Available online at www.sciencedirect.com

ScienceDirect

Procedia Manufacturing 45 (2020) 343–348

Procedia MANUFACTURING

www.elsevier.com/locate/procedia

10th Conference on Learning Factories, CLF2020

Analysis of High Frequency Data of a Machine Tool via Edge Computing

Stefan Trabesinger[a,*], Andre Butzerin[a,b], Daniel Schall[b], Rudolf Pichler[a]

[a] *Institute of Production Engineering, Graz University of Technology, Inffeldgasse 25f, Graz 8010, Austria*
[b] *Siemens AG Austria, Siemensstraße 90, Wien 1210 , Austria*

Abstract

New technological capabilities of digitalization are enablers of processing a broad range of machine data. While so-called Low-Frequency Data (LFD) is captured at a sampling rate of several hundred milliseconds, High-Frequency Data (HFD) is based on a sampling rate in the single-digit millisecond range. In this paper, HFD is used to implement an edge-based analytics application for prediction purposes in a machine tool. This edge application leverages Siemens SINUMERIK Edge to capture HFD from a machine tool to recognize anomalies of any kind. The edge application is implemented as a show case in the Learning Factory of Graz University of Technology, the smartfactory@tugraz.

Keywords: Edge Computing; High-Frequency Data; Prediction of Tool Breakage; Anomaly Detection; Machine Learning

1. Introduction

By definition, edge computing is a distributed cloud-computing paradigm [1]. Edge computing, unlike cloud computing, refers to distributed data processing in close proximity to devices, such as machine tools, that generate data for further analysis [2]. By contrast, edge computing allows the analysis of HFD on its own platform - typically implemented as an embedded computer in the automation network. The fields of application can be found preferably in time critical industrial applications where this data stream must be stored and evaluated in a well-defined timeframe. Time-critical applications in an industrial context, for example, are the timely shutdown of a machine or the reduction of the feed rate of tools to avoid breakages. Whereas in traditional cloud computing environments, the data generated by various assets and machines is typically passed to cloud services in an uncompressed way and without data pre-processing. In the cloud environment, various software tools are used to analyze the data. However, the slowdown in broadband expansion and delays in data transmission between central cloud servers and end devices at the edge of the network prove to be an obstacle in growth. To combine benefits of both systems, edge computing is often used in

* Corresponding author. Tel.: +43-316-873-7675 ; fax: +43-316-873-7678.
E-mail address: stefan.trabesinger@tugraz.at

10.1016/j.promfg.2020.04.028

combination with cloud computing [3]. This allows to implement the requirements for data protection, response time behavior and autonomy [4].

2. Motivation for doing Edge Computing

With the technologies mentioned in the introduction, the example of the defined showcase for prediction of drill breakage will be used to show how meaningful the results will turn out and if they provide benefits at all. In addition to the demonstration of the interplay of edge and cloud computing, the networking integration of the edge devices with all its IT security aspects is also very important. Likewise, the comparison of the LFD with the HFD is of high interest. Aside the reading and saving of data another motivation lies in the correct identification of anomalies, which is based on data analysis on approaches of machine learning algorithms. As a conclusion to this showcase, an interactive display board will be created as part of the learning factory smartfactory@tugraz. It will be used to present and explain the functionality of edge computing. This is a good starting point for further research and development activities and learning opportunities.

3. System architecture for the Edge Computing Show Case

The already implemented network infrastructure between office and shop floor will now be expanded by connecting machines in the shop floor to the Internet [5]. The required components for the layout of the network are shown in Fig. 6a. The Siemens numerical control unit (NCU) SINUMERIK 840d sl and the HMI are basic features of the machine tool Spinner U5-630. The edge device is a Siemens industrial computer IPC227E. Combined with the SITOP power supply the edge device is operative. For integrating the edge device, the data network is retrofitted with a managed Ethernet switch Scalance X208G inside the machine tools control cabinet. To guarantee a secure logic separation of the two networks machine LAN and factory LAN VLANs are installed [6]. Configuration and management of the edge device is transacted via the IoT operating system Mindsphere. For ensuring secure data exchange to the cloud the Edge Device offers two independent network ports.

4. Setup of Experiments for Data Generation

4.1. Planning and execution

Many components of the wave gear – this is the demonstration part of the learning factory “smartfactory@tugraz” - to be manufactured feature single drill holes with a diameter of 2.8 mm. Such a small-dimensioned drill hole exhibits

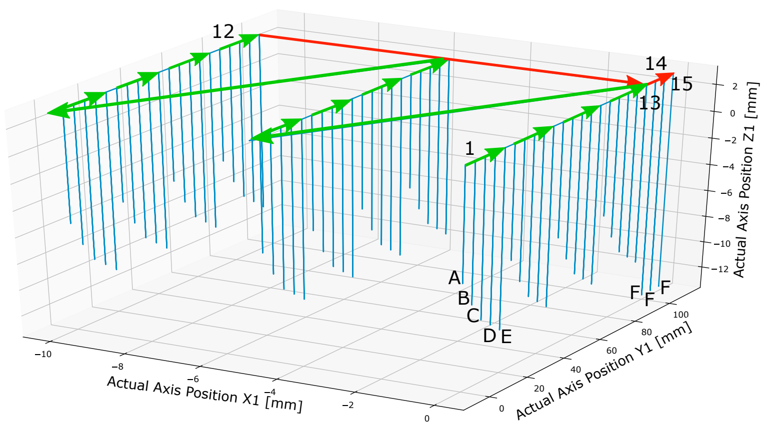

Fig. 1. Drill travel length.

a high risk of drill breakage. This provoked the idea of using machine generated data as input for Edge Computing to investigate the settings for avoiding drill breakage. An NC program is written for automation of experiment conduction and a better reproduction of the tool path. A high-speed camera is used to support the recognition of the moment of breakage. Experiments are conducted on an aluminum cuboid with dimensions 20 mm x 15 mm x 125 mm. Experiment preparation is finished after cutting the raw material, performing the tool change and the clamping of the work piece. The recording of data and high-speed video footage is recorded after start of the NC program. In order to reconstruct the realistic efforts of the drilling process parameter sets for a drill breakage are built, see Fig. 1. The whole drilling cycle includes the processing of parameter set A to E iterated until parameter set group no 12. Within a parameter set sequence A to E spindle speed and drilling depth steadily increase while keeping a constant duration of half a second. If there is no breakage, the NC program sets the drill to position no 13 where the NC program performs the highest rotational speed to force drill breakage.

5. Predictive data analytics by means of machine learning

After successful capturing and import of data, it is most important to understand the physical mechanism that leads to the generated data [7]. Afterwards that the eligibility of an appropriate machine-learning model follows.

5.1. Data capturing

The capturing of HF (High-Frequency) drive signals is driven by a sampling rate of 2 ms starting from the HF probe as initial sensor inside the SINUMERIK 840d sl NCU [8]. An upload stream by a proprietary protocol with a sampling rate of 100 ms transfers data to the SINUMERIK adapter. The edge app “AMW /capture” (Analyze My Workpiece /capture) finally stores the data on a hard drive, see Fig. 2a. The capturing of LF (Low-Frequency) drive signals is driven by a sampling rate of 100 ms by means of an encrypted OPC UA server-client connection shown in Fig. 2b. The user triggers start and end of data capturing.

5.2. Processing of drill data

Two different types of measurement patterns of data of one drill are important when regarding the parameter set A up to F in its entirety. After the import, the measured data is stored in a single CSV file in the form of a time series. The measurement data of the last drill hole is the one of breakage. The single CSV file is separated into single files which characterize each single drill hole. Only the data where the drill is engaged with the material of the work piece effectively is stored. All other data is discarded.

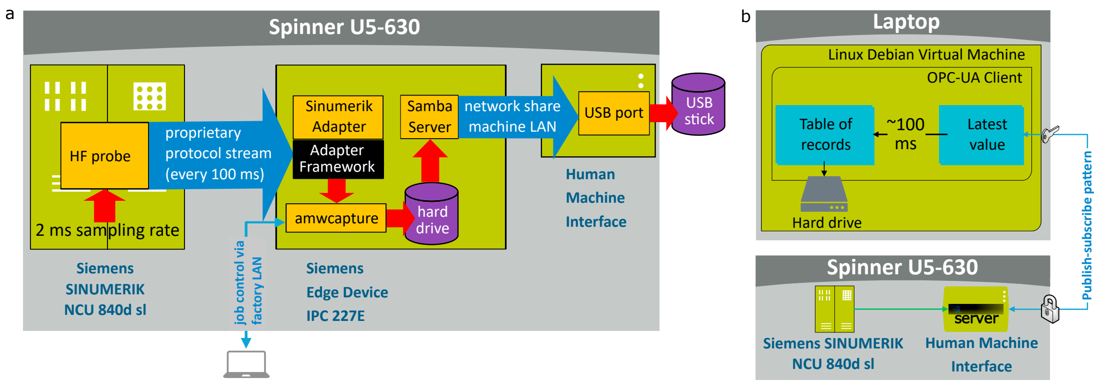

Fig. 2. (a) HFD capturing architecture; (b) LFD capturing architecture.

5.3. Drill data assessment

The measurement data of a single drilling is shown in Fig. 3b. The red lined progress of current in case of breakage shows major deviations compared to drills in idle mode (no contact to the work piece) respectively during a drilling

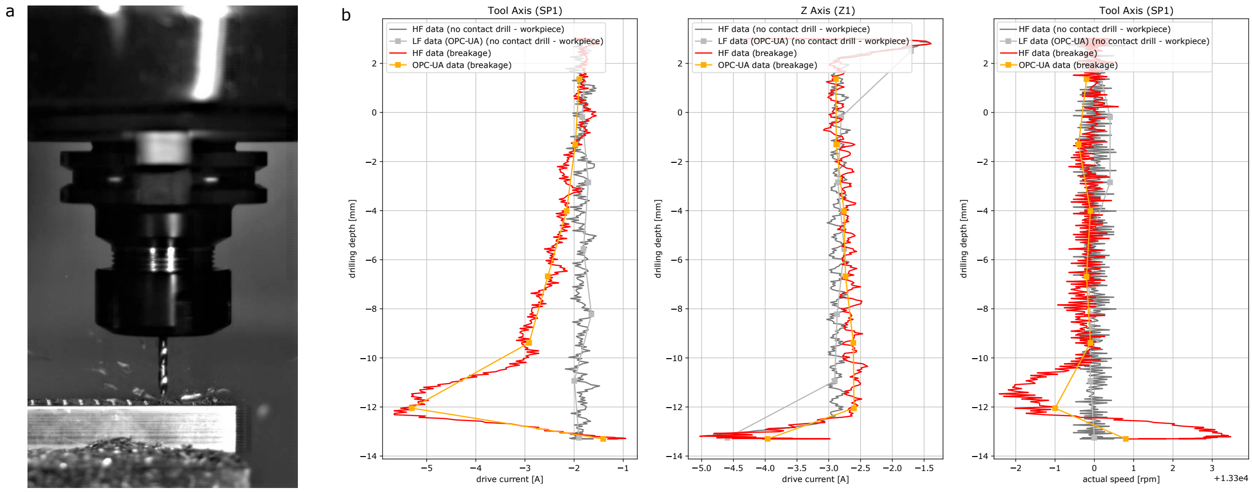

Fig. 3. (a) Drilling procedure; (b) Current and speed of single drillings.

process without breakage. Based on these results, current of the rotational z-axis (SP1) and current of the translational z-axis (Z1) are chosen as evaluation parameter. To determine the drilling depth at the time of breakage without insights into the drill hole a manual synchronization between camera frames and z-coordinates received from HFD enables high benefit. The initial contact between drill and work is set as starting point and detected by use of the video software “virtual dub”. Fig. 3b shows the coherence between current of SP1 and Z1 and the corresponding video frame. At the instance of breakage, current SP1 suddenly sinks, the drill breaks and the remaining part of the drill staggers. The effects described below always occur at constant feed. The drilling edge is getting dulled, less material is removed and thus the set speed of 13 300 rpm is undershot. The machine control tries to retain the set speed, and increases the current of SP1. The current of Z1 decreases since the drill pulls itself into the material. Thereby the cutting edge is getting duller, material removal decreases while current of SP1 increases leading to an overstressing of the drill which results in failure.

5.4. Machine Learning approaches for HFD

There is the idea of searching for indicators of anomalies to prevent tool breakage. For that reason, two different artificial intelligence approaches are used. LSTM (Long Short Term Memory) is a variant of recurrent neural networks for accurate prediction of future values for repetitive procedures [9,10]. In this case the main influencing parameter of LSTM is the forward and back-propagation from the time steps -10 to +10. The orange curves in Fig. 4 shows the prediction of values; the blue curves shows the real measurement values. To evaluate this result a benchmark with the Isolation Forest (IsFo) model is of interest [11]. IsFo is a very fast and robust outlier detection approach to classify values. In this case the main influencing parameter of IsFo is called “contamination” and it is defined as the ratio between the number of expected anomalies related to all measurement values in the training set. The higher the “contamination” the higher the anomalies. For detection, it is necessary to merge the individual data sets into a single dataset. Fig. 5 shows the identified anomalies and the anomaly density over the drilling depth. The isolation forest model was chosen because the decision tree calculation method is easier for understanding and interpretation than the neural network calculation method of LSTM. As consequence of the detection of anomalies, commonly countermeasures are needed. If anomalies are detected the anomaly density value is calculated. In case of excessing a given limit of anomaly density values, raw measurement data (HFD) is uploaded to the cloud. It is conceivable to develop a combined approach, which allows an anomaly detection based on the predicted values. Such a combinations contains first a prediction done via LSTM and secondly the detection of anomalies by using the isolation forest model on the predicted values.

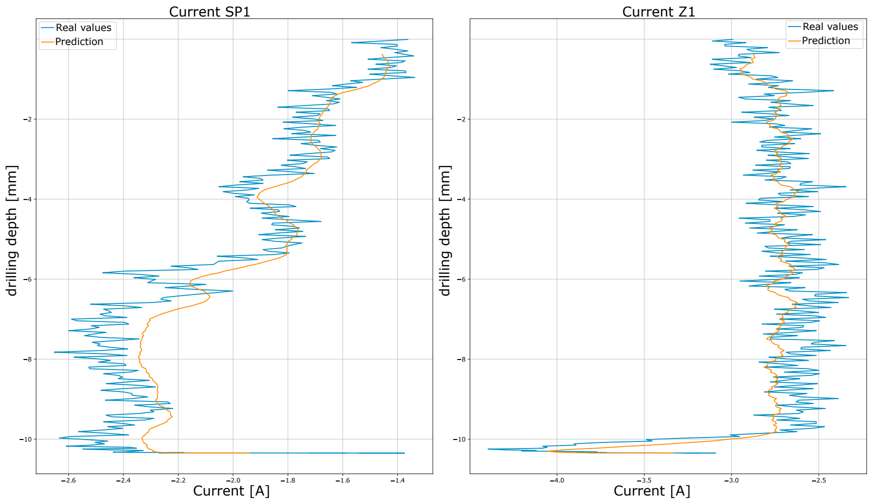

Fig. 4. Current prediction with LSTM (test dataset).

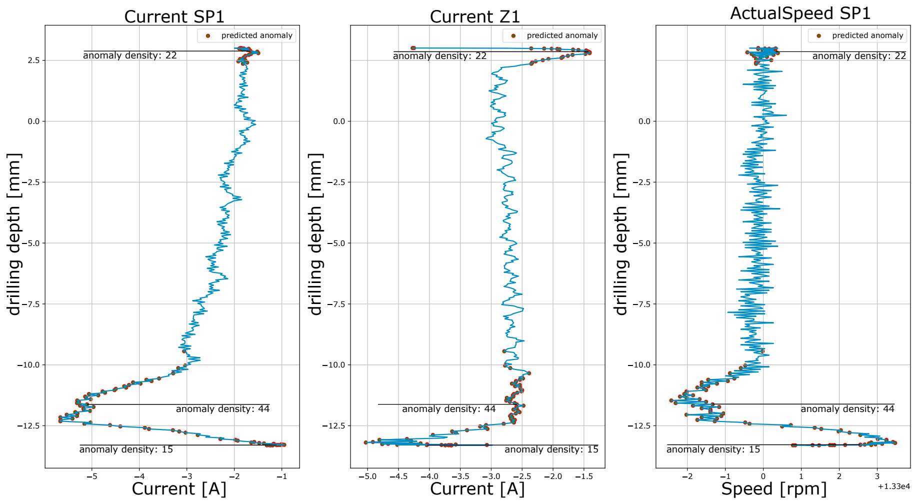

Fig. 5. Anomaly detection with isolation forest.

5.5. *Machine Learning approaches for LFD*

The amount of data based on the LFD capturing approach is too low for meaningful evaluation with the proposed machine learning approaches. Both experiments using LSTM and isolation forest have not yielded reliable results for accurate prediction nor detection of anomalies.

6. Edge App Development

The analyzed machine data is evaluated by means of the machine-learning model in the latest developed Edge App ”DADetection” (Drilling Anomaly Detection). If anomalies occur, they are sent to the MindSphere Cloud. For the software development, Siemens provides an Edge App Software Development Kit (SDK). The Edge Device runs an industrial OS based on Debian 9 with an execution environment for industrial apps. In order to make the Edge App available for the Edge Device it is uploaded via the MindSphere functionality “App Publishing”. It is ready for use on the Edge platform once the download and subsequent installation finishes by using another MindSphere functionality called “App Management”. Fig. 6b shows the data capturing from the HF probe and how upload data is sent.

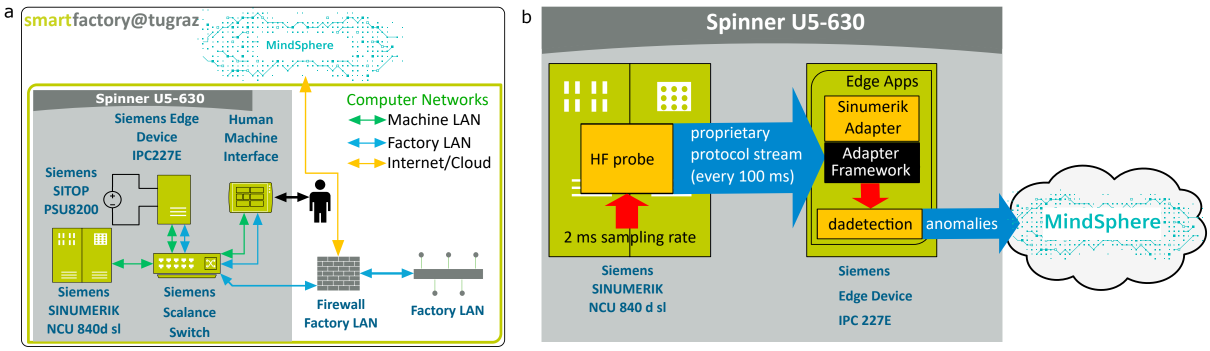

Fig. 6. (a) Edge Computing Network Architecture; (b) Edge App Architecture.

7. Conclusion

In this paper Edge Computing was shown as a strong method for getting more knowledge about the actual condition of a drilling tool while being in action. One of the most positive effects of edge computing are based on the fact that a huge amount of data is generated without the need of additional sensor installations and the reliable and secure exchange of data into the cloud. With such a data set and its computed results, the breakage of drill and other tools can be predicted and when applying additional control systems even prevented. Tool usages can be increased and tool costs can be cut down. A prerequisite of edge computing is a profound network knowledge for the alignment of data streams and the ongoing experience at the handling of data analytics and machine learning models.

8. Acknowledgements

The project smartfactory@tugraz is funded by the Austrian Ministry for Transport, Innovation and Technology and 19 industrial partners (see also: www.smartfactory.tugraz.at) and surveilled by the Austrian Research Promotion Agency FFG. The project itself runs by the Institute of Production Engineering at Graz University of Technology.

References

[1] W. Shi, J. Cao, Q. Zhang, Y. Li, L. Xu, Edge computing: Vision and challenges, IEEE Internet of Things Journal, 3 (5) (2016) 637–646.
[2] Y. Ai, M. Peng, K. Zhang, Edge computing technologies for Internet of Things: a primer, Digital Communications and Networks, 4 (2) (2018) 77 – 86.
[3] J. Pan, J. McElhannon, Future Edge Cloud and Edge Computing for Internet of Things Applications, IEEE Internet of Things Journal, 5 (1) (2018) 439–449.
[4] C. Esposito, A. Castiglione, F. Pop, K. R. Choo, Challenges of Connecting Edge and Cloud Computing: A Security and Forensic Perspective, IEEE Cloud Computing, 4 (2) (2017) 13–17.
[5] S. Trabesinger, R. Pichler, D. Schall, R. Gfrerer, Connectivity as a prior challenge in establishing CPPS on basis of heterogeneous IT-software environments, Procedia Manufacturing, 31 (2019) 370 – 376.
[6] S. A. Alabady, F. Al-Turjman, S. Din, A Novel Security Model for Cooperative Virtual Networks in the IoT Era, International Journal of Parallel Programming, (2018) 1 – 16.
[7] C. I. Noshi, J. J. Schubert, The Role of Machine Learning in Drilling Operations; A Review, Society of Petroleum Engineers, Pittsburgh (2018).
[8] S. Kehne, T. Berners, A. Epple, C. Brecher, Automatic system identification of forward feed drives in machine tools, Advances in Production Research: Proceedings of the 8th Congress of the German Academic Association for Production Technology (WGP), (2019) 144 – 152.
[9] R. C. Staudemeyer, E. R. Morris, Understanding LSTM – a tutorial into Long Short-Term Memory Recurrent Neural Networks, (2019).
[10] D. Park, S. Kim, Y. An, J.-Y. Jung, LiReD: A Light-Weight Real-Time Fault Detection System for Edge Computing Using LSTM Recurrent Neural Networks, Sensors, 18 (7) 2018.
[11] F. T. Liu, K. M. Ting, Z. Zhou, Isolation Forest, 2008 Eighth IEEE International Conference on Data Mining, (2008) 413-422.