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ScienceDirect

Procedia CIRP 118 (2023) 145–150

www.elsevier.com/locate/procedia

16th CIRP Conference on Intelligent Computation in Manufacturing Engineering, CIRP ICME '22, Italy

# Potential of systematically generated training datasets on the accuracy and generalization of AI-based approaches for the automated identification of machine control signals

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**Abstract**

The automated identification of data sources in machine tools is steadily gaining importance due to the growing use of data-driven methods. However, due to small size and volatile information content of training data sets, even promising AI approaches are increasingly reaching their limits. With systematically generated unique reference trajectories, large-scale data sets with high information content can be created. In this paper, the effects of these data sets on accuracy and generalization of AI-based approaches are investigated in comparison to the training with process data. In particular, the subset optimizing the identification of real-world process data is addressed.

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Peer-review under responsibility of the scientific committee of the 16th CIRP Conference on Intelligent Computation in Manufacturing Engineering

*Keywords:* Artificial intelligence; Automation; Computer numerical control (CNC); Digital manufacturing system; Identification; Machine tool

## 1. Introduction

With regard to the potential offered by digitalization and Industry 4.0, many companies aim to achieve positive effects and benefits through the use of data-based approaches in their production, for example to increase equipment availability through condition monitoring and predictive maintenance or to increase performance through process optimization. A decisive basis for this is the extraction and provision of the data required for the various approaches, which comes from the control systems of the machines and equipment. For the applications mentioned above, signals from the machine axes, such as motor current, torque, feed rate and position data, are particularly relevant for users. [1]

Access to the control system data depends in each case on the age and the associated technical generation of the machine, but can also vary depending on the manufacturer. For example, newer machines in many cases have OPC UA interfaces, which in some cases even include standardized Companion Specifications, but other machines in many cases do not have a standardized information interface, which makes accessing and assigning the data more difficult. This especially applies to typical brownfield productions environments, which are characterized by a high degree of heterogeneity in the age and manufacturer of the machines and equipment. [1,2]

More than 80 % of the companies state that the connection and data use for the described use cases is inhibited by a lack of personnel resources and technical knowledge. Less than 5 % of the companies have no concrete ideas and see no benefit for specific use cases. Therefore, tools are needed to facilitate the extraction and identification of signals such as motor currents and position data from machine control systems. [2]

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10.1016/j.procir.2023.06.026

### 1.1. State of the art and preliminary work

Signals from machine control systems as motor currents and position data mainly represent time series data. Approaches focusing on classification of time series can be distinguished in rule based and machine learning (ML) based. The majority of the existing approaches are ML based.

Recent work [3,4] analyzed data sets of time series from versatile application areas. They showed that the artificial neural networks (ANN) are particularly well suited, especially Fully Convolutional Networks (FCN) and Residual Neural Networks (ResNet). Exemplary signals on a CAN bus were automatically classified in four signal classes of a CAN bus [5] using automated feature selection and handcrafted feature selection. The handcrafted feature selection tend to show higher accuracies. However, the ML models were not tested for generalizability. This is an important factor for machines, because the machine signals of different manufacturers often differ, but are similar in their characteristics and should be identified by a generally valid ML model.

Currently, there is no general ML approach for the classification of signals in the form of time series data from machines and equipment Industry 4.0 standards are often already implemented in newer machines, which means that Overall Equipment Effectiveness (OEE) optimizations are already directly applicable. However, brownfield machines are not equipped with them, which is why control signal identification must be performed by external applications.

In order to support users in the extraction and identification of machine control signals, in preliminary work published in [6,7], an assistance system was conceptualized that automatically recognizes and provides them to the user based on machine learning and domain knowledge. Here, first approaches for ML model-based control signal identification of machines have already been investigated. Thereby, selected signals of a machine were successfully classified. Building on these approaches, machine control signal identification was extended and optimized in this paper.

**Nomenclature**

| | |
|---|---|
| AKI | Akima interpolation |
| ANN | Artificial Neural Network |
| CBS | Cubic B-Spline interpolation |
| EXP | Exponential distribution |
| FCN | Fully Convolutional Network |
| GAM | Gamma distribution |
| LBS | Linear B-Spline interpolation |
| LSTM | Long Term-Short Memory |
| ML | Machine Learning |
| OEE | Overall Equipment Effectiveness |
| PCHIP | Piecewise cubic hermite interpolating polynomial |
| ResNet | Residual Neural Network |
| RF | Random Forest |
| SBS | Quadratic B-Spline interpolation |

## 2. Own approach

Since signals are recorded in many brownfield machines, but it is not known which signals they are, the objective is to classify these signals independently of the machine in order to be able to use them for further applications. This signal recognition is to be implemented with the help of an ML model. For the validation of the ML model, meaningful data sets must be available in order to ensure not only high accuracy of the individual classes but also good generalizability.

Therefore, in order to achieve an information-rich data set, an approach for machine reference runs was developed in [8], which is explained in more detail in the following chapter and provides a basis with very high information content. Subsequently, the recorded reference runs were used to train different ML models. It was investigated at which parameter settings signals can be identified best and which signals can be separated particularly well. In addition, different feature groups were created. In order to not only check the accuracy of the reference runs of one machine, validations were carried out with test runs of another machine. This should also make it possible to evaluate the generalization capability of the ML models to other machines.

## 3. Unique trajectories for datasets with high variability

The runs for the dataset were created with the algorithm described in [8] paragraph 3, which has been expanded regarding the probability distribution and the types of interpolation. To ensure versatile datasets and thus represent as many cases as possible, an ID system is used which ensures the uniqueness of the generated. Therefore, the ID system assigns unique bit sequences to each axis of the machines, which represents the direction of two subsequent support points of a spline interpolation. For this purpose, an ID pool is generated from all possible binary sequences. Based on this ID pool, an assignment takes place according to predefined rules. If the pool contains 100 or fewer free IDs, all of them are considered for the assignment, if more than 100 IDs can be assigned, a random subset of 100 IDs is generated. The ID from the subset with the maximum Hemming distance to all used IDs is assigned to the axis. If more than half of all possible IDs have been assigned, all new IDs are assigned randomly.

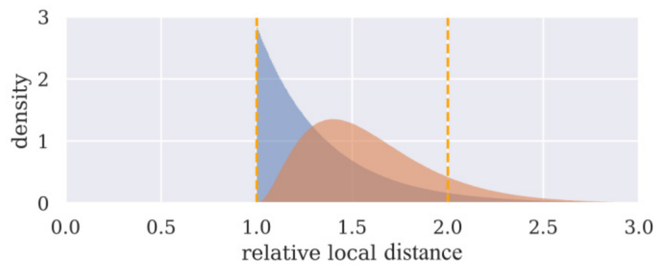


Fig. 1. Density function of the gamma (orange) and the exponential (blue) distribution used to generate the consecutive support points (unitless).

As in [8], IDs with a length of 12 bits were used in this paper. If an ID has been assigned, it is used to determine the support points for the interpolation of the trajectory. Therefore, the ID indicates the relative position of the consecutive support points. With the next support point represents a higher value and with 0 a smaller value than the previous one. To generate different movements even with the same predefined direction and thus to maximize the variability of the training data the allocation of support points is based on probability distributions. Starting from the direction specified by the ID, the relative position of the support points is generated using a gamma (GAM) or an exponential (EXP) distribution. For this purpose, the surrounding range of the previous support point is divided into three areas, whereby in both cases no support point is placed in the left area to ensure a minimum distance. As can be seen in Fig. 1, there is a sudden increase in the probability density in the case of EXP during the transition from the left to the middle area. Starting from this, the density function drops sharply towards the right area. As a result, support points tend to be similarly spaced. GAM, on the other hand, leads to a smooth transition and a high probability for support points in the center of the middle area as well as a slow decrease towards the right area.

Since splines are particularly suitable for generating complex trajectories from a limited number of support points, spline interpolations are used to interpolate the movement path. For this purpose, linear (LBS), square (SBS) and cubic B-splines (CBS) as well as piecewise cubic hermite interpolating polynomials (PCHIP) and Akima interpolations (AKI) should be used for the creation of the training datasets. As can be seen in Fig. 2, the interpolations differ in the continuity of their derivatives, which leads to different signal curves. Thus, it should be facilitated to classify signals with a high similarity such as current and torque.

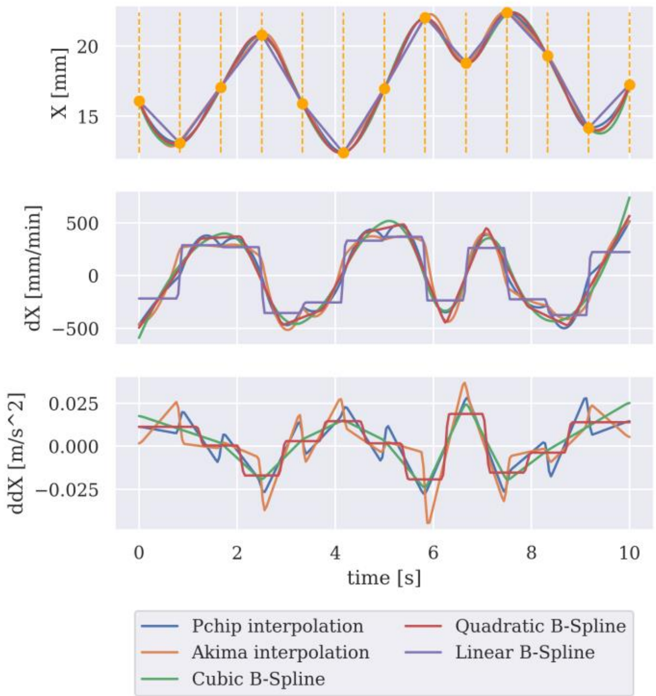


Fig. 2. Example of generated trajectories for an x-axis with the times of the predefined support points in the upper plot (vertical lines). In the bottom plot, the different accelerations due to the interpolation types can be seen.

To define as few changes as possible in the spindle movement and thus to minimize the time domain based distortion of the trajectory, a piece-wise constant spindle movement is used. In addition, the movements of all axes and the spindle are synchronized to generate training datasets with the highest possible information content. Finally, all movements are converted to a predefined range of values. For the experimental machine, analogous to [8], 10 mm for translatory axes, 2 ° for rotary axes and 200 rpm for the spindle were used as value ranges for the creation of the datasets.

As shown in [8], the movements correspond most closely to the predefined trajectory when using an axis interpolation where each axis is interpolated individually but synchronously with a block change at the start of the breaking ramp. In this paper, each movement is defined by 250 G-Code blocks representing the predefined points from the interpolations generated for a duration of 10 s.

## 4. Creation of training datasets

As described above, datasets can be generated with reference runs where all axis movements are unique, which leads to high information content. To be able to specifically examine the effects of the probability distribution and the type of interpolation as well as the differences between translational and rotational axes, 100 subdatasets were generated on the test machine for all axis. Each subdatasets consists of 30 recordings based on the same ID pool and is recorded with a sample rate of 500 Hz and a length of 10 s. For this purpose, the different probability distributions (GAM, EXP) and interpolation types (LBS, SBS, CBS, PCHIP, AKI) are combined for translatory and rotatory axes.

## 5. Experimental setup

The training datasets were created with a DMC 60H - HDM milling machine with three translatory axes (X / Y / Z), one rotary axis (B) and a spindle. The brownfield machine was retrofitted with a new SINUMERIK control system and additional sensors to make it industry 4.0 capable.

For a test dataset, additional data from a CMX 600 V milling machine was used. This machine has three translatory axes (X / Y / Z) and is equipped with the same SINUMERIK control system as the DMC 60H - HDM.

## 6. Basic approach of training the ML models

In order to gain as much knowledge as possible from the training and to take advantage of different approaches, different ML models were chosen for the training. On the one hand, ANNs were trained in the form of a ResNet, a FCN and a single-layer Long Short-Term Memory (LSTM). On the other hand, a Random Forest (RF) was trained. ResNet and FCN were selected based on their ability to classify time series, which was demonstrated in [3], and the structure was also adopted from them. Moreover, this time series classification capability of ResNet and FCN were reconfirmed in [4]. LSTM and RF showed decent results in previous studies, moreover, RF is easy to train and gives simple insight into the classification task [7]. Another advantage of RF is that domain-based expert knowledge can be incorporated into it through feature selection.

Before the actual training, the recordings of the created reference runs are prefiltered. Here, zero output signals, signals without numerical values, binary signals, constant signals, cyclic signals and double signals are assigned to their class via rules, since generally valid rules exist for this. For the ML models, the focus is thus on the detection of the important useful signals, including current, torque, speed and position, which are also recorded by most brownfield machines [2]. After this filtering and classification, the individual reference runs still contain 50 signals from the initial 100 signals. These 50 signals include the current, the torque, the load, the speed signal, which is acquired at the drive, the preset position after fine interpolation of all four axes and the spindle. In addition, the feed rate, which is fed to the controller, the control difference, the position of the indirect and the direct measurement, the position at the input of the position controller and the power signals of all four axes plus the actual position of the spindle are included.

An overall data set was created from these filtered reference runs with the unclassified signals. For this purpose, samples of the same length were extracted for each signal. The following sample lengths were chosen: 100, 500, 1000, 2500 and 5000 data points. 5000 data points represents the maximum, since most reference runs have approximately this length. The shorter sample lengths were chosen, on the one hand, to be able to classify shorter time segments later, on the other hand, to find an overall optimal length for the classification. From these samples, the samples that had only zeros or a constant value were again filtered to ensure for the training data that they had the highest information.

For training of the RF, features were calculated from the individual samples. Three different feature groups were chosen for this purpose. Feature group 1 contains ten conventional statistical features used for classifications, taken from [7]. In feature group 2, these ten features were supplemented by seven features related to a priori knowledge about machine tools. Feature group 3 contains only the seven features based on a priori knowledge. For the ANNs, the time series are directly usable as training data, they were only normalized using a z-transformation as in [3].

Prior to the actual training, the total data set created was stratified split up into 80 % training and 20 % test data. Finally, with the 80 % training data, the RF and ANNs were trained for the different sample lengths and features.

In first trainings and also by previous findings from [7], it was shown that there are dependencies or similarities between some signals, which make a distinction clearly difficult. This concerns among others current, torque and load, indirectly and directly measured positions, given position after fine interpolation and positions at the input of the position controller and generally equal signal groups of the different axes. Based on these findings, these difficult-to-distinguish signals were combined to signal groups for the final training. For the RF, 19 target classes resulted, for the ANNs 15 target classes.

After training, the ML models were tested with the remaining 20 % of the data set from the reference runs of the DMC 60H - HDM machine. Additionally, a test was performed with data from the CMX 600V machine to make statements about the generalizability of the ML models to other machines.

## 7. Results

Table 1 and Table 2 show the results of the ML models of the training, the validation during the training and the final test of the trained ML model with data from the DMC 60H - HDM and the CMX 600 V. The accuracies of the classification using the ML models are presented as results. These accuracies refer to the ratio of correctly classified samples and the total number of samples.

For the training of the LSTM, only the sample length 100 led to a convergence in the training and thus to a stable training result, which can also be further evaluated. For this reason, only the result of the LSTM with the sample length of 100 data points is listed here.

Table 1. Training, validation and test results of RF.

| Features (group) | Sample size (data points) | Training accuracy | Validation accuracy during training | Test accuracy (DMC data) | Test accuracy (CMX data) |
|---|---|---|---|---|---|
| 1 | 100 | 99.89 % | 75.27 % | 75.04 % | 34.99 % |
| 1 | 500 | 99.99 % | 81.27 % | 81.09 % | 33.71 % |
| 1 | 1000 | 99.99 % | 82.78 % | 82.74 % | 34.41 % |
| 1 | 2500 | 100 % | 84.91 % | 84.74 % | 31.77 % |
| 1 | 5000 | 99.99 % | 87.75 % | 87.48 % | 33.48 % |
| 2 | 100 | 100 % | 99.64 % | 99.59 % | 37.49 % |
| 2 | 500 | 100 % | 99.93 % | 99.92 % | 33.95 % |
| 2 | 1000 | 100 % | 99.95 % | 99.94 % | 29.91 % |
| 2 | 2500 | 99.99 % | 99.96 % | 99.96 % | 31.39 % |
| 2 | 5000 | 99.99 % | 99.98 % | 99.96 % | 31.26 % |
| 3 | 100 | 99.99 % | 98.74 % | 98.63 % | 35.84 % |
| 3 | 500 | 100 % | 99.72 % | 99.69 % | 38.13 % |
| 3 | 1000 | 100 % | 99.84 % | 99.82 % | 32.44 % |
| 3 | 2500 | 99.99 % | 99.95 % | 99.90 % | 31.54 % |
| 3 | 5000 | 100 % | 99.93 % | 99.91 % | 29.00 % |

Table 2. Training, validation and test results of KNN.

| ML model | Sample size (data points) | Training accuracy | Validation accuracy during training | Test accuracy (DMC data) | Test accuracy (CMX data) |
|---|---|---|---|---|---|
| ResNet | 100 | 98.40 % | 97.78 % | 97.75 % | 41.94 % |
| ResNet | 500 | 99,00 % | 99.00 % | 98.98 % | 28.33 % |
| ResNet | 1000 | 99.20 % | 99.11 % | 99.20 % | 35.86 % |
| ResNet | 2500 | 97.30 % | 97.19 % | 97.30 % | 36.81 % |
| ResNet | 5000 | 98.30 % | 98.13 % | 96.81 % | 23.50 % |
| FCN | 100 | 91.00 % | 90.84 % | 90.22 % | 30.11 % |
| FCN | 500 | 93.20 % | 90.70 % | 91.55 % | 25.49 % |
| FCN | 1000 | 93.10 % | 89.72 % | 92.43 % | 25.49 % |
| FCN | 2500 | 94.50 % | 91.05 % | 84.94 % | 33.70 % |
| FCN | 5000 | 73.20 % | 72.51 % | 71.49 % | 25.06 % |
| LSTM | 100 | 91.30 % | 89.71 % | 90.54 % | 37.87 % |

## 8. Evaluation of results

As the results from the previous section show, the ML models obtained by training on the DMC 60H - HDM reference runs provide very good classification results with an overall accuracy of 90 % to 99 % in most cases for this machine's data. The RF and the ResNet provide the best results. For the RF, it must be noted that feature group 1 in the results show a tendency towards no optimal fit in classification, especially for smaller sample lengths. Similar results are shown by the FCN for sample lengths of 2500 and 5000 data points.

When transferring the ML models to the CMX 600V, it becomes clear by the strong decrease of the classification accuracy that no universal generalization capability of the ML models to other machines could be achieved. This problem shows up independently of the type of ML model.

One reason for this could be that the reference runs of the DMC 60H - HDM cover too much the characteristics of exactly this machine and therefore there is an overfitting of exactly this machine in the training. In addition, the dependencies and similarities of different signals may also differ for different machines, which makes a universal generalization of a ML model difficult. In general, it also shows that for overall accuracy on CMX 600V data, sample length and feature group play only a minor role in RF, but features based on a priori knowledge tend to classify better. For ResNet, there is a clear difference in overall accuracy with respect to sample length. Sample lengths of 100, 1000, and 2500 data points provide significantly higher accuracies than 500 and 5000 data points. For the FCN, the sample length of 100 and 2500 data points provide the highest overall accuracy.

Due to the poor results on the CMX data with no overall accuracy higher than 42 %, these results were analyzed again in more detail to see whether, if necessary, individual signals or signal groups such as the position signals of the translational axes were detected in a meaningful way in order to be able to use the trained ML models for partial classification or in combination. In addition, this was used to check whether the selection of the target classes based on the reference runs of the DMC 60H - HDM machine was too specific, which was already indicated by the training results of FCN and LSTM.

This analysis showed that the RF with feature group 3 and a sample length of 500 data points provided the best results. With this, three individual signals (speed of the spindle, preset position after fine interpolation of the spindle and actual position of the spindle) and two signal groups (positions of the translatory axes and control differences) could be classified with more than 92 % accuracy, whereby none of the other signals was incorrectly assigned to one of these signals or signal groups with a proportion greater than 5 %. In addition to these signals, also the feed rates, which are fed to the controller, summarized as a signal group of all axes reached an accuracy of more than 84 %, whereby no other signal with a share larger than 0.3 % was wrongly assigned to this signal group. In Table 1.3 the result of this evaluation is shown again in detail. It shows the overall accuracy and the maximum incorrectly assigned share of another signal. The latter indicates the percentage of the signal that was most often incorrectly assigned to the signals indicated in Table 3.

This finding again shows that features based on a priori knowledge can better separate signals from each other. This is also in line with the results of a similar scenario from [5], in which feature-based classification of sensor signals from vehicles was performed, also involving time series between which different dependencies occur. This showed that with features based on a priori knowledge from vehicle technology provided the best classification accuracy when assigning signals to signal classes. [5]

Table 3. Evaluation of RF with a sample size 500 and feature group 3.

| Signal/ Signal group | Accuracy | Max. incorrectly assigned share of another signal |
|---|---|---|
| Spindle speed | 95.10 % | 0 % |
| Actual position of the spindle | 98.96 % | 0 % |
| Preset position after fine interpolation of the spindle | 100 % | 4.02 % |
| Axis positions as total class | 92.89 % | 1.63 % |
| Control differences as total class | 100 % | 0.59 % |
| Feed rates of the axes as a total class | 84.98 % | 0.28 % |

The ResNet with the sample length of 1000 data points was also able to classify the power signals with more than 78 % accuracy, with no other signal being misclassified as a power signal with a percentage greater than 1 %.

## 9. Conclusion and outlook

Due to the fact that no ML model achieved sufficiently good results for both high accuracy and high generalizability, as shown in chapter 7 and 8, further adaptations of the overall model have to be made. Since the overall model is to be used in a standardized way in brownfield environments, it is necessary that the signals of different machines can also be identified with high accuracy. Two concrete approaches are available for further improvements.

### *9.1. Optimization of the existing model*

One approach would be to improve the ML model by extending the data base of different machines, which is used as a training basis. The creation of additional reference runs and the recording of process data could lead to a higher accuracy and generalizability. The problem of specific characteristics of the training data would be mitigated by the additional data of further machines. This would generate a commonly applicable image that can be used to train the ML model. The pre-filtering as well as the separation according to the classification of the ML model still exist.

### *9.2. Hybrid approach*

Based on the good identification capability of signal types, the ML approach can be enriched using a set of rules built on a priori knowledge. This hybrid approach promises to result into higher identification accuracy.

This could result from a multi-step process in which signals are first prefiltered. Among other things, binary and cyclic signals are already classified, which can be identified by simple rule bases. The advantage of a filter with classification is that the data is not sorted out, but can be used for further data processing by assigning it to classes. Subsequently, signal classes, such as current / torque, could be classified according to [7]. These can be classified with high accuracy by ML models according to [7]. Also, the results from chapter 7 show that. e.g. position signals can be classified particularly well in the case of a RF. Due to physical relationships and correlations, large dependencies exist, which is why the corresponding classes can be further separated by rule-based models. This allows further information to be generated from the data. By means of the breakdown of the signals, these can be assigned to the respective machine addresses. This enables the direct assignment of the signals to the classes in real time.

Using the hybrid approach, the accuracy issues identified in Chapter 8 related to high generalizability could be solved by merging ML models and rule-based approaches.

The identified signals can then be used to apply OEE optimizations such as predictive maintenance, condition monitoring, and process optimization in the brownfield industry. In subsequent work, the approach for identification by prefiltering, ML models and rule bases without additional reference runs will be developed as a hybrid approach and validated on various machines.

## Acknowledgements

We extend our sincere thanks to the German Federal Ministry of Economic Affairs and Climate Action (BMWK) for supporting this research project 13IK001ZF “Software-Defined Manufacturing for the automotive and supplying industry” (SDM4FZI).

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