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Speeding Up CNC Tool Manufacturing: Implementing Explainable AI for Setup Time Reduction and Production Agility

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Abstract

Long setup times in CNC tool production significantly hinder operational efficiency, characterized by reduced machine utilization, increased planning efforts, and subsequent delivery delays and production bottlenecks. These inefficiencies not only escalate production costs but also tie up capital, compromise order flexibility, augment storage expenses, and prevent the capitalization on market opportunities. This paper explores the application of explainable AI to analyze process data within CNC setups, aiming to identify and elucidate patterns that contribute to prolonged setup durations. By implementing AI models with explanation methods, this research transparently highlights critical improvement points, facilitating targeted interventions to enhance production agility. The outcome is a dual advantage of reducing setup times and operational costs, thereby speeding up overall manufacturing processes. This approach emphasizes innovative manufacturing systems and provides practical insights on using artificial intelligence to enhance efficiency in CNC tool production.

Keywords: Explainable Artificial Intelligence; CNC Tool Manufacturing; Setup Time Reduction; Manufacturing Efficiency

1. Introduction

German production technology is characterized by SMEs specializing in diverse and varied products, hence dealing with high product variety and low production volumes [1, 2]. This presents challenges to classical Artificial Intelligence AI algorithms, which largely relies on the statistical analysis of extremely large datasets [3]. AI models are often called black box models because they are not easily interpretable. Created by algorithms from data, these models combine variables in complex ways that are difficult for even their designers to understand, making it hard to trace how inputs lead to predictions [4, 5].

Nomenclature

AI	Artificial Intelligence
XAI	Explainable Artificial Intelligence
CNC	Computerized Numerical Control
SME	Small and Medium sized Enterprises
SHAP	SHapley Additive exPlanations

Machine learning models have achieved significant success in areas such as image processing and speech recognition. However, these models are currently limited when applied to small datasets, that is, datasets with a small number of samples and high-dimensional features [6, 7].

The challenges of producing customer-specific products are significant, especially for high-quality items [8]. One of the difficulties in adhering to quality parameters is that numerous factors influence setup time. Factors such as the components'

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characteristics (geometric dimensions, deviations, alloys, etc.) and the parameter settings of the production machines affect setup time. Additionally, the combination of various factors can lead to extended setup times, even if a single factor would be non-critical. The production numbers for specialty products are typically small, while the combinations of factors create a large parameter space. Moreover, the specific configuration of production is complex [9]. Minimizing setup times for maximum machine utilization and avoiding quality defects are crucial levers in reducing production costs for manufacturing sites in Germany [2, 8–10].

The causal relationships of complex production processes are often incompletely mapped and understood. Data-intensive modeling methods from the field of AI, particularly machine learning, offer a promising way to uncover correlations and describe causal relationships [2, 11].

The goal of this work is thus to test AI methods specifically in the context of production technology. Within the framework of an exemplary case study of manufacturing CNC specialty tools through a CNC grinding process, issues in production technology are discussed.

Optimizing the setup times of grinding machines to produce CNC tools, such as high-precision gear skiving tools, is a critical factor for operational efficiency and production capacity [12]. Longer setup times lead to unproductive use of resources, which impacts responsiveness to market demand and may affect financial performance [13]. In response to this challenge, the industry continuously strives to improve setup procedures to swiftly switch between different product variants without compromising product quality [14]. However, the inherent complexity of setup processes often leads to difficulties in streamlining and optimizing operations [15]. In this paper, we present a data-driven decision model that uses explainable artificial intelligence (AI) to improve the setup times of grinding machines.

Our model aims to decipher the complex relationships between various setup parameters to enhance understanding and optimization of these processes. The model predicts setup times for each machine using production and product parameters, offering explainable predictions. By avoiding poor parameter combinations, it helps reduce setup times, boost productivity, and enhance the economic sustainability of the industry partner.

The paper is organized as follows: Section 2 addresses methods of Explainable AI; Section 3 introduces a specific AI-supported model; Section 4 explains its development and practical application; Section 5 discusses the results; Section 6 presents the conclusion and discusses future research approaches for optimizing setup times in grinding machine processes.

2. State of the Art in Explainable AI

In complex operational contexts, nonlinear machine learning models are often used to map multidimensional relationships [16]. However, interpreting decision-making in such models is not always intuitive [17]. To address this issue, methods have been developed to enhance the traceability of conclusions drawn from nonlinear models. These approaches, known collectively as explainable AI, focus particularly on analyzing feature importance and attributing influences on specific features.

To date, the concepts of feature importance and feature attribution have generally been treated independently. The following sections detail both approaches:

i. The assessment of feature importance aims to determine the impact of individual features on the outcomes of a prediction model. One method involves comparing the model's performance with and without the specific feature to evaluate its contribution, considering all possible interactions. Another method measures the impact on prediction accuracy when a feature is randomly modified. Additionally, model-specific techniques exist for determining feature importance, as used in decision trees and support vector machines [18, 19].
ii. Feature attribution evaluates the specific contribution of a feature to a model's prediction. This involves examining how changes to the feature affect the prediction. In linear models, this contribution is represented by the coefficients. In nonlinear models, feature attribution can be done using partial dependence plots or through locally interpretable, model-agnostic explanations to quantify a feature's influence on the prediction [5, 20].

The SHAP value method integrates the concepts of feature importance and attribution to make decision-making in prediction models transparent by breaking down predictions into individual feature contributions, known as SHAP values. It is based on a combination of local model explanations and game-theoretical principles, with SHAP values calculated individually for each observation within a feature vector [21]. This method allows for detailed analysis on both a local and global scale and is applied in this work to decipher complex relationships between production parameters and setup times in the manufacturing system described subsequently.

3. Explainable Model

In this section, we develop an AI-based model to reduce setup times in manufacturing, specifically for setting up grinding machines. We define a formal workshop environment, outline our problem of setup time inefficiency, and provide detailed specifications of our model.

3.1. Production Environment

The production environment includes ten groups of workstations, organized according to the specific product families they manufacture. Our focus is on a group of workstations equipped with grinding machines.

In this production environment, we analyze sequential processes, each characterized by specific parameters that potentially influence setup time. The overall outcome of these processes is assessed based on setup times. The setup process is defined as the totality of all steps required to switch a machine from producing the last good piece of one order to producing the first good piece of the next order (see equation 1) [22]. This includes activities such as exchanging tools and molds, cleaning, adjusting machine settings, and loading and unloading blanks.

$$Total\ setup\ time = \sum (Time\ for\ each\ individual\ task) \quad (1)$$

In the production environment, various production parameters such as maintenance data, production data, sensor data, machine data, machine parameters, tool data, and product data are generated. A data model in the form of an Entity-Relationship Diagram represents the relationships between these types of data, thereby facilitating efficient data management and analysis.

The manufacturing system generates data concerning production parameters x and setup time results y. In total, there are $j=1, \ldots, N$ production parameters and $i=1, \ldots, M$ measurements (setup operations).

3.2. Problem Description

Our objective is to avoid combinations and sequences of production parameters N that led to lengthy setup operations M, which significantly affect system performance, specifically the total setup time. This goal aligns with quality management theory on reducing setup times, which suggests addressing the causes of variation [14, 23–25].

In practice, each setup operation results in durations that vary. For the purposes of this discussion, we assume that shorter setup times are desirable. The dispersion around the mean setup time provides a measure of potential system improvement. If there are fluctuations in setup times, there is an opportunity to learn from faster setup times (beginning of the distribution) and to avoid slower ones (end of the distribution). See Figure 1 with the probability density p before and after implementation, as well as the estimated function value of the setup time E.

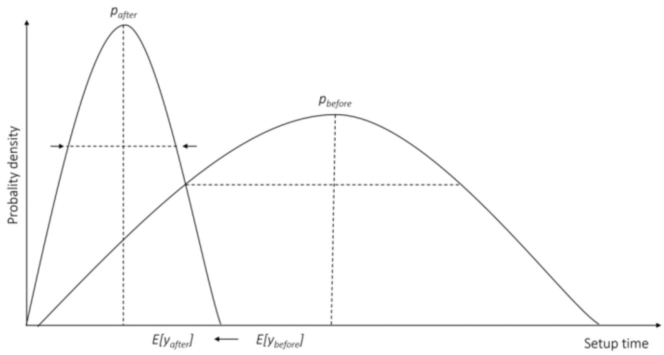


Fig. 1. Example of expected setup time before and after improvement

Therefore, the objective in a production environment is to shift setup times from the right end of the distribution to the left start of the distribution. This can be achieved by avoiding the combinations of production parameters that are responsible for variations in total setup times, thereby implicitly reducing the average duration of setups.

An approach to this can be to first identify the processes that offer the greatest potential for improvement, and then define improvement measures only for these selected processes and parameters. The implementation of improvement measures depends on the specific characteristics of the production parameters. For some production parameters, it is possible to directly adjust the absolute values. For example, if the temperature in a particular process affects process quality, an improvement measure could involve adjusting temperature levels. However, in some processes, it is not feasible to directly alter the production parameters.

3.3. Model Definition

The starting point for the model is historical manufacturing data $(x^i, y^i)_{i=1}^{M}$. Based on these data, a nonlinear model f is learned that replicates the relationships between production parameters $x^{(i)}$ and setup times $y^{(i)}$. The model $f: R^N \rightarrow R$ is based on one estimated from past observations of production parameters and setup times.

This can be any predictive model f capable of replicating high-dimensional and nonlinear relationships (e.g., decision tree methods, neural networks). The model f is estimated with the objective of minimizing the error between the true and estimated setup times,

$$min_{\top f}\, E\,[l\,(y, f\,(x))] \quad (2)$$

where l is a convex loss function (e.g., mean squared error). If f is well-specified, we obtain a model of the processes that explains how various production parameters and setup times are related.

The underlying relationships in the production environment are computed using the SHAP value method [21]. Specifically, we use SHAP values to explain how the estimated setup time changes when the effect of a production parameter is omitted. Here, the SHAP value method locally explains the model f at each observation i. The explanation is formally provided by additive feature attributions that sum up to the output of the model. In our context, a SHAP value indicates the estimated deviation from the expected setup time $E[f(x)]$ that can be attributed to an observed production parameter $x^{(i)}$. Negative SHAP values indicate a reduction, positive values an increase in the estimated setup time. The larger the absolute SHAP value, the greater the estimated change in setup time. Calculation of SHAP values is repeated for all observations, thus providing feature attributions.

The SHAP value method guarantees three properties:

i. misattribution,
ii. consistency,

iii. local accuracy.

In our context, misattribution ensures that absent production parameters receive no feature attribution. Consistency is required to allow meaningful comparisons of feature attributions across production parameters. Local accuracy ensures that the feature attributions sum up to the model output, thus providing an estimation of the changes in setup time.

4. Application in CNC Tool Manufacturing

The manufacturing of CNC tools typically involves multiple interconnected processes that can take minutes to hours to complete. Due to the high complexity resulting from the tolerances required for the tools being manufactured, identifying the driving factors of setup time is challenging.

Consequently, contract manufacturers or tool manufacturers often face significant bottlenecks in production. These bottlenecks can arise from occupied machines, as well as from skilled labor shortages, with skilled workers tied up in lengthy setup processes. Against this backdrop, improving setup time promises to have a significant economic impact.

Our application partner is a German SME that leads in the production of special and standard tools. The goal of our collaboration is to transparently demonstrate the connections and patterns of disadvantageously long setup times and to propose a better course of action, such as choosing a different, more suitable machine for the specific product to be produced.

4.1. Historical Data

Our application partner has provided us with historical data from $M = 12{,}300$ setup operations. Each setup operation is described by $N = 144$ production parameters from $K = 8$ different machines. The company protected confidential information by scaling the setup time between 0 and 100:

$$y^{(i)} = 100 \times \frac{y^{(i)} - y_{min}}{y_{max} - y_{min}} \tag{3}$$

This normalization preserves the distribution pattern, thereby still allowing for the indication of the actual improvements achieved.

4.2. Descriptive Statistics

The distribution of the normalized setup time of our training data is shown in Figure 2.

The average normalized setup time is 28.01, with a standard deviation of 22.95. Approximately 50% of the setup processes have a normalized setup time of over 21.87 (median). According to our industrial partner, setup times with a normalized setup time of more than 22.00 are considered in need of improvement, as they do not meet the predetermined target time highlighted in a red dashed rectangle in the following figure.

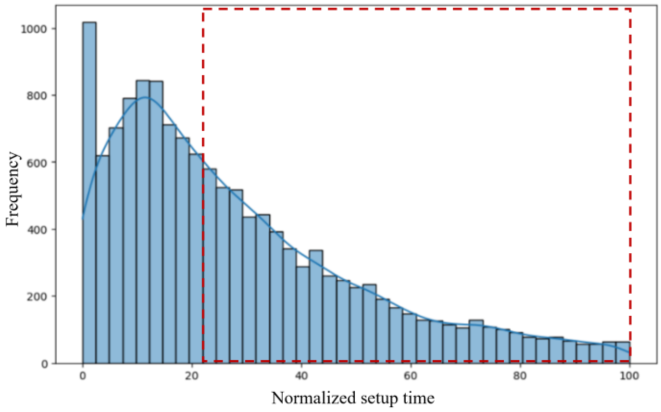


Fig. 2. Histogram of normalized setup time

For confidentiality reasons, we will later refer only to the anonymized production parameters $x^{(i)}$. Generally, production parameters are distinguished between process-level, machine level and product-level parameters. Process parameters specify for example the types of grinding arbors used, machine parameters specify machine-related characteristics, such as the average pressure measured in a machine, while product parameters relate to the physical properties of products during manufacturing.

Table 1. Example production parameters

Description	Production parameter x	Unit	Level
Grinding Arbor	x^{101}	-	Process
Blank Thickness	x^{202}	Millimeter	Product
…	…	…	…
Number of Machine Disturbances	x^{203}	-	Product
Similarity Coefficient	x^{301}	-	Machine

4.3. Model Implementation

The model is estimated based on all production parameters and the normalized setup time using XGBoost [26]. XGBoost is part of the category of Boosting Tree Ensemble algorithms, known for their strong performance on complex datasets and already utilized in other operational applications [16, 27]. We employ standard procedures and divide our data into a training set (80% of the data) for parameter estimation and a holdout set (remaining 20%) to assess modeling performance. The training set includes 9,840 setup processes, and the holdout set contains 2,460 setup processes. The allocation was made randomly to ensure robustness.

The model is trained and tuned solely based on the training set (grid search with cross-validation for hyperparameter optimization). We calculate the feature attributions of all production parameters using the tree implementation of the SHAP value method (for details, see [21]).

5. Results

We determine the predicted treatment effect through statistical analyses of historical setup processes in the holdout set. To avoid overfitting, the predicted treatment effect for the selected improvement measures must be based on observations that were not included in the estimation of the model itself. For this purpose, the 375 setup processes in the holdout set are considered. The box plot shows the normalized setup times from observations in the holdout set that would be configured using the predicted combinations of the model, compared with data that had no model. The length of the whiskers is determined by the 1.5 interquartile range, and the 50th percentile is highlighted as a line.

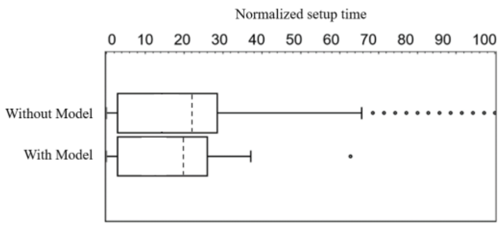


Fig. 3. Predicted effect of the model

The box plot indicates that the model can reduce normalized setup times. Two key observations are apparent. First, outliers, which lead to extended setup times, are reduced. Second, this consequently lowers the average value of setup times. Setup times with the model are on average 6% lower (new average normalized setup time of 26).

The extrapolated treatment effect results from the average difference in normalized setup time, which amounts to 6 normalized minutes.

With 375 setup operations per week, this translates to 2,250 $(375\times 6=2,250)$ normalized minutes, allowing for 160 ($2,250/26=87$) more setup operations per week in the same time, with the same machines, the same count of operators, etc.

This enables more flexible production planning. Initial estimates suggest over 4,524 $(87\times 52=4,524)$ additional setup operations per year, just within the one workstation group examined.

The production partner has a total of 12 workstation groups. If the results continue across all groups or even improve through transfer learning, the immense scope of the savings potential becomes apparent. But an analysis of historical observations alone is insufficient to demonstrate that the model will be effective in the future. Therefore, a longer field experiment is being conducted with the industrial partner.

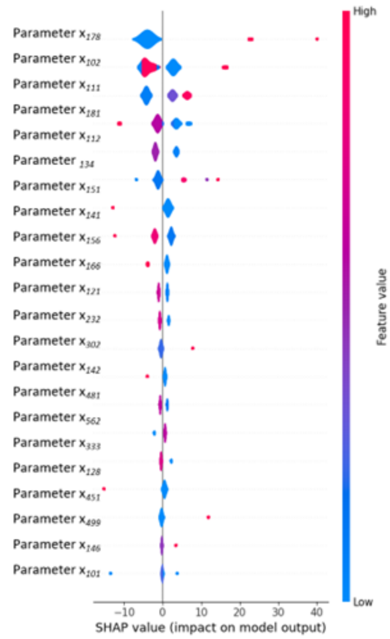
5.1. Overall Explanation with the AI Approach

In the previous section, it was assumed that the model f had been followed in the application of parameter combinations. However, research indicates that employees may be skeptical about an AI model. Therefore, we aim to ensure that the impact of parameters on setup time is understood and how their values can positively or negatively influence it.

This understanding can generally foster a new company-wide process insight that can be utilized for optimizations. Figure 4 illustrates the distribution of values for each parameter, their impact on setup time, and whether higher or lower values produce positive or negative effects. Such pattern relationships can be supportive in training, education, shop floor meetings, or even in addressing quality issues.

For example, we look at the production parameter x^{178}. Let's assume it describes the applied layer thickness on a blank. We observe that a lower value has a positive impact on setup time. Simultaneously, we note that the value distribution is typically low. When the value is high, it increases its influence on the model and correspondingly increases the setup time.

Fig. 4. Overall significance of parameters and distribution of SHAP values



5.2. Setup Times Based on Production Combinations

It is planned that the worker will be shown the prediction for the setup time for the next type of production for all available machines. The displayed prediction for one machine is illustrated in Figure 5. For instance, the worker is presented with predictions for four available machines. They can then choose freely which machine to set up. The displayed forecast time and parameters provide crucial information on why one machine might be more suitable than another. For example, parameter x^{166} might be the die already installed in the machine. If the next product can be made with the same die, the worker can save 11 normalized minutes on setup. On other machines, for instance, the worker might need to change the die. The decision model predicts a normalized setup time of 39.87

normalized minutes. The visualization clearly shows which parameters positively and negatively impact the setup time. For instance, the average setup time from the data distribution is 58 normalized minutes, the baseline. The parameter x^{166} reduces the setup time by 11 normalized minutes, while other parameters like x^{178} increase the setup time.

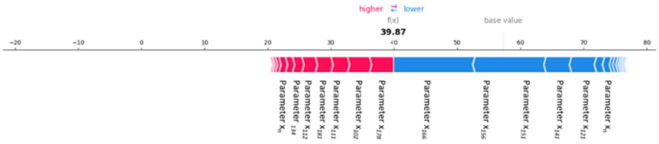


Fig. 5. Example of a setup time prediction for a machine

6. Conclusion

The article presents a decision model based on data analysis to reduce setup times in production. The model excels in processing complex and nonlinear production data and offers transparency regarding the significance of various parameters. This enables manufacturers to prioritize process optimizations, which can lead to improvements in setup times, which in turn enhances production performance and reduces costs.

The AI model enables a reduction in setup times by approximately 6%, resulting in increased productivity and lower operational costs. This reduction alone is expected to allow for an additional 4,524 setup operations annually due to the time thus made available. This improves production planning and control, allowing for greater flexibility and adaptation to customer needs. If the additional time can be utilized to produce products, we anticipate an increase in turnover, with fixed costs remaining constant, potentially reaching the six-figure range for just one group of workstations. The positive results highlight the potential of explainable AI in CNC tool manufacturing for optimizing setup times. Future research should focus on enhancing the accuracy of AI forecasts, advancing integration into planning systems, and developing user-friendly interfaces to make AI decisions more understandable.

The model has limitations, as it relies on correlations that can lead to misinterpretations without clear causality. Additionally, the methods of explanation are vulnerable to retrospective challenges, underscoring the importance of involving experts in the development process to address such vulnerabilities. The presented decision model facilitates efficient integration into production planning and provides new insights from existing data. It is generically designed, requiring only production parameters and reduces setup times through optimized production combinations. The effectiveness of this approach is validated by the combination of nonlinear modeling and SHAP values from the realm of explainable AI. The design of the model promises broad applicability in data-rich manufacturing environments and opens new possibilities for the use of explainable AI in production planning and control.

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