A Machine Learning-Based Approach for Predicting Tool Wear in Industrial Milling Processes*

Mathias Van Herreweghe[1], Mathias Verbeke[2], Wannes Meert[1], and Tom Jacobs[3]

[1] Dept. of Computer Science, KU Leuven, Leuven, Belgium
[2] Data and AI Competence Lab, Sirris, Brussels, Belgium
[3] Precision Manufacturing Lab, Sirris, Diepenbeek, Belgium

Keywords: Tool wear prediction · Industrial Milling Processes · Temporal Convolutional Network · Gradient Boosting Machine.

1 Introduction

In industrial machining processes, the wear of a tool has a significant influence on the quality of the produced part. Therefore, predicting wear upfront can result in significant improvements of machining processes. This paper investigates the applicability of machine learning approaches for predicting tool wear in industrial milling processes based on real-world sensor data on exerted cutting forces, acoustic emission and acceleration. This is an extended abstract of the full paper presented at the ECML/PKDD 2019 Workshop on IoT Stream for Data Driven Predictive Maintenance [4].

2 Model selection

As the goal of this paper is to test the industrial applicability of machine learning for tool wear prediction, the methods were selected based on their computation speed (to enable near-real time prediction) as well as their accuracy, were we put a threshold error margin of 20 μm in order to be industrially relevant. Gradient Boosting Machine was selected due to its accuracy in predicting the tool wear as well as its computation speed for predictions on new input data. As a second model, Temporal Convolutional Network (TCN) was selected due to its ability to exploit the temporal properties of the data, which voids the need for manual feature engineering.

3 Experimental validation

The validation was performed using the PHM 2010 tool wear prediction dataset as a benchmark, as well as using a proprietary dataset gathered from an industrial milling machine. Each of these datasets is divided into three subsets, of which each time two subsets were used for training the model and the remaining one for testing.

The results expressed in terms of mean absolute error (MAE) for both datasets are shown in Table 1. The rows marked with a star indicate that for this model the hyperparameters were optimized using grid search. The other models were trained using the default hyperparameters of the scikit-learn [2] (GBM) and Keras [3] (TCN) implementations respectively. The results are given in micrometer and are rounded to 1 decimal. The results are the average of 3 predictions with the same parameters.

Table 1. MAE for different models on the benchmark data (C1, C4, C6) and the industrial data (I1, I2, I3)

Model	**C1**	**C4**	**C6**	**I1**	**I2**	**I3**
GBM	10.9	14.4	13.7	17.5	22.3	16.6
GBM*	10.9	14.4	13.7	13.7	21.1	16.6
TCN	**9.3**	**10.9**	16.4	14.3	24.1	14.3
TCN*	9.5	**10.9**	**8.5**	**13.3**	**20.8**	**12.8**

Overall, the TCN with optimized hyperparameters obtains the best results for the benchmark dataset. The results of the mean MAE are 2.5 μm worse than the state-of-the-art models. For these models, however, no additional statistics regarding the number of runs that were required to obtain these results are provided. Furthermore, these results need to be interpreted with caution because at least one of the papers applies randomized cross-validation across the different (time-dependent) subsets. As pointed out by Bergmeir, Hyndman and Koo [1], this is an incorrect approach when dealing with time series data. The TCN also achieves the lowest mean standard deviation of errors per predicted set. This means that the size of the errors within a prediction does not differ that much from one another. Also for the industrial dataset, the TCN obtains the best results for all calculated statistics.

4 Conclusions

In this paper, we investigated the applicability of two machine learning methods for predicting tool wear in industrial milling processes using sensor data on exerted cutting forces, acoustic emission and acceleration. To this end, the use of Gradient Boosting Machines and Temporal Convolutional Networks was validated on both a benchmark dataset as well as on a real-world industrial dataset. The results show that both methods are able to predict the tool wear within an industrially-relevant error margin of 20 μm in an acceptable computation time.

Acknowledgements This work was partially supported by Flanders Innovation & Entrepreneurship (VLAIO) through the SBO project HYMOP (150033) and by the Brussels-Capital Region - Innoviris through the TeamUp ROADMAP project. Part of the computational resources and services used in this work were provided by the VSC (Flemish Supercomputer Center), funded by the Research Foundation - Flanders (FWO) and the Flemish Government - department EWI.

References

1. Bergmeir, C., Hyndman, R.J., Koo, B.: A note on the validity of cross-validation for evaluating autoregressive time series prediction. Computational Statistics & Data Analysis **120**(C), 70–83 (Apr 2018). https://doi.org/10.1016/j.csda.2017.11.003
2. Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M., Prettenhofer, P., Weiss, R., Dubourg, V., Vanderplas, J., Passos, A., Cournapeau, D., Brucher, M., Perrot, M., Duchesnay, E.: Scikit-learn: Machine learning in Python. Journal of Machine Learning Research **12**, 2825–2830 (2011)
3. Rémy, P.: Keras TCN (2018), "https://github.com/philipperemy/keras-tcn", [Online; May 26, 2019]
4. Van Herreweghe, M., Verbeke, M., Meert, W., Jacobs, T.: A Machine Learning-Based Approach for Predicting Tool Wear in Industrial Milling Processes. In: Ribeiro, R., Bifet, A., Gama, J., Holst, A., Pashami, S. (eds.) ECML/PKDD 2019 Workshop on IoT Stream for Data Driven Predictive Maintenance (2019)