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# SOFTWARE-DEFINED WORKPIECE POSITIONING FOR RESOURCE-OPTIMIZED MACHINE TOOL UTILIZATION

Advancing climate change, tense world markets, and political pressure steadily increase the demand for resource-optimized production solutions. Herby, the positioning of the raw material in the machine tool is an important factor that has received little attention. Traditionally, this is done centrally on the machine table, which leads to locally increased wear of the feed axis. Furthermore, positioning directly influences energy consumption during machining. Consequently, the longest possible component utilization through optimum wear and energy optimization creates a direct conflict of objectives. To solve this conflict, this paper presents an automated approach for software-defined workpiece positioning and NC-Code optimization regarding the axis-specific energy consumption and the spindle condition of ball screws. An approach for mapping the energy consumption and the directly measured spindle condition is presented. Both represent input variables of the cost function. Approaches for the optimization of the position as well as for the practical implementation are proposed.

## 1. INTRODUCTION

As a result of ongoing social change, uncertainties in the raw material markets, and unstable global supply chains, the resource-optimized production of our goods is becoming increasingly important. Hereby, energy consumption plays a central role. For instance, companies aim to run their business more cheaply by saving $CO_2$-certificates or to fulfil ESG (environmental, social, and corporate governance) criteria. Furthermore, industrial electricity prices in Germany, for example, have reached unprecedented highs [1]. Another highly topical aspect of resource efficiency is the sustainable use of existing machines and their components. This effort is reinforced by unprecedented material scarcity [2]. In addition, there is a lack of trained specialists, especially in developed countries, so solutions must be as automated as possible [3, 4]. In the context of machine tools, these points motivate an individual consideration of each machine tool. Here both, the individual properties and their behaviour over time must be mapped.

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Milling machines are one of the most common manufacturing machines in production. Many different processes and machine tool simulation models have been developed for these over the past few years and decades. These models can now be thought of as part of the machine with which they form a CPS (Cyber-physical system). One of the least optimized and automated steps in milling is still the positioning of the workpiece on the machine tool table. Traditionally, the positioning is done centrally on the table by the operator resulting in local loading of the translatory feed axis components. This increases the risk of wear effects, which leads to premature component failure. However, ball screw drives represent one of the most important causes of translatory feed axis downtime with 38% [5]. Furthermore, due to axis-specific energy consumption, the orientation of the process direction can result in higher energy consumption of up to 29% [6]. The worker will not be further affected by an optimized clamping of the workpiece, however, additional parameters for orientation on the machine table are required. This motivates the search for suitable approaches for optimized positioning of the workpiece, taking into account the axis-specific energy consumption and the position-dependent spindle condition.

Table 1. List of abbreviations

| Abbreviations | Meaning |
|---|---|
| $X,\ Y,\ \gamma,\ \bar{\boldsymbol{S}}, \bar{\boldsymbol{F}}$ | Specified *X* and *Y* position, *Z* orientation as well as the block-dependent spindle speed and feed vector |
| $x_b, y_b, z_b,\ s_b,\ f_b,\ t_b$ | *x*, *y* and *z* position, spindle speed, feed rate and execution time for block *b* |
| $\bar{\boldsymbol{x}}, \bar{\boldsymbol{y}}, \bar{\boldsymbol{z}}, \bar{\boldsymbol{s}}, \bar{\boldsymbol{f}}, \bar{\boldsymbol{t}}$ | *x*, *y* and *z* position, spindle speed, federate and execution time for all blocks |
| $b$ | NC code block number for blocks with kinematic information content |
| $i$ | Axis number |
| $v_{b,i}, a_{b,i}$ | Velocity and acceleration for axis i in block *b* |
| $p_{motion,b,i}$ | Power prediction based for axis i in block *b* excluding process forces |
| $p_{en,b,i}$ | Power prediction based for axis i in block *b* including process forces |
| $\alpha_{1,i},\ \beta_{1,i},\ c_{1,i},\ \alpha_{2,i},\ c_{2,i}$ | Power prediction parameter for axis i |
| $f_{en,b,i}(X, Y, \gamma, s_b, f_{b,i}, t_{b,i})$ | Axis-specific energy consumption for block *b* |
| $f_{en}(X, Y, \gamma, \bar{\boldsymbol{S}}, \bar{\boldsymbol{F}})$ | Term of fitness function based on the combined axis-specific energy consumption |
| $l_{sensor},\ l_{screw\ nut}$ | Length of the sensor system and the screw nut |
| $\varepsilon$ | Damage function of a damage present on a spindle |
| $f_{cond,b,i}(X, Y, \gamma)$ | Axis-specific condition for block *b* |
| $f_{cond}(X, Y, \gamma)$ | Term of fitness function based on the combined feed axis condition |
| $f_{ges}(X, Y, \gamma, \bar{\boldsymbol{S}}, \bar{\boldsymbol{F}})$ | Total fitness function |
| $p(X, Y, \gamma)$ | Penalty term of the fitness function for illegal positions and orientations |
| $\epsilon$ | Manipulatable weight of the fitness function |
| $n_{eng}, n_{cond}$ | Normalization factor of the individual terms of the cost function |

## 2. STATE OF THE ART

This chapter lists all relevant work and summarizes the state of the art. In particular, the prediction of the axis-specific energy consumption and its optimization based on the positioning are discussed. Furthermore, the state of the art regarding the direct as well as the indirect determination of the ball screw condition will be discussed. In particular, the focus will be on the position-dependent screw condition. Finally, this section discusses the optimization of the position of the workpiece in machine tools.

### 2.1. ENERGY PREDICTION AND OPTIMIZATION

In order to make existing systems more energy efficient, Asrai [7] developed a mechanistic energy consumption model using a linear regression model and a variation of cutting parameters for validation. However, due to strong measurement uncertainties, the validity of the prediction model could not be confirmed. Frigerio and Matta [8] developed an approach to reduce energy during warm-up and setup by implementing control strategies. The time-dependent warm-up duration and stochastic arrival times were taken into account to shut down the machine during interruptions. Peng and Xu [9] studied the energy consumption of machining systems centers and found that machine tool structure, setup conditions and machining parameters represent the greatest influence on energy consumption.

To develop a new energy consumption model, Pavanaskar and McMains [10] investigated the influence of process time and other known parameters on the energy consumption of CNC machines. In contrast to previous energy models, the geometric aspects of the toolpath parameters were considered. Based on the new model, software was developed that predicts energy consumption with maximum deviations of 6%. To make pocket milling more energy efficient, Pavanaskar et al. [11] used digital micrography based on streamlines of a vector field to determine tool paths. Initial experiments showed that energy savings are possible by using this approach, although the results have not yet been validated. Edem and Mativenga [12] developed a model to estimate the electrical energy demand of CNC machines, taking into account the weights of the feed axes and the weights of the materials positioned on the machine table by measuring the energy demand during air cutting as well as during cutting of actual masses. Furthermore, the influence of the alignment of components and tool paths on energy consumption during milling operations was investigated [6]. The findings of the study showed that compared to the optimum, up to 29% more energy is needed and improved surface properties can be achieved. In addition, Edem and Mativenga [13] summarized previously developed energy prediction models for toolpaths based on CNC codes. These findings were used to develop an algorithm for an energy prediction software based on NC-code.

Through sensors and data analysis of digital twins in an SMT-PCP assembly line, Karanjkar et al. [14] observed that the use of workpiece buffers can save 2.7 times the average energy consumed. Rodrigues et al. [15] analysed electricity consumption in manufacturing processes using computer-based discrete event modelling and optimization software to investigate more energy-efficient and sustainable production, although the model has not yet been validated. Denkena et al. [16] analysed the energy requirements of machine tool components to enable energy-efficient operation of machine tools. This reduced energy consumption between 30% and 52% in the cases studied. In order to create transparency about the energy consumption during the production process, Mose [17] developed a characteristic value to subsequently reduce energy consumption. Using various machine learning algorithms to accurately predict the energy requirements of CNC machining operations based on real production data, Brillinger et al. [18] were able to develop a prediction that deviated only 7.16% from the real value. Cao et al. [19] developed a method to efficiently determine the total energy consumption of CNC machines using program parsing and parallel neural networks. The method has been verified by case studies and can determine the total energy consumption with a deviation of 5% for each NC-block. Furthermore, a statement about the total energy consumption is made with a prediction error of 0.85%.

### 2.2. CONDITION MONITORING OF BALL SCREWS

Condition monitoring of drive components is a field that has already been extensively researched. For instance, Verl, et al. [20] determined information about the feed axis wear using sensorless automated condition monitoring (SACM) algorithms based on position-controlled drive signals, such as position, velocity, and motor current. Schmid et al. [21] used a wireless sensor network (MEMS) for continuous condition monitoring of ball screws. Verl and Frey [22] have shown that the value of the preload in ball screws changes depending on the speed of the feed motion, which influences the load and thus the service life. By deliberately provoking damage and using a SACM algorithm, [23] developed an automated condition monitoring system for feed axis that is capable of directly inferring the cause of damage from the vibrations that cause it. Möhring und Bertram [24] deal with the monitoring of the wear progress by an integrated sensory ball screw double nut system with preload as wear indicator. For condition monitoring and a wear and life estimation, Helwig [25] uses a semi-automated approach for feature extraction, selection, and classification based on heterogeneous sensor data, where the basis of all sensor data yields a high explanatory contribution for the life estimation. To monitor the ball screw's preload condition, Benker et al. [26] chose a probabilistic classification approach based on the natural frequencies of ball screws. With an average accuracy of 96% for each fault found, Riaz et al. [27] were able to develop an efficient condition monitoring of ball screws using a deep learning-based technique. Using Guard-Plus technology, Veith et al. [28] developed a successful approach to finding preload losses in ball screws. Xi et al. [29] developed a new method for detecting zero backlash and loss of stiffness in ball screws without preload to simulate the dynamic behaviour of the machine axis as a function of wear. For this purpose, a spacer sleeve was developed to ensure that the axial stiffness of the feed axes is effectively reduced, allowing a rapid change in wear condition of the machine axes. By using deep learning methods, Riaz et al. [30] succeeded in developing an approach that is significantly superior to existing approaches for detecting and classifying errors in linear motion systems.

In order to detect damages on the surface of ball screw spindles at an early stage, Schlagenhauf et al. [31] developed a monitoring approach using an integrated camera system. To enable machines to detect and predict the spindle condition, a method based on machine learning was developed in [32] to interpret defects in ball screws automatically and autonomously. An intelligent defect quantification module quantifies the defects, which are then predicted by a prognosis module in a combined approach. Based on all previous findings

Schlagenhauf [33] developed a machine learning approach for monitoring the entire wear development on the surface of ball screws based on image data.

### 2.3. OPTIMIZATION OF THE WORKPIECE POSITION

Li and Melkote [34] were able to improve the positional accuracy of the clamped workpiece through their fixture layout optimization model. According to Li and Melkote, the inaccuracies in workpiece position are due to localized elastic deformation at the fixturing points, resulting in rigid-body motion of the workpiece. The improvement in workpiece position resulted in more uniform and less intense deformation of the workpiece, and the distribution of lateral reaction forces on the positioners has also become more uniform due to the improved fixture layout. In order to reduce the deformation of the workpiece during machining, Kaya [35] combined finite element method and genetic algorithms (GA) to optimize the position of supports, fixtures and clamps, since these are decisive for geometric errors on the workpiece. Kaya has shown with his approach that optimization problems of this type are multimodal problems and therefore heuristic rules for fixture design in GA are best suited to select the best fixture layout. Using data acquisition and analysis software, Liu et al. [36] measured the chatter behaviour during robotic milling for different clamping positions and milling paths to select a clamping position and milling path with minimal chatter behaviour.

Weber [37] deals with a method for the automated generation of alternative workpiece and tool positions in a simulation environment and the associated simulation-based verification and NC program adaptation. Hereby, the focus was on time savings through a suitable choice of workpiece and tool position and collision-free manufacturing. Based on this, Weber et al. [38] developed an optimization process using the validity of workpiece positioning parameters and supervised learning algorithms.

### 2.4. SUMMARY AND RESEARCH DEFICITS

The energy consumption of machine tools has already been discussed in a number of publications. It was found that the alignment of a movement along the different axes has a direct influence on energy consumption during machining. In addition, there have been studies on the prediction of energy consumption. However, the prediction of the total energy consumption was the primary goal where auxiliary units represent one of the relevant influences. Furthermore, the time-dependent characteristics of the machine tool, for example as a result of feed axis wear, were not taken into account. Accordingly, for the implementation of the presented approach, there is a need for a precise prediction of the axis-specific energy consumption. Furthermore, the question arises of how this mapping can be implemented taking into account the individual and time-dependent machine characteristics.

Condition monitoring of ball screws is an extensively researched field. However, the focus has always been on the general condition of the component. This is decisive for the further use of the components and whether they need to be replaced. In order to enable a component- and thus resource-efficient processing, an extension of existing approaches is required. An approach is needed on how to use position depending condition information of the feed axis in order to adjust the usage and thus the load appropriately.

The steadily enhancing digital representations of machine properties are increasingly providing a better basis for optimizing the position of the raw material and, consequently, the machining process. In particular, reference should be made to [37], where the optimization of the raw material position with respect to the machining time has been investigated. There is, however, a gap in the optimization with respect to several, possibly contradictory, targets enabling software-defined positioning.

## 3. OWN APPROACH

The aim of the presented approach is to find the optimal position of a given workpiece on the machine table based on the consumed energy and the current position-dependent condition of the translational feed axes. Accordingly, the optimal coordinates in the $x$ and $y$ directions ($X$ and $Y$) as well as the optimal orientation around the main spindle axis $\gamma$ are to be determined. It should be noted, however, that depending on the type of construction, the plane of the machine table and thus the axis names can vary. In the first step, the individual machine properties are to be mapped, taking into account their change over time. For this purpose, an adaptive approach for the determination of the axis-specific energy consumption based on the NC-code and the raw part is developed. For the digital mapping of the position-dependent feed axis spindle state, a machine learning-based imaging method for the determination of the condition is further developed. Both models represent the basis of the fitness function. This is the optimization goal, for which an optimal configuration is to be found under variation of $X$, $Y$ and $\gamma$ as well as the block-dependent spindle speed $\overline{\boldsymbol{S}}$ and feed rate $\overline{\boldsymbol{F}}$. Finally, the presented components are to be merged into a simple-to-use approach, which can be executed as automatically as possible.

## 4. PREDICTION OF THE AXIS SPECIFIC ENERGY CONSUMPTION

A precise prediction of the axis-specific energy consumption is necessary to reliably determine the optimized raw part position and orientation. The presented approach for energy estimation uses the NC-code of the produced workpiece and the raw part characteristics as input data. Relevant raw part characteristics are the workpiece position described by the coordinates $X$ and $Y$, as well as the workpiece orientation described by the angle around the main spindle axis $\gamma$. From the NC-code, the blockwise spindle speed $s_b$ and feed rate $f_b$ are required. By geometric decomposition, the feed rate $f_b$ can be divided into axis-specific feed rates $f_{b,i}$. Furthermore, the axis-specific time needed for the execution of a block $t_{b,i}$ is calculated from the NC code. This calculation is based on a machine model, which is described in more detail in the following paragraph. With these input variables, the axis-specific energy consumption of a block $f_{en,b,i}$ can be estimated. By adding up the values for all blocks $B$ and all axis $I$, an estimation of the total energy consumption for executing the whole NC code $f_{en}$ can be made (eq. 1).

$$f_{en}(X,Y,\gamma,\overline{\boldsymbol{S}},\overline{\boldsymbol{F}}) = \sum_{i=1}^{I}\sum_{b=1}^{B} f_{en,b,i}\big(X,Y,\gamma,s_b,f_{b,i},t_{b,i}\big) \tag{1}$$

Hereby, the machine is assumed as a system of rigid bodies. Under consideration of the equation of motion, the axis speeds, the axis accelerations and the process forces acting on the axis as external forces were identified as the variables primarily influencing the power requirements of the axis drives. In this way, the state of wear of the tool can also be taken into account, since it results in an increase in friction and thus in process force. These variables serve as input parameters for a machine learning model. For each data tuple of the input data, a power value is predicted. Hence, at least one power value is calculated per NC-code block and axis. Moreover, the process time for each predicted power value is modelled in order to get the total axis-specific energy consumption.

To calculate the velocity and acceleration components $v_{b,i}$ and $a_{b,i}$, a model of the machine behavior is needed. For this purpose, it is assumed that the jerk rate represents an axis-specific constant. This constant is determined by evaluating data sets, ensuring that machine-specific technological constraints are taken into account. Through integration, acceleration and velocity curves can be calculated, which in discretized form serve as input for the machine learning model. The appearance of statistical errors in the determination of the axis-specific acceleration and velocity must be accepted when using the described model. Due to the large number of data points generated during the execution of an entire NC-code, a balancing effect of the errors should occur, so that the local deviations are relativized in the overall prediction. Therefore, the NC-code length might have an important influence on the prediction quality.

The process forces $F_{process,b,i}$ occurring during milling are determined by a process force simulation. Chattering influences the energy demand of the machine. Therefore, the machine is considered as a system that can vibrate. In contrast to acceleration and velocity, the process force for training the model cannot be determined from datasets without additional force sensors. Thus, a two-stage training approach will be used for each axis $i$. For the determination of the parameters $\alpha_{1,i}$, $\beta_{1,i}$ and $c_{1,i}$ of the motion power $p_{motion,b,i}$ (eq. 2) a sub dataset without process forces will be used. These parameters remain constant in the following. In a second step, datasets occurring force components are used to determine $\alpha_{2,i}$ and $c_{2,i}$ so that subsequently the power $p_{en,b,i}$ can be determined for a given block (eq. 3). Since the consumed electrical energy is represented by the integral of the power over time, it is multiplied by the estimated block duration $t_{b,i}$, which gives the block- and axis-specific part of the fitness $f_{en,b,i}$ as shown in equation 4. In order to achieve the best possible results, it is important to provide training datasets with great variation of the spindle speed and the axis-specific feed.

$$p_{motion,b,i} = \alpha_{1,i} * v_{b,i} + \beta_{1,i} * a_{b,i} + c_{1,i} \tag{2}$$

$$p_{en,b,i} = p_{motion,b,i} + \alpha_{2,i} * \int F_{process,b,i}\, dv_{b,i} + c_{2,i} \tag{3}$$

$$f_{en,b,i}(X, Y, \gamma, s_b, f_{b,i}, t_{b,i}) = p_{en,b,i} \cdot t_{b,i} \tag{4}$$

To get a first impression of the correlation between axis-specific velocity, acceleration and power, existing data sets were analyzed. The recordings were made on the three-axis milling machine CMX 600V from DMG Mori using the reference runs described in [39] and a sampling rate of 500 Hz. The block change was performed at 80% of the braking ramp. No process forces occur in these reference runs. The evaluations show a recognizable correlation between axis speed and axis-specific power despite the partly poor resolution of the measured values (Fig. 1). For the correlation between speed and power, only data tuples were considered which show a very small acceleration. This ensures that the measured power of the data tuple is strongly dependent on the velocity component. The *z*-axis differs from the *x*- and *y*-axis by its vertical orientation, so that the weight force has a characteristic influence.

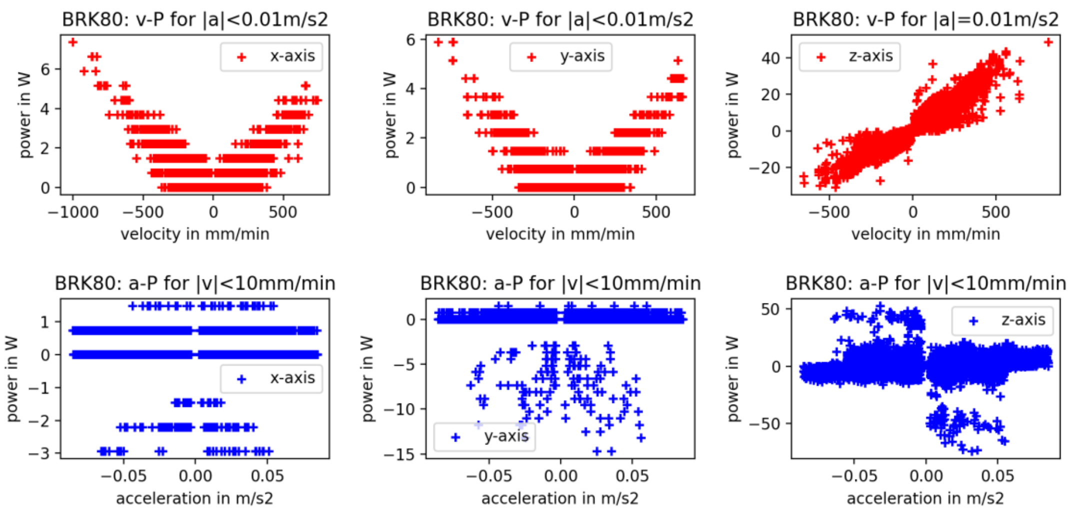


Fig. 1. Relation between axis-specific speed/acceleration and power of an example data set

For the correlation of acceleration and power, a simultaneous approach was taken. Therefore, only data tuples with a velocity close to zero appear in the plot. A weak correlation can be recognised for non-zero values. One reason for this may be the poor resolution of the measured values for the power signal, which can be clearly seen in the graphs. Another relevant reason may be that due to the described selection of the data tuples, relatively few and specific data points appear in the plots. For example, data tuples in which acceleration and velocity components overlap are not considered at all. Therefore, only data tuples with comparatively small accelerations up to 0.1 m/s² were selected. Data tuples with larger accelerations, which could potentially show a stronger correlation to the power value, were filtered through the velocity condition. As shown in the overall diagram (Fig. 4), the parameters of the energy prediction model are continuously updated during the operation of the machine, so that the model database is constantly growing. Hence, it can be assumed that the correlations will be much better identifiable than in the plots shown as examples.

Based on a reliable model for predicting the axis-specific energy demand, simulations for an energy-optimised workpiece position and orientation can be made. Since [6] found that the workpiece orientation can increase energy consumption by up to 29%, an optimization can be expected to result in a significant reduction. With an iterative procedure, different clamping positions and orientations of the raw part can be simulated. By considering the vibration behaviour of the machine, it can be assumed that an optimization also leads to the minimisation of chattering. In the best case, the simulation can thus improve the workpiece quality in addition to minimising the energy requirement.

## 5. DIRECT MAPPING OF THE POSITION-DEPENDENT AXIS STATE

As illustrated in Section 2.2, there are many different approaches to determining the condition of a ball screw. Since the aim of the presented approach is to improve component lifetime through the orientation of the workpiece, pitting on the spindle is the relevant damage pattern which can be influenced. Pitting can cause a loss of preload, representing one indicator for the remaining lifetime [26]. Therefore, the aim of the presented approach is to shift the component utilization to areas without damage by a specific shift of the local movements and thus to extend the useful component lifetime. For this reason, it is highly relevant that the local damage of the ball screw can be determined directly and precisely. Due to the precise measurement of the size and position of pitting, an optical system should be used as presented in [31]. Here, a camera system is attached to the ball screw nut. Fig. 2 shows on the right an example of spindle damage. It should be mentioned that damage can vary extensively depending on the prior usage. Furthermore, difficult conditions such as particles due to abrasion or lubricants (cf. Fig. 2 left) must be expected during machine tool operation.

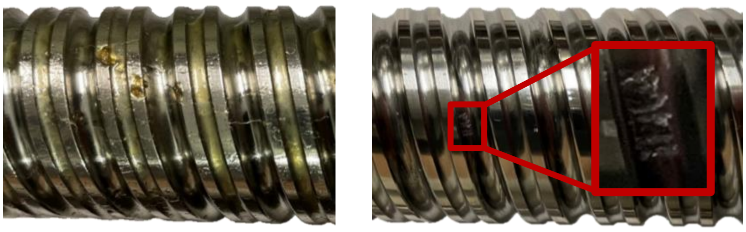

Fig. 2. Ball screw contaminated by lubricant grease (left) and local damage on a ball screw (right)

Based on features such as the size of the damage, the remaining lifetime of the ball screw can be estimated [32] and thus its condition appropriately quantified. If the information of the local ball screw condition is fused with the position of the recording, countermeasures for the wear progress can be initiated. However, it should be noted that the position at which the damage is detected must be shifted by the length $l_{sensor}$ (cf. Fig. 3) left).

Based on this, a damage function of length $l_{screw\ nut}$ can be applied. Accordingly, for damage $d$ there is a damage function $\varepsilon_d$ of length $l_{screw\ nut}$ shifted by $l_{sensor}$ with a height corresponding to the intensity. It should also be noted that the tool path is programmed in NC-code, so an additional tool length-dependent $Z$-axis offset must be taken into account. According to [33], particles resulting from damage on the spindle increase the probability of further damage. According to this, it can be assumed that damages occur more frequently in areas where damage is already present on a spindle. Hence, two damage functions $\varepsilon_1$ and $\varepsilon_2$ must be combined to a function $\varepsilon_{1,2} = \varepsilon_1 \cap \varepsilon_2$ as shown in Fig. 3 on the right. The cost function $f_{cond,b,i}$ of an axis results from the fusion of all damage functions of the damages on the axis. Based on this cost function, the evaluation of a point given by the coordinates $x_b$, $y_b$ and $z_b$ can now be carried out with respect to all machine axis. The evaluation of a manufacturing process given by configuration $X$, $Y$ and $\gamma$ is done by the cumulation of all $B$ kinematically relevant blocks of the transformed NC-code. Thus, the evaluation of a given configuration within the optimization loop can be formulated by

$$f_{cond}(X,Y,\gamma) = \sum_{i=1}^{I}\sum_{b=1}^{B} f_{cond,b,i}(X,Y,\gamma)\,. \tag{5}$$

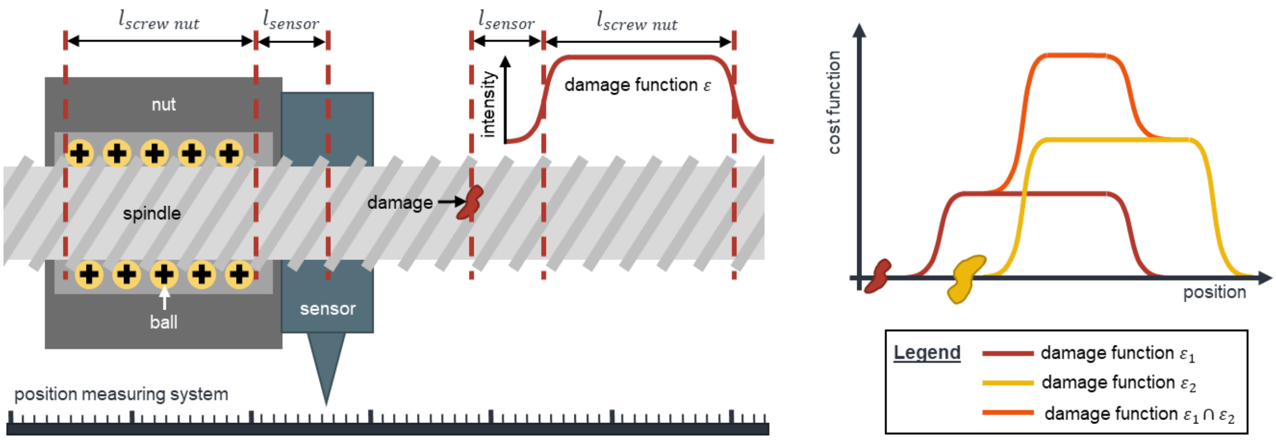


Fig. 3. Optical measuring system attached to the nut of the ball screw drive with the corresponding dimensions (left) as well as the individual and combined damage functions (right)

## 6. WORKPIECE POSITION OPTIMIZATION

The goal of the presented approach is to enable resource-optimized production by positioning the raw part based on the axis-specific energy consumption and the position-dependent condition of the feed axes. The positioning is to be carried out on a clamping system with a rotary disk, which is positioned on the table of the machine tool. This results in the optimization variables $X$ and $Y$ for the translational positioning and $\gamma$ for the rotation on the rotary disk. It should be noted that the domain of $X$ and $Y$ represents continuous values for machine tables with notches and discrete values when mounted by screws. The rotation $\gamma$, on the other hand, can be specified continuously by $[0°; 360°)$. As explained in the previous sections, the energy component of the cost function is given by $f_{en}(X,Y,\gamma,\overline{\boldsymbol{S}},\overline{\boldsymbol{F}})$ and the condition component by $f_{cond}(X,Y,\gamma)$. By the factors $1/n_{en}$ and $1/n_{cond}$ a normalization of the terms is made, so that the optimization goal can be manipulated by $\epsilon$. Thus, by $\epsilon$=1 the focus can be put on an energetic optimization and by $\epsilon$=0 on a wear optimization. Additionally, a penalty term $p(X,Y,\gamma)$ is needed. Through this, configurations, which lead to movements at the edges of the definition range are to be strongly overweighted. The fitness function of the optimization problem is given by

$$f_{ges}(X,Y,\gamma,\overline{\boldsymbol{S}},\overline{\boldsymbol{F}}) = \epsilon \cdot \frac{1}{n_{en}} \cdot f_{en}(X,Y,\gamma,\overline{\boldsymbol{S}},\overline{\boldsymbol{F}}) + (1-\epsilon) \cdot \frac{1}{n_{cond}} \cdot f_{cond}(X,Y,\gamma) + p(X,Y,\gamma). \tag{6}$$

Since the required energy represents the integral of the electrical power over time, the minimization of the production time is an indirect optimization goal. Formula 6 represents the optimization goal. In [36], particle swarm algorithms are successfully used for optimizing the position with regard to processing time. Thus, these and evolutionary algorithms should be examined in the present approach. The results of the optimization loop is a configuration $X,Y$ and $\gamma$ for the positioning of the raw part and the transformed NC-code using $\overline{\boldsymbol{S}}$ and $\overline{\boldsymbol{F}}$.

## 7. PRACTICAL IMPLEMENTATION

The paratactic implementation of the presented cyber-physical approach is shown in Fig. 4. Input is the NC-Code as well as information about the raw part. The NC-code is fed into the digital optimization loop using an initial configuration $X$, $Y$ and $\gamma$. The postprocessor evaluates all blocks and determines the required parameter for all kinematically relevant blocks. The positions given by $\overline{\boldsymbol{x}},\overline{\boldsymbol{y}}$ and $\overline{\boldsymbol{z}}$ are passed to the condition module, which determines $f_{cond}$. To determine the energy consumption, the values $\overline{\boldsymbol{x}},\overline{\boldsymbol{y}}$ and $\overline{\boldsymbol{z}}$ as well as $\overline{\boldsymbol{s}}$ and $\overline{\boldsymbol{f}}$ are inserted in the process force simulation together with the raw part and process information. The process force, together with the kinematic information $\dot{\overline{\boldsymbol{x}}},\dot{\overline{\boldsymbol{y}}}$, $\dot{\overline{\boldsymbol{z}}}$ and $\overline{\boldsymbol{t}}$ as well as $\ddot{\overline{\boldsymbol{x}}},\ddot{\overline{\boldsymbol{y}}}$ and $\ddot{\overline{\boldsymbol{z}}}$, represent the input of the energy prediction module, which determines $f_{en}$. The fitness module calculates the overall fitness $f_{ges}$ using $f_{cond}$ and $f_{en}$. If $f_{ges}$ meets the termination criterion, the optimization loop is exited. If this is not the case, the configuration is varied, the NC-code is transformed and the loop repeats itself. If the termination criterion is met, the optimized NC-code and the parameters $X$, $Y$ and $\gamma$ for the positioning of the workpiece are output. Based on this, positioning and production of the part is performed on the real machine.

During production, data representing the current axis-specific energy consumption and the axis condition are recorded. This data forms the basis for the update of the energy consumption model and the condition model. The model update loop now closes the circle between the digital model and the real production, which fulfils the criteria of a digital twin.

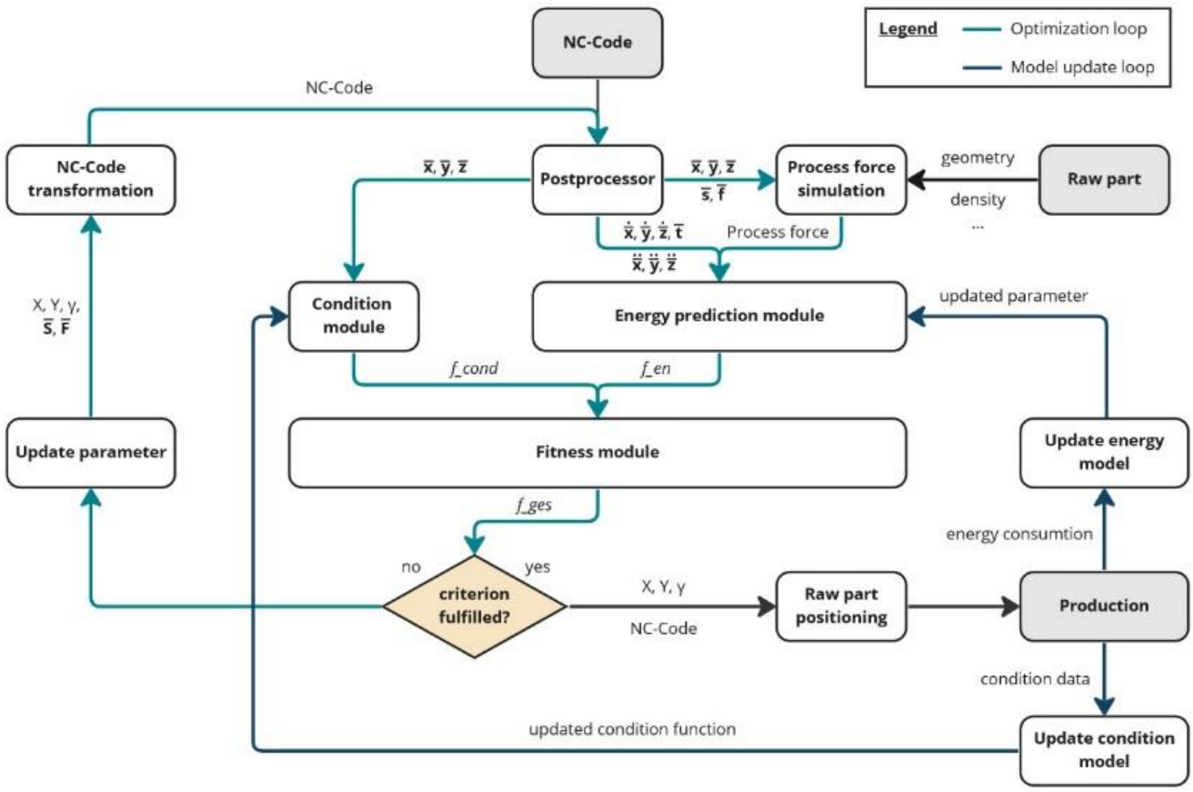


Fig. 4. Diagram for practical implementation of the presented approach and information flow. The inner optimization loop is surrounded by an outer model update loop

## 8. SUMMARY AND CONCLUSION

This paper introduces an approach for resource-optimized production by optimizing the workpiece position as well as the NC code. For this purpose, the individual characteristics of the machine are at the center of the considerations. Due to the high relevance, the optimization shall be done with respect to the axis-specific energy consumption as well as the condition of the translational drive components. For the mapping of energy consumption, an approach for the prediction of consumption based on a given NC-code as well as the raw part geometry was presented. Speed, acceleration and process force were chosen as input variables of an ML-model. This model is to be trained continuously during operation in order to represent the current state at all times with the highest quality possible. The mapping of the position-dependent feed axis state must be done on the ball screw spindle. Here, only an image-based method can guarantee the requirements of precise quantification of the current condition. An approach was presented to convert the local damage into a position-dependent damage function. Both estimation functions $f_{en}(X,Y,\gamma,\overline{\boldsymbol{S}},\overline{\boldsymbol{F}})$ and $f_{cond}(X,Y,\gamma)$ are part of the optimization function $f_{ges}(X,Y,\gamma)$ by which a given configuration can be evaluated with respect to the resource consumption. The implementation of the approach is structured in two loops, the optimization loop and the model update loop. Within the optimization loop the search for the optimal configuration takes place. If this was executed within production, the update of the models takes place.

Future research should focus on the implementation of models for the axis-specific energy consumption and the condition of the axis. In particular, the question of a continuous representation of the machine tool characteristics has to be addressed. It must be determined how and in particular using which optimization algorithms a suitable configuration can be found. Furthermore, the question arises of how a practical implementation on a given machine tool, in particular with the participation of the machine operator, can be realized. When a solution is implemented, it should be investigated how cost and effort for the application of the system can be minimized. This includes the implementation costs. Here, for example, it can be examined whether pitting can also be determined with sufficient accuracy using vibration sensors. Furthermore, it should be investigated how frequent the models have to be updated in order to optimize computing effort. An additional reduction can be achieved by adapting the model resolution.

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