HALFBACK Project: The Use of Machine Learning to Achieve High-Availability in Production

Christoph Reich[1] and Ahmed Samet[2]

[1] Furtwangen University of Applied Sciences
christoph.reich@hs-furtwangen.de
[2] INSA, Strasbourg, France
ahmed.samet@insa-strasbourg.fr

Abstract. The HALFBACK project's goal is to achieve a high-available production, mainly by predicting failure of a manufacturing machine and machine tool to avoid downtime, associated costs, and reputation loss.
In this paper two different approaches of machine learning prediction are described. First a pattern mining approach analysing condition events and second a neural network based approach. Further, the paper discusses the need for data pre-processing and ideas how to achieve high-availabilty in production.

1 Introduction

The unexpected failure of machines or tools has a direct impact on production availability (+6% increase in costs in 2015 according to the Association of German Machine Tool Builders (VDW)). This gives rise to risks in terms of product quality, profitability and competitiveness. The exact planning of a preventive maintenance is therefore an essential prerequisite for positively influencing quality and production.

The HALFBACK project extracts expert knowledge from sensor data of the production line in order to be able to detect defects and to detect them, and to implement optimized maintenance planning. In order to improve the availability of your own production without having to rely on cost-intensive reserve machines or other means of minimizing downtime, it is necessary to reduce production in part and in each case by to be able to outsource the production as required. For this purpose, an intelligent machine broker will be implemented, which will coordinate the and machinery. The HALFBACK project thus aims to improve the cross-border production process between SMEs. This makes it possible to realize the enormous potential for value creation, strengthens the the digitization competencies of companies, intensifies industrial cooperation and promotes the formation of Company networks in the Upper Rhine.

The aim of this paper is to focus on machine learning concepts, which have been used in the HALFBACK project in order to predict machine maintenance and quality maintenance to re-plan the production line to achieve high available smart production.

The paper is organized as follows: Section 1 outlines the HALFBACK project and its need for machine learning. After the Section 2 two machine learning based approaches are described for predictive maintenance (Section 3) and quality prediction (Section 4). Section 5 points out the importance of data pre-processing and Section 5 shortly explains how to support cross-boarder production. Section 7 concludes the paper.

2 Related Work

There have been a number of papers published using machine learning methods for predictive maintenance. Here is just a selection of some.

Mining from dataset to extract correlation is a task that has been well treated in literature [1]. However, it has been shown recently that sequential patterns are not sufficiently informative in several application fields such as network alarm [2] or analysis of human activity [2]. Therefore, the chronicle pattern model, that is an extension of sequential patterns, has been introduced [3]. In [4], Dousson and Duong made the foundation of what has been later known as chronicle mining. In [5], Cram et al. introduced the HCDA algorithm, to mine the complete set of chronicles. Finally, in [6], Dauxais et al. proposed a new approach to extract discriminant chronicles in to the context of pharmaco-epidemiology.

A typical approach is to build an IoT infrastructure and collect data from machines and use neural networks to build a forcast model, as Kanawaday and Sane [7], in their paper did, by modelling slitting machines by AutoRegressive Integrated Moving Average (ARIMA).

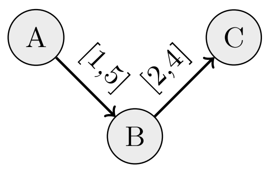
In the paper from Sezer et.al [8], they outline the base concepts, materials and methods used to develop an Industry 4.0 architecture focused on predictive maintenance, while relying on low-cost principles to be affordable by Small Manufacturing Enterprises. The result of this research work was a low-cost, easy-to-develop cyber-physical system architecture that measures the temperature and vibration variables of a machining process in a Haas CNC turning centre, while storing such data in the cloud where Recursive Partitioning and Regression Tree model technique is run for predicting the rejection of machined parts based on a quality threshold.

3 Pattern Mining for Failure Understanding

To optimise machines' performance, critical events should be anticipated. Predictive maintenance is based on this principle. It consists of collecting and analysing the data from industrial equipment. Then, an alert system learn from previous event sequences and prevent from imminent failures. Intelligent systems that allow this kind of maintenance are based on analysing collected signals, that are generally a set of timestamped events. For this aim, data mining techniques are particularly suited for this task, especially sequential data mining and frequent sequential pattern mining to extract failure cause from collected data. Moreover, patterns mining output could be difficult to read and interpret even for domain experts. A graph based and richer pattern exists that break this limit and is called *chronicle*. Chronicle are a kind of patterns that represents events related with time constraint within a same model.

Example 1. Assuming a sequential database that collect data from machine regularly. The graphical model below details a chronicle pattern extracted from the database of frequent events with their time constraint intervals.

Sequence Id	Events
1	(A,0), (B,5), (C,7)
2	(A,2), (B,3), (C,7)



In this work, we seek to develop an approach to mine information from machine data log. These extracted data are modelled as chronicles. Our contribution solves this problem and aims to answer two distinct questions, i.e. a) Is there a correlation between sensors data values and failure? b) How can we use temporal constraints between events, and therefore chronicles, to predict anomalies before they occur?

To answer these questions, we introduced a new approach, called CPM for *Chronicle mining for Predictive Maintenance*. Our interest in this kind of temporal pattern lies not only in predicting an event, but especially in the time interval in which that event will occur (in our case a machine failure). Like any knowledge discovery process, our approach starts with a pre-processing step, a mining step and a third step for the interpretation of extracted knowledge.

The CPM approach is validated through a set of experiments performed on the mining phase as well as the prediction phase. Experiments were achieved on synthetic data as well as in a real industrial data set. Figure 1 shows the developed CPM software for chronicle mining.

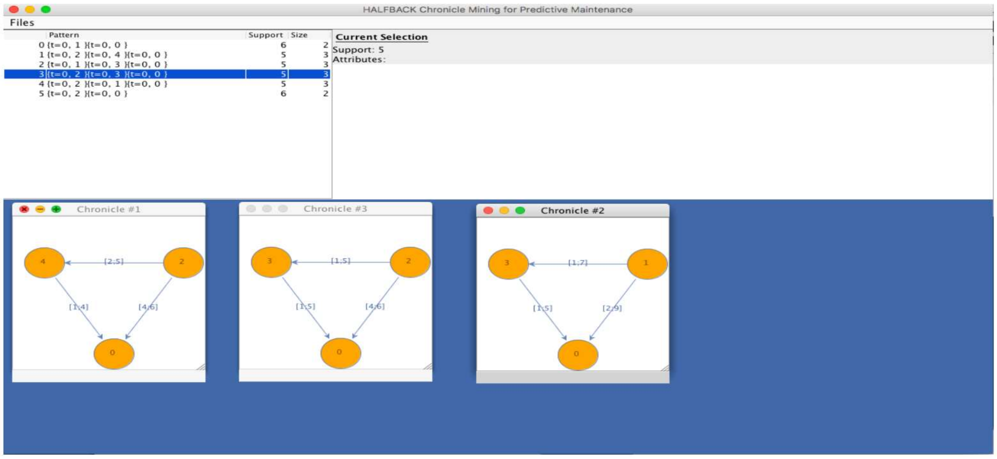


Fig. 1. CPM software

4 Predictive Maintenance and Quality Prediction with Neural Networks

Figure 2 shows the most important items to be considered, if you want to achieve high-availability for production. If one of these aspects are causing trouble the overall production will stutter. The approach of the HALFBACK project is to ensure high-availability

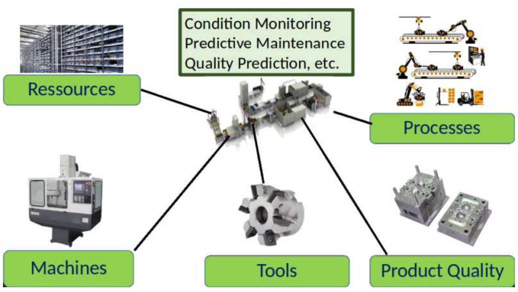


Fig. 2. Prediction in Production

manufacturing processes by forecasting failures of machines, tools, product quality losses, resource flow problems, etc. and through optimized and intelligent ways to plan maintenance at the right time, replace components in time, re-plan manufacturing processes and even plan production relocation to another company. This is to be achieved by collecting data on machines and tools using suitable sensors. In addition, information is collected from the manufacturing environment, the product itself, and the operator's expert knowledge. Big Data algorithms analyze the collected data in the cloud [9] to understand processes and learn from operators' experiences with the goal of avoiding machine damage, loss of quality or maintenance requirements in the future. to predict. This allows the company to act before the manufacturing process stops.

The area of Machine Learning includes different methods / technologies to enable a computer to make decisions based on data. The computer learns to draw conclusions about the correct result on the basis of training data, without a human being (expert) having to define fixed if-then rules. For maintenance prediction, a typical use case for using neural networks (NN) for modelling a multi classifier. The classification trains the NN model to assign the input vector x to class y. The classes are predefined before the training (in case of anomaly detection the classes could be e.g. "anomaly" and "no anomaly"). The need for neural network as a justified by Susto et.al [10] in Figure 3. In Figure 3 you see two-dimensional data space with orange circles (correct behaviour)

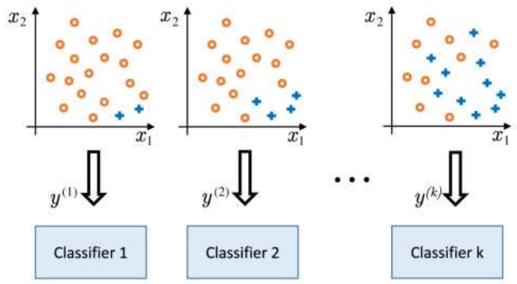


Fig. 3. Classifier a) one-dimensional b) two-dimensional c) multi-dimensional (see [10])

and blue plus (failure behaviour). It can easily be seen, that linear classifier is sufficient enough for a) and a non-linear for b) and a multi multi classifier for c), which can be realized by neural networks.

First results in the HALFBACK project have shown, that for predictive maintenance the vibration of a certain parts of the machine are important input values for a neural network. Bo Luo et.al [11] used a deep learning model to construct automatically select the impulse responses from the vibration signals to predict the next maintenance of a machine. A good start for training the NN for classifying the part which will have to be replaced during the maintenance phase are the machine parts, that historically have failed.

More often then failures are downtime because of quality loss during production, and therefore downtime caused from tool maintenance. In [12], Bai et al. compared feed forward neural networks, least squared support vector machines, deep restricted Boltzmann machines and stack autoencoders to predict quality in a manufacturing process. The dataset consisted of 19 process parameters, some are adjustable parameters and some non-adjustable, and one quality index in a range between zero and one. They trained different models via trial and error method to find the best fitting model for each architecture. Furthermore, they tried different sample sizes, 100 and 1000. It turned out that the deep restricted Boltzmann machines and stack autoencoders outperformed the other model architectures. They have also shown that the bigger the samples, the better the performance.

5 The Need of Data Pre-Processing

An important aspect is the pre-processing after the data has been collected from the machine. Data collected from various sources will contain noise, redundancy, and inconsistency and hence it is a waste of time and resources to to store such data. Analytical methods have requirements of data quality therefore, for proper data analysis per-processing data is important. The data has to be cleaned depending upon the kind of noise or artifacts present in it also depending on the kind of analysis that will be performed on the data. To do so a highly scalable infrastructure has been build for HALFABCK, as seen in Figure 4, provided in a cloud [13]. Only with high-quality data

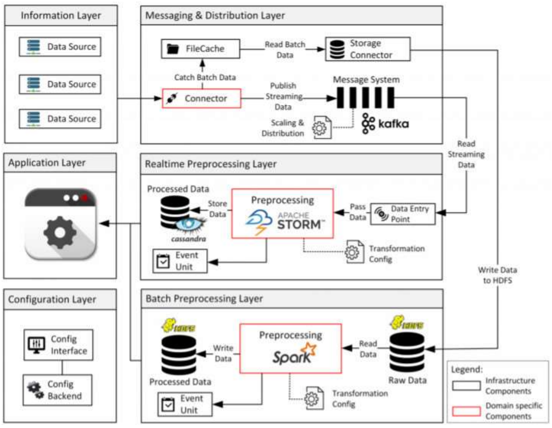


Fig. 4. Data Analysis and Modelling Infrastructure in the Cloud

high-quality models can be build.

6 High-Availability Factory by Cross-Boarder Production

In case the maintenance of a machine can not be planed without causing high cost, because of failed delivery times and therefore high penalty costs and reputation loss. A solution could be to shift the production to another factory. Prerequisites are to find a company, which has the same or an equivalent machine to overtake the production. Therefore a goal of the HALFBACK project is to describe a machine's static information (type of tool holder, etc.) and dynamic information (speed, etc.), called a virtual profile (footprint). To support the search for a suitable machine, the virtual profiles (footprints) of the machines are to be registered in the cloud with a "High Availability Machine Broker". The footprint of a machine contains the location of the machine, Machine availability, functional description, etc. The broker enables the machine to be used as a to be able to offer services to other companies, like "Machine as a Service". In case of unavoidable machine failure the HALFBACK software can use the "High Availability Machine Broker" to create an adequate search for a machine replacement and move production to another plant, as depicted in Figure 5.

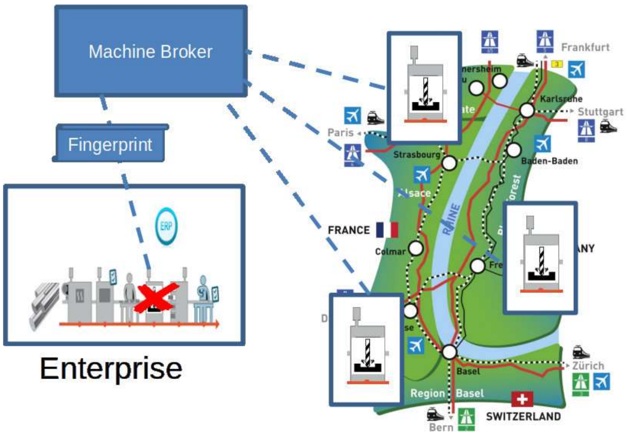


Fig. 5. Cross-Border Production

7 Conclusions

This paper discussed two machine learning approaches the *Chronicle mining for Predictive Maintenance* to analyse log events and predict the maintenance of a machine and the Neural Network approach for predicting the quality of a workpiece. Both approaches are used to plan actions to overcome the downtime of a machine. In order to avoid contractual penalties for late product delivery to the customer, the concept of Machine as a Service has been introduced. This can help the factory owner to shift the production to a factory near by.

References

1. Srikant, R., Agrawal, R.: Mining sequential patterns. In: Proceedings of the International Conference on Data Engineering, Taipei, Taiwan, March 6-10. (1995) 3–14
2. Mannila, H., Toivonen, H., Verkamo, A.I.: Discovery of frequent episodes in event sequences. Data Mining and Knowledge Discovery **1** (1997) 259—289
3. Dousson, C., Gaborit, P., Ghallab, M.: Situation recognition: Representation and algorithms. In: Proceedings of the International Joint Conference on Artificial Intelligence. Chambéry, France, August 28 - September 3. (1993) 166—-174
4. Dousson, C., Duong, T.V.: Discovering chronicles with numerical time constraints from alarm logs for monitoring dynamic systems. In: Proceedings of the International Joint Conference on Artificial Intelligence, San Francisco, CA, USA, July 31 - August 06. (1999) 620–626
5. Cram, D., Mathern, B., Mille, A.: A complete chronicle discovery approach: application to activity analysis. Expert Systems (5 2011) 321–346
6. Dauxais, Y., Guyet, T., Gross-Amblard, D., Happe, A.: Discriminant chronicles mining: Application to care pathways analytics. In: Proceedings of the Conference on Artificial Intelligence in Medicine, Vienna, Austria, June 21-24. (2017)
7. Kanawaday, A., Sane, A.: Machine learning for predictive maintenance of industrial machines using iot sensor data. In: 2017 8th IEEE International Conference on Software Engineering and Service Science (ICSESS). (Nov 2017) 87–90
8. Sezer, E., Romero, D., Guedea, F., Macchi, M., Emmanouilidis, C.: An industry 4.0-enabled low cost predictive maintenance approach for smes. In: 2018 IEEE International Conference on Engineering, Technology and Innovation (ICE/ITMC). (June 2018) 1–8
9. Reich, C.: Industry 4.0 and cloud computing. The Sixteenth International Conference on Networks: ICN 2017, April 23 - 27, 2017, Venice, Italy (2017)

10. Susto, G.A., Schirru, A., Pampuri, S., McLoone, S., Beghi, A.: Machine learning for predictive maintenance: A multiple classifier approach. IEEE Transactions on Industrial Informatics **11**(3) (June 2015) 812–820
11. Luo, B., Wang, H., Liu, H., Li, B., Peng, F.: Early fault detection of machine tools based on deep learning and dynamic identification. IEEE Transactions on Industrial Electronics **66**(1) (Jan 2019) 509–518
12. Bai, Y., Sun, Z., Deng, J., Li, L., Long, J., Li, C.: Manufacturing quality prediction using intelligent learning approaches: A comparative study. Sustainability **10** (12 2017) 85
13. Hölscher, D., Bayer, T., Ruf, P., Reich, C., Gut, F.: A big data quality preprocessing and domain analysis provisioner framework using cloud infrastructures. ALLDATA 2018: The Fourth International Conference on Big Data, Small Data, Linked Data and Open Data, April 22, 2018 to April 26, 2018 - Athens, Greece (2018) 53 – 58