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Energy prediction for CNC machining with machine learning

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ABSTRACT

Nowadays, the reduction of CO_2 emissions by moving from fossil to renewable energy sources is on the policy of many governments. At the same time, these governments are forcing the reduction of energy consumption. Since large industries have been in the focus for the last decade, today also small and medium enterprises with production lot size one are increasingly being obliged to reduce their energy requirements in production. Energy-efficient CNC machine tools contribute to this goal. In machining processes, the machining strategy also has a significant influence on energy demand. For manufacturing of lot size one, the prediction of the energy demand of a machining strategy, before a part is manufactured plays a decisive role. In numerous previous studies, analytical models between the energy demand and the machining strategy have been developed. However, their accuracy depends largely on the parameterization of these models by dedicated experiments. In this paper, different machine learning algorithms, especially variations of the decision tree ('DecisionTree', 'RandomForest', boosted 'RandomForest') are investigated for their ability to predict the energy demand of CNC machining operations based on real production data, without the need for dedicated experiments. As shown in this paper, the most accurate energy demand predictions can be achieved with the 'RandomForest' algorithm.

Introduction

Many government's environmental policies of the last decades focus on decarbonizing of their energy power plants and the reduction of energy consumption [31,37]. With a primary energy consumption of more than 30%, industrial manufacturing is one of the main sources of pollution [23]. As a consequence, attention for energy-efficiency must be paid and is divided in two scopes: Environmental friendly product design and energy-efficient production. Hence, a comprehensive energy aware product design and a low energy production strategy fosters governments environmental policies [1,7]. Therefore, linking product geometry features and energy consumption of production is inevitable for this objective. With focus on CNC machine tools this can be achieved by linking the NC code, which determines the geometry of the part, with the energy consumption of the CNC machine tool.

The aim of this paper is contributing to a highly accurate NC code based energy consumption and power curve prediction for CNC machine tool aggregates with variable power demand (x, y and z axis, spindle and tool change system) at CNC machine tool level. First, this contribution will help to derive low energy machining strategies with respect to geometry features to create awareness for design engineers. Second, this helps determining the energy consumption of a part before manufacturing and therefore allowing to optimize in design phase for energy demand. Third, power demand prediction can help for peak power balancing to reduce the overall power spikes at factory level as a contribution to an increased electric grid stability [24].

State of the art

In order to develop a prediction model for the energy consumption during CNC machining, both are inevitable: the knowledge about characterization of the single elements responsible for the energy consumption during machining as well as a broader understanding of the already taken efforts in building predictive models for the energy consumption. Those two domains are elaborated below:

Characterization of energy consumption in machining

In the past, research in machining was focused on developing models to predict fundamental variables as stresses, strains, strain-rates, temperatures, etc. [3]. Recently efforts were made to understand the fundamental influences on the energy consumption of a CNC machine tool.

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As one of the first, [13] investigated the energy demand for different manufacturing processes (injection molding, machining, grinding, cutting, etc.) and characterized the energy needed for machining with $E = (P_0 + k_c Q)t$. Where for a process duration of t, P_0 is a constant power consumption required to support the process, k_c the specific cutting force and Q the material removal rate.

[36] presented a way to calibrate a force estimation model using the motor spindle power in flat and ball end milling processes. The energy consumption was expressed in terms of material removed and contact area $E = K_{TC}Q + K_{TE}A$, with the tool/material cutting energy K_{TC} and the tool/material edge force K_{TE}.

[8] searched for possible improvement measures to reduce the constant part of the energy consumption of discrete part production CNC machine tools. Also the effects of stand-by phases in a lean production setting was found out to effect the energy consumption.

[10] proposed a generic model to forecast the energy consumption of manufacturing equipment by separation in statistical discrete events. The total energy consumption was calculated with $E = \sum_c \sum_i (\Delta t P_{c,i})$, whereas, $P_{c,i}$ being the power consumption of a component c in state S_i. Later [11] further developed this methodology for the usage in multi-machine manufacturing systems and expanded the model for different energy carriers (electricity, pressured air and coolant).

[34] monitored the energy consumption of CNC machine tools in order to assign every operation performed by the CNC machine tool to the correlating energy consumption. In a case study a rule based framework was developed to simulate the end milling of aluminium with the operational states: startup, shutdown, idle, and machining process.

[27] modelled the energy consumption of a turning process in order to optimize the machining process in regards to tool life and energy consumption. The proposed model decomposes the total energy consumption into the idle energy, the cutting energy as proposed by [13], as well as the energy consumed by the tool change system and the energy needed to produce the cutting tool.

[17] discovered through experiments with a CNC lathe that the additional energy losses in machining, which in previous energy models were summarized in a constant energy loss, are on the contrary dependable on spindle speed and cutting torque. In the suggested model, energy losses from the electrical machine (windings and core) as well as the mechanical setup (friction, transmission) were added.

[12] formulated a multi-objective energy and product quality model using multi-gene genetic programming. The chosen approach includes both, statistical and classification strategies. The model was validated through analyzes of the turning process of steel and aluminium alloy. In the formulated model the cutting speed was most influential on the energy consumption.

[22] studied the relationship between the parameters depth of cut, spindle speed, feed rate, and nose radius of a dry milling operation and modeled their highly nonlinear impact on the specific cutting energy. The parameters with the most effect on the specific cutting energy were found out to be (in descending order): depth of cut, feed rate, spindle speed and nose radius.

Prediction of energy in machining

After characterizing the energy consumption of CNC machine tools, the question arose, if those gained insights could be used to create models to forecast the energy consumption during machining of a part. As one of the first, [9] noticed the absence of a suitable forecasting technique for the energy consumption of CNC machine tools and proposed a model formalism to predict and optimize the energy-efficiency: the process was divided into operations, for each of which a static energy consumption was determined by measurements. In a case study simulating a milling process, this approach was able to achieve an overall accuracy within 5%. Only a simple machining operation with a constant cutting depth was performed. Basic assumptions made in order to refine this simulation to achieve given accuracy stay unclear.

[4] developed a model to estimate the energy demand of the spindle and feed aggregates of a CNC machine tool based on the constant and variable power flows occurring in different operations. In a case study aluminium milling with differing parameters was modelled. An error of 3.8–18.1% was achieved thereby. Only simple operations e.g. pocketing or contour milling were tested. Also does this model require advanced measurements in beforehand (masses of axis, idle power).

[20] developed an empirical model to characterize the relationship between energy consumption and process variables for different machining processes. In validation tests of the

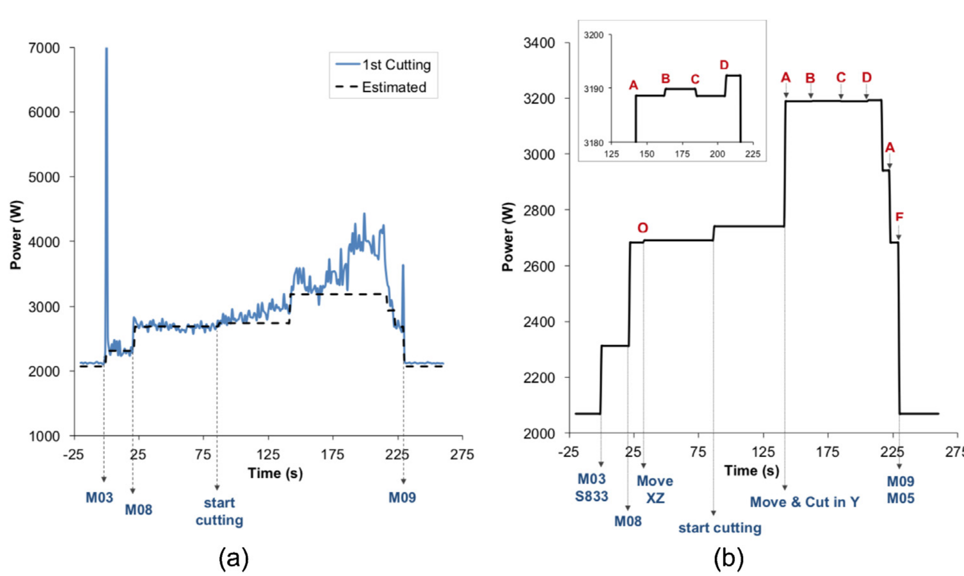

Fig. 1. Comparison of measurements (a) and predictions (b) of an existing energy model by [2].

prediction model with eight different CNC machine tools an error of 2.37–8.05% was measured. This was possible by keeping the parameters like feed rate, depth of cut and thus, material removal rate constant and neglecting auxiliary processes like the start-up.

[26] trained an artificial neural network (ANN) model with the data from 250 high-speed ball end milling operations but did not provide evaluation measures for the predictions. Every sample consisted of seven inputs (spindle speed, feed rate, feed per tooth, axial depth of cut, radial depth of cut, tool radius, usage of coolant) and five power consumption outputs of the aggregates.

[14] analyzed the correlation between NC codes and energy consumption of single machine components. In the proposed analytical method the energy needed for every component was calculated based on the NC instruction and summed up to obtain the energy needed to execute given NC instruction. Considered components were the spindle, the feed axes, coolant pump and the tool change system as well as a constant energy consumption. One milled and one turned part were produced to evaluate the calculations. Despite the complex model and simple machining operations, an error of 9.3% occurred. This model also requires process parameters, e.g., depth of cut, that were not included in the NC instruction.

[16] proposed an energy-efficiency monitoring model that was not dependent on torque or force, but on the energy consumption of the CNC machine tool. In the several tests that were performed on one of the CNC milling machines, the cutting power was predicted with an accuracy of 1.57–3.11%; by keeping the parameters (such as, spindle seed, feed rate and cutting depth) constant for each test.

[2] included auxiliary operations as start-up and non-cutting movements into the proposed NC code based energy model. On a simple test piece (machining one pocket) the difference between prediction and test piece was 5.23%. In Fig. 1 the plots of the measurement and the prediction are compared: The power peak was neglected by the prediction and the prediction does not fit the actual measurements but generalizes on a large scale (see Table 1).

[6] proposed an energy prediction model created with the help of an ANN. The network with two hidden layers was able to predict the energy consumption in a not further specified test with an error of 2.46%.

[18] developed a multi-objective predictive mathematical energy model for a turning process based on different methods of data analysis (response surface methodology, grey relational analysis and principal component analysis) to optimize machining parameters.

[25] proposed an energy model based on the force estimation with finite element modeling simulation. The conducted experiments involving dry turning of a titanium alloy could be predicted with an error in the range of 1–8%. The evaluation tests were conducted by machining a fixed length (60mm) with constant cutting speeds.

[19] created an model by training an ANN to predict the cutting energy while machining carbon steel. The training data was obtained from 27 machining operations, with different input parameters (spindle speed, feed rate, depth and width of cut). The difference between measured and predicted cutting energy was 1.50%.

[21] developed an analytical predictive model by decoupling the energy of the components of the CNC machine tool from the cutting energy. On validation tests on two different CNC machine tools the model differed from the measurements within an error of 0.36-0.55%. For the model extensive measurements of every decoupled state were necessary, what limits the usage to predefined operations.

[29] decomposed the NC code into single instructions and proposed a model to predict the energy consumption to further use those results for online optimization. A polynomial regression model (PRM) and an ANN were tested with different pocketing, slotting and drilling operations, where an error of 0.02–1.08% occurred. Only material removing NC instructions were taken into account and the depth of cut was fixed.

[5] generalizes an energy prediction model over multiple process parameters and processes in order to optimize tool paths. The model based on Gaussian process regression (GPR) predicted the energy consumption within an error of 3.288–5.744%. Only certain operations were studied (face milling, pocketing, plunge, air cut and rapid motion) and the depth of cut was fixed. It was noted, that the accuracy of the predictions fell if the machining parameters of the test part were too different from the training data.

[30] developed a Therblig-based energy model to calculate the energy demand while machining. In a case study the model was 2.23-10.22% off the actual measurements. Besides the simple test piece (face milling, slotting and drilling), extensive manual work had to be done to assign the corresponding Therbligs to each of the 215 NC instructions.

[15] compared the ability of different algorithms to train energy prediction models from milling and grinding operations. It was shown that deep learning algorithms exceed in prediction accuracy compared to the Gaussian process regression (GPR).

Table 1
Comparison of the different forecasting models.

Reference	Method	Machining Op.	Aggregates					Accuracy
			Axes	Spindle	Tool change	Coolant pump	Auxiliaries	
[9]	Rule based	Milling	•	•		•	•	~5%
[4]	Rule based	Milling	•	•	•		•	3.8–18.1%
[20]	Rule based	Milling &turning	•	•		•	•	2.37–8.05%
[26]	Artificial Neural Network	Milling	•	•				N/A
[14]	Rule based	Milling &turning	•	•	•	•		9.3%
[16]	Rule based	Milling	•	•		•	•	1.57–3.11%
[2]	Rule based	Milling	•	•	•	•	•	5.23%
[6]	Artificial Neural Network	Milling	•	•			•	2.46%
[18]	Rule based	Milling	•	•				4.79%
[25]	Finite Element Method	Turning	•	•			•	1–8%
[19]	Artificial Neural Network	Milling	•	•			•	1.50%
[21]	Rule based	Milling	•	•		•	•	0.36–0.55%
[29]	ANN &Polynomial regression	Milling	•	•		•	•	0.02–1.08%
[5]	Gaussian process regression	Milling	•	•		•	•	3.288–5.744%
[30]	Rule based	Milling	•	•	•	•	•	2.23–10.22%
[15]	Deep Learning	Milling &grinding	•	•	•	•	•	N/A

The shown literature study in the field of energy prediction of CNC machine tools do not fully cover the topic with respect to the motivation of this paper. The missing links are elaborated in the following chapter and an approach is developed.

Research gap

Derived from the previous mentioned state of the art, the research gap can be summarized as follow:

Previous research papers investigated the energy consumption of a CNC machine tool in comparison to simulated data like depth of cut and production strategy. Furthermore, a reference part to parameterize energy consumption models had to be produced. Towards data acquisition, low-frequency data with a sampling interval of 200ms or more were collected via the standard OPC-UA interface. In the evaluation state outliers in the gathered data were excluded due to the negligible influence of single power spikes on the overall energy consumption. [33] evaluated that besides significant effort made to understand the complex interactions causing energy consumption in machining, the validity of analytical energy models remain highly questionable.

Mitigating these disparities, our approach uses only direct accessible data from CNC machine tool and neither simulation data nor rule-based energy models are included, which is the origin of this paper. Furthermore, no special reference part for energy consumption model parameterization is needed. Gathering high-frequency data with sampling interval of 2ms is done via a innovative SIEMENS Edge Device. Outliers in the collected data set are included. Our approach is to investigate three different machine learning models, namely 'DecisionTree', 'RandomForest' and boosted 'RandomForest', for high precision energy prediction of CNC machining strategies.

Approach of study

As previously shown, numerous parameters on the energy consumption of a machining process exist. In this study the parameters are limited to one CNC machine tool, one material and dry machining. After those preliminary restrictions the approach of study is depicted in Fig. 2:

1 First, a training part is machined and high frequency measurements and the NC instructions are acquired.
2 Based on this data, a Machine Learning model is trained.
3 Post this, the validation part is machined.
4 The NC instructions from the validation part are passed to the already trained model.
5 The model then predicts the energy consumption.
6 The actual measurements obtained while machining the part are compared to the predicted values.

Besides the restrictions met, the state of the art shown above takes into account multiple parameters for the energy consumption (e.g. material removal rate, spindle speed, feed rate, effective cutting, air cutting, idle, start-up and shut down, etc.). Therefore, measures were taken to enable the Machine Learning model to distinguish between those operations.

Methodology and challenges

In this chapter we describe each step individually. We elaborate on how the study is carried out and the challenges occurring.

Data acquisition

The data from the machining process is the foundation for developing a prediction model. In this chapter the procedure is elaborated to derive a data set for the Machine Learning model out of the obtained data from the experiments [35].

Manufacturing process

Part For our approach two different parts, shown in Fig. 3, are machined. The raw material is an aluminium alloy (AlCuMgPb, ISO No. 1645) with the size 125.3mm × 19.34mm × 14.52mm.

CNC machine tool The machining parts are machined on a SPINNER U5630 5-axis simultaneous CNC machine tool with a SINUMERIK 840D SL v4.8 numerical control unit (NCU).

Tools The tools being used in the machining process are given in Table 2. While four tools are used in both manufacturing processes, the other seven are used in either of the two. Hence, the validation data set contains tools which are not in the training set.

Data acquisition The power measurements are not performed with a conventional electricity meter but with a SIEMENS edge device. This high frequency software sensor installed onto the NCU provides high resolution data with a sampling interval Δt of $2ms$. This has be shown by [32] to be beneficial compared to conventional low frequency data. The NC code used in this study is acquired in a retroactive readout process from the NCU. This NC code is extracted after the machining and therefore, compared to the output of a CAM software, contains additional internal machine instructions and possible changes of the machine operator, ensuring the usage of the accurate NC code responsible for the measurements [28].

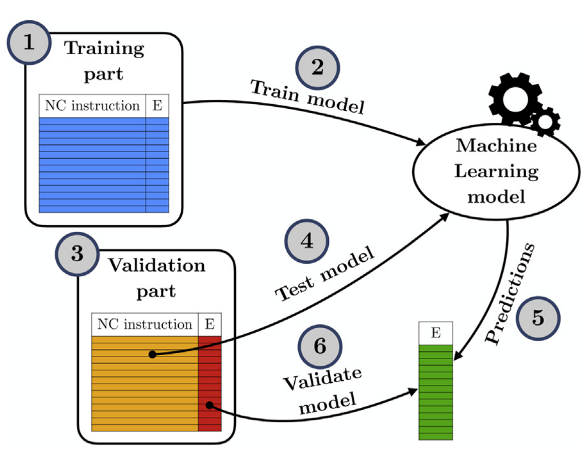

Fig. 2. Approach of study.

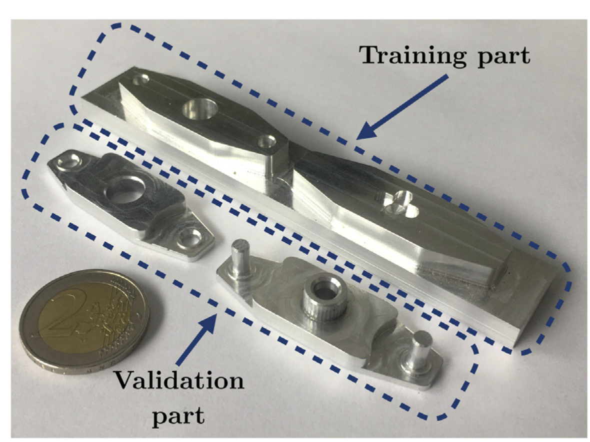

Fig. 3. Manufactured parts used for the study.

Table 2
Tools used to machine the parts.

Tool	Diameter and angle	Part	
		Training	Validation
Ball Mill	∅4 mm	•	
Center Drill	∅8 mm &90°	•	•
Chamfer Mill	∅8 mm &60°	•	
Chamfer Mill	∅10 mm &90°	•	
End Mill	∅3 mm	•	•
End Mill	∅6 mm	•	
End Mill	∅10 mm	•	•
End Mill	∅16 mm	•	
Reamer	∅5 mm	•	
Twist Drill	∅2.8 mm		•
Twist Drill	∅4.7 mm	•	•

Merge measurements and NC code

The NC code, containing all the NC instructions to machine a given part, and the power demand measurements are matched via a time stamp. Dependent on the execution length of each individual NC instruction i, m consecutive measurement results j have to be assigned to the NC instruction. To merge those two data sets, every power demand measurement $P_{i,j}$ is multiplied by the sampling interval of the measurement device Δt to obtain the current energy consumption. The total energy consumption E_{total} is then:

$$E_{total} = \sum_{i=1}^{n} \sum_{j=1}^{m} P_{i,j} \Delta t \tag{1}$$

Syntax interpretation

In this step of the study, the NC code has to be processed to make the hidden information accessible for further usage, e.g. the category of operation (rapid positioning, material removal, miscellaneous function, etc.) or the go-to positions, in the text of the unprocessed NC instructions, see Fig. 4. For this data transformation task domain knowledge is necessary in order to improve the data quality set containing information, that can be used later by a ML algorithm. Following chapters are elaborating this issue.

Negligible code lines

A part of the retained machine instructions don't contain information in regard to the energy consumption (e.g. "STOPRE", "GETSELT", etc.). All those instructions that do not lead to an significant energy consumption higher than the idle power consumption can be identified and summarized into a negligible category.

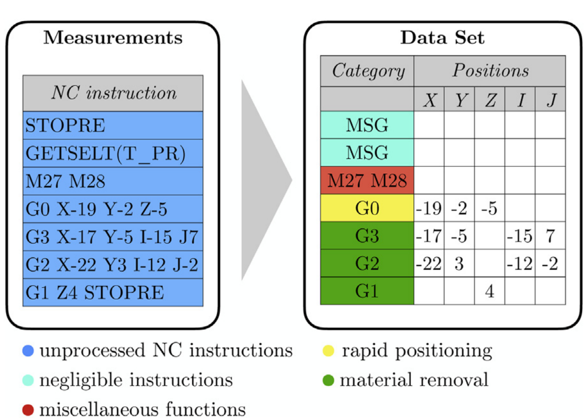

Fig. 4. Syntax interpretation of the NC code.

Multiple elements in one instruction

One NC instruction can contain more than one element, responsible for different, simultaneous CNC machine tool operations. However, the energy consumption measurement for the NC instruction is conducted as a whole and retrospective separation and allocation to the respective CNC machine tool aggregates is not possible.

Feature extraction and feature engineering

The input parameters, called features, are generated from the data set with respect to their relevance for the machining process according to the analytical and technological considerations. A part of the needed information can be directly used from the data set in the given form (e.g. the spindle speed). In other cases, the information needs to be transformed prior the be ready for the Machine Learning model. In the feature engineering process, domain knowledge or additional information, like the diameters of the tools, is added and mathematical transformations, like the path between two positions, are implemented on the information prior to transferring it to the data set for the Machine Learning model. The model is trained and validated with 37 input features, of which a selection is deeper discussed hereafter.

Length of tool path

As the literature above suggests, one main parameter of the cutting power consumption is the material removal rate $Q = v_c A$. Multiplied with the specific cutting force k_c one obtains the power demand $P_c = k_c Q$. Given those prerequisites, one can calculate the energy consumption of a milling process:

As the run time of one NC instruction Δt_i is not directly utilizable out of the data, one has to substitute it by the feedrate v_c and the length of the tool path l_p. With further simplifications one finally obtains:

$$\begin{aligned} E_c &= k_c \cdot Q \cdot \frac{l_p}{v_c} \\ &= k_c \cdot A \cdot l_p \end{aligned} \tag{2}$$

where, k_c is a material constant that can be neglected in this regression study as only one material (aluminium alloy) is used. It is assumed that the cross section A is also constant for a given operation. In Eq. (2), it is shown that the cutting lengths for every feed axis $\vec{l}_i$ is an important feature in the data set, which can be calculated by the difference of the current position of the tool $\vec{x}_i$ and the position $\vec{x}_{i+1}$ after execution of the NC instruction i:

$$\vec{l}_i = \Delta \vec{x}_i = \vec{x}_i - \vec{x}_{i+1} \tag{3}$$

The cutting lengths $\vec{l}_i$ are calculated for every feed axis separately and not with the amount of the vector $|\vec{x}_i - \vec{x}_{i+1}|$. The power consumption is measured and later predicted for every axis separately, therefore also a separate cutting length for every axis is needed.

Feed rate determination

The feed rate is included in the data set as variable parameters and set for each tool and each operation mode. Hence, an external database with those settings has to be build. Therefore, based on the tool and operation mode for each NC instruction, the correct feed rate can then be assigned (see Fig. 5).

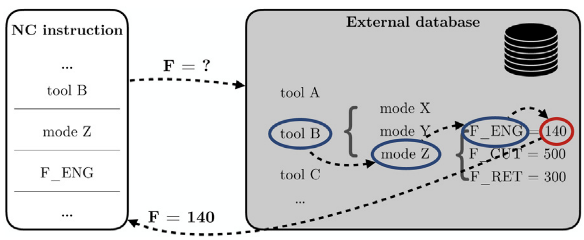

Fig. 5. Determination of feed rate through external database.

Internal machine variables

Positions in the NC code can be given not by their numerical coordinates but by a variable name. While variables like X_HOME, Y_HOME, etc. can be replaces by their numerical value, others remain unknown.

Material engaging and effective machining

As the tool engages into the part, the material removal rate Q is not constant. During engaging the material removal rate increases with the length of the tool path l_{run}, from the beginning until attaining a constant material removal rate at a specific length $l_{threshold}$.

$$Q = \begin{cases} \text{variable}, & \text{if } l_{run} < l_{threshold}. \\ \text{constant}, & \text{otherwise}. \end{cases} \tag{4}$$

An additional feature marks all those NC instructions that meet the condition $l_{run} < l_{threshold}$. For the Machine Learning model those instructions will be recognizable as a group of instructions that take place at a beginning of every removal process. The value of $l_{threshold}$ is retained by minimizing the error of the predictions for NC instructions of the engaging process.

Tool diameter

The removed area A correlates to the tool diameter d_{tool} as bigger tools will be used to remove more material at a time. As the removed area A correlates to the material removal rate Q and in consequence to the energy consumption.

$$E_c = k_c \cdot f(d_{tool}) \cdot l_p \tag{5}$$

If material and tool path length l_p are constant, the energy consumption of a bigger tool is higher than the energy consumption of a known tool.

Categorical variables

Of large importance for the energy consumption is the operating state of the machine. This is defined by the 'G' and 'M' codes in the NC instruction. E.g. the command 'G01' is not less then 'G02' but defines a different operating method of the machine, therefore those variables cannot be handled in the same way as continuous variables like e.g. the tool diameter discussed earlier. Those variables are turned into an one-hot encoded feature matrix, with every possible operating state as a separate feature. Than, for every NC command the activated operating states are set to '1' while the others remain deactivated with a value of '0'.

Model training and prediction

Three different models have been trained using the 'scikit-learn' package: 'RandomForest', 'DecisionTree' and 'DecisionTree' including the 'AdaBoost' method. As the later does not support multioutput predictions, for every output a separate model was trained. The models have been trained with all of the training data, gathered during machining of the training part, while the data obtained during machining of the validation part was used to evaluate the predictions of the three algorithms.

Results and discussion

The statistical measures, specifying the quality of the predictions, are given in Table 3 for all five considered CNC machine tool aggregates (x, y and z axis, spindle and tool change system) and for the three trained algorithms. The total deviation of the energy predictions from the measurements for a real part geometry including auxiliary operations like tool change system and start up phase is 7.16% for the DecisionTree model. The comparison between the algorithms for one of those aggregates (y axis) is depicted in Fig. 6. Although there are exceptions for specific

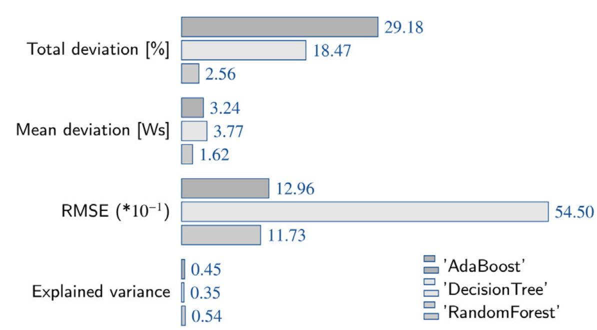

Fig. 6. Comparison of the prediction quality for the y-axis of part B of different Machine Learning algorithms.

Table 3
Validation of the three investigated machine learning algorithms with the test data set.

Algorithm	Measure	x axis	y axis	z axis	Spindle	Tool change system
'RandomForest'	Total deviation (%)	0.2	−2.56	3.29	11.66	46.14
	Mean deviation (Ws)	5.02	1.62	3.1	199.62	2.38
	RMSE	48.45	11.73	32.95	1301.92	18.03
	Explained variance	0.72	0.54	0.9	0.42	0.52
'DecisionTree'	Total deviation (%)	−9.12	−18.47	3.96	8.9	11.75
	Mean deviation (Ws)	7.44	3.77	5.69	258.76	3.21
	RMSE	58.77	13.96	54.5	1368.99	17.72
	Explained variance	0.59	0.35	0.73	0.36	0.54
'AdaBoost' + 'DecisionTree'	Total deviation (%)	−14.25	−29.18	−10.71	−13.48	15.19
	Mean deviation (Ws)	5.61	3.24	3.63	277.71	2.91
	RMSE	51.98	12.96	53.1	1330.77	19.33
	Explained variance	0.68	0.45	0.74	0.4	0.45

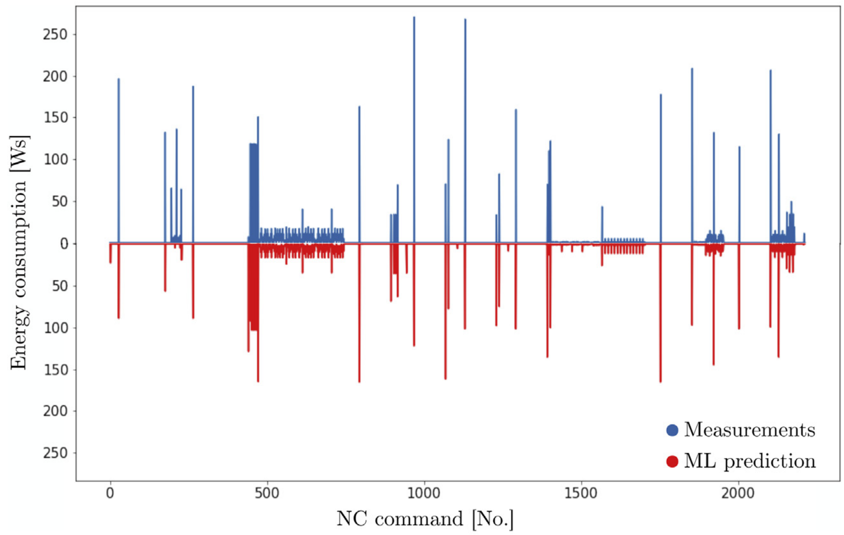

Fig. 7. Comparison of the prediction quality for the *y*-axis for the whole machining cycle.

measures and aggregates, the most accurate predictions can be achieved with 'RandomForest' algorithm. In Fig. 7, the plot of the predictions of the energy consumption of the *y* axis aggregate is compared to the measurements. Hence, the energy demand curve of the machining process gets predicted accurately. Also the peaks, although differing in their value, are correctly predicted by the trained model.

Tool change system

For the tool change system the 'DecisionTree' algorithm achieves the lowest total deviation compared to the 'RandomForest'.

This is caused by performing the tool change operation only several times during machining. Besides those singular events the tool change system is turned off. In contrast to the other aggregates, where a regression problem is to be solved, in this case an algorithm has to distinguish between the NC instructions, where a tool change operation takes place, and those, where not. This decision problem is better performed by the 'DecisionTree' than by a model, that was build using the 'bagging' method (e.g. 'RandomForest'). In 'bagging', the data set is split into smaller sub data sets and those are used to train sub models, which leads to an averaging effect or a smoothing of the regression function. For singular operations as the tool change operation this leads to disadvantageous predictions caused by underfitting in the single sub data sets.

Spindle

The errors for the predictions of the energy consumption of the spindle (see Fig. 8) are higher than for the remaining aggregates. This is caused by three main issues:

- The acceleration and the deceleration of the spindle are responsible for exceptional high power peaks. This leads to a high range of current energy consumption between those rare peaks and effective CNC machine tool operation. The algorithm averaging those, leads to a high error.

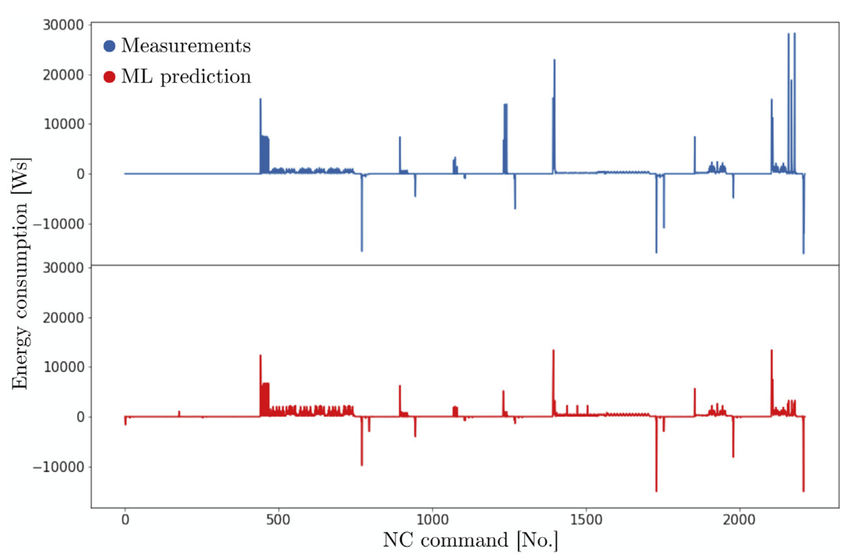

Fig. 8. Comparison of the prediction quality for the spindle aggregate for the whole machining cycle.

- Those power peaks occur rather rarely compared to effective machining. This leads to an underfitting of the models of this power peaks. This problem of unbalanced data influences also other domains with power peaks, like rapid movement of the axis.
- Acceleration and the deceleration are not only energy intense processes but also time consuming. The NCU moves ahead after initiating the spindle deceleration while the spindle is still decelerating and acts like a generator, thereby influencing the energy consumption of the following NC instructions.

Peak consumption

The deviation of the predictions for the peaks in Fig. 7 are posed on several reasons concerning especially the energy consumption of CNC machine tools and the milling process:

- There are NC instructions, which are directly followed by an identical copy of themselves, e.g. 'G0 G40 G60 G90 Z=$TC_CARR40[_TC1]-_TOOLL[2]*_FAK1' or 'G90 D0 SPOS=0 POS[X]=_X FA[X]=RED_RAPID_SPEED POS[Y]=_Y FA[Y]=RED_RAPID_SPEED POS[Z]=_Z FA[Z]', whereas only one of those instructions leads to an significant energy consumption of the machining operation. This is a challenge in data acquisition, which leads to high prediction errors: Having two identical inputs generating highly different energy consumption, the model has to average the output and produce high errors.
- Despite being similar, NC instructions can differ in energy consumption. For example the energy needed for the tool change system is dependent on the position in the tool magazine. This information is not available in the data set and therefore it can not be considered.

Outlook

Besides of addressing the challenges discussed above, several opportunities for future research can be divided into two categories:

Physical scope

Materials

In this study, only one material is used. Therefore, training and prediction is based on the same raw stock. Research question arises to create a model for multiple materials. A feature taken this into account is e.g. the specific cutting force k_c. It has to be investigated to what extend it is possible to calculate accurate predictions if:

- A common model will be trained based on training data containing different materials,
- Predictions will be made for materials, which were not in the training data set.

CNC machine tools

The data used in this research represents machining processes on one specific CNC machine tool. Further studies should investigate the possibility to integrate multiple CNC machine tools.

Tools

Linking data with simple geometries of the tools (e.g. tool diameters), was found to deliver highly accurate results. Hence, including more information e.g. if the tool is used for face, chamfer, etc. milling might be advantageous.

Computational scope

Algorithms

Similar studies often used artificial neural networks (ANN). It should be examined if more accurate predictions are possible, although results will not be easily explainable, because of the hidden layers and the multiple connections between the neurons of such a network.

Data processing

It poses a challenge that NC instructions can contain more than one element responsible for energy consumption of the CNC machine tool. The data could be processed in a way that those elements will be separated and individual predictions for them will be computed. Another possibility in this domain is, to integrate a duration component to the NC instructions, as the run time was neglected in this study.

Data acquisition

In this study the instructions used were extracted from the CNC machine tool after the machining. As this contains additional machine specific instructions, in a further study the input NC code could be used.

Expansion

Energy aware design

Connecting this model with CAD-Systems would give the design engineers feedback about energy-efficient design of their parts.

Online optimization of parameters

In CNC machine tools the parameters like feed rate and spindle speed are usually fixed according to experience values. This model with its high prediction quality of the energy consumption time series could enable the energy prediction during the machining process and an online optimization of the cutting parameters in respect to a constant load of the CNC machine tool.

The results obtained in this study with ML provide accurate predictions of the power consumption for the whole machining cycle. Those results prove that the developed energy model can be used to predict the energy consumption and is a valid tool to help reduce cost in machining and to give direct feedback to part designers before machining as proposed in the introduction.

Declaration of interests

None.

Authors' contribution

Markus Brillinger: Conceptualization, Methodology, Writing – Reviewing and Editing. **Marcel Wuwer**: Investigation, Writing – Original draft preparation. **Muaaz Abdul Hadi**: Resources. **Franz Haas**: Supervision.

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