which considered to predict tool wear. Reference

[27], used 3D and flank wear patterns to predict a tool life during turning operation of InconelDA71 with two different coated tools in four cutting speeds.

All the studied mentioned in the last section were applied on the certain machining conditions and environment. In addition, those productions were in the big lot size and tried to optimize tool life to produce more products in the defined process condition before reaching breakage. However, the production story in the small lot size is different because of expensive instinct of the production, efforts have done to save the resources called setup time, setup cost and production cost. Estimate the tool life needs for scheduling before production to use the same tool for as much as possible different ordered products. To reach this aim, using digital twin before starting manufacturing process is suggested. Digital twin framework presented in [5] considered as an effective solution due to it covers physical modelling and data modelling.

3. Result and discussion

In this section, we propose a digital twin framework to estimate the tool life in small lot production. The model starts from virtual space then connects to the physical space. Figure 5 illustrates the framework that was created based on the authors earlier study (reference 5) which is mentioned in the research method. As figure 5 depicts, to create a digital twin of the turning process, we make the digital twin of each part of the turning process. Each digital part contains the CAD model based on the physical part and related database. In this study, different workpieces will be produced with a same turning tool. To fill out the database in the second step of creating the digital twin, we divide it to three options.

First option happens when there is available similar data regarding to the process of the desired tool and workpieces. In this case, we obtain the sensor data from the several studies of demand workpiece monitoring tool condition. From the other experiences in industry whether the mass production or not there are available sensor data of the acoustic emission, cutting forces, torque, tool temperature, and other important parameters in turning process. The sensory data of the similar kind of studies will be gathered in a training vector. A Bayesian network is a proposed solution in this case because it is based on the probability. A Bayesian network finds the probability of the tool wear progress and then estimates tool life. Bayesian methods are able to estimate the future probabilities based on historic available data and background knowledge. Although the literature review revealed that a neural network approach was the strongest method for monitoring and estimating tool wear, because this study will be applied on the case that the knowledge of system behaviors is not known in advance. The input of the Bayesian network is the vector contains the training data of workpiece type 1, workpiece type 2, and workpiece type 3.

The second option happens when there is no experimental data related to the desired process. However, the work piece and tool properties and environmental features are available.

As it is mentioned in the literature review, extended Taylor tool life equation, equation 4, has been a suitable method to estimate the tool life predictions and under certain conditions. Extended Taylor tool life equation includes some variables, constant and exponents. Variables represent the effect of cutting speed, feed rate, depth of cut, rake angle of the tool, and chip thickness. Constant implies the effect of tool-workpiece properties, machining environment, and limitation for values. Authors suggest using hierarchical clustering method to find the tool life exponents l , m , and n in equation 4. Using hierarchical clustering provides a decision framework which enables user to find the accurate values for exponents in the Taylor equation to find the tool life in turning.

The third option represents a new tool working on a new work piece so there is no historical data. Therefore, there is no foundation that can be used to develop the digital twin. This is perhaps a weakness that will be addressed by future research.

These solutions are considered for each option according to the problem type. Depending on the available data there are three types of problems:

1. There is already experimental data regarding work piece and tool (classification problem)
2. There is no experimental data, but work piece and tool characteristics and environmental features are defined (clustering problem)
3. No data

These machine learning methods is trying to find the optimum production plan (the order of producing different workpieces) by estimating the tool life.

4. Conclusion

The literature revealed both direct and indirect methods to monitor tool wear during a process and estimate the remaining tool life in certain conditions. However, predictions of tool life *before* starting the process remained unaddressed. This case is significant when producing small lot products so that they this type of production can benefit from an efficient production plan that avoids unnecessary tool changes or tool damage or breakage.

This study identifies three distinct cases that determine the appropriate method for creating a general digital twin of a turning process for small lot production:

1. When there is access to available historical data of the similar production, the solution can be using Bayesian method.
2. When only features, properties and condition data are available, the solution can be using extended Taylor equation with hierarchical clustering method.
3. When there is no relevant available data. the solution is not available yet.

The first case is treated as a classification problem. We suggest using Bayesian methods to estimate the tool life for this case. The second situation is a clustering problem where the combination of mathematical modelling and hierarchical clustering is expected to accurately predict the result. According to the digital twin definition and platform, the

third case would not yield any useful predictions, at least not with existing methods. In future work, the proposed solutions will be applied to a case study involving the production of a small number of products with different geometries or materials to find out the exact accuracy and/or precision of the methods.

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