STEPS AND CHALLENGES IN ANALYZING REAL SENSOR DATA FROM A PRODUCTIVE PRESS SHOP AND ITS VALUE FOR PREDICTIVE MAINTENANCE APPLICATION

Safa Evirgen[1] and Maylin Wartenberg[2]

[1]Volkswagen AG, Berliner Ring 2, 38426 Wolfsburg, Germany
[2]Hochschule Hannover, Recklinger Stadtweg 120,
30459 Hannover, Germany

ABSTRACT

This paper highlights the significance of AI-powered maintenance strategies in modern industry for operational optimization and reduced downtime. It emphasizes the crucial role of sensor data analysis in identifying anomalies and predicting failures. The research specifically examines sensor data from an automotive press shop, addressing questions related to data selection, collection challenges, and knowledge generation. By utilizing unsupervised learning on compressed air data from a press line, the study identifies patterns, anomalies, and correlations. The results offer insights into the potential for implementing an effective predictive maintenance strategy. Additionally, a systematic literature review underscores the importance of data analysis in production systems, particularly in the context of maintenance.

KEYWORDS

Predictive Maintenance, smart database, sensor data analytics, data science, production.

1. INTRODUCTION

In today's increasingly connected industrial landscape, AI-powered maintenance strategies of production facilities are gaining importance as companies strive to minimize downtime and ensure more efficient operations. A key component of these maintenance strategies is the use of sensor data to detect anomalies and predict potential failures[1]. In this paper, we focus on the analysis of sensor data from a production press shop of an automotive manufacturer. Essentially, the following research questions, the answers to which are structured according to the principle of the core process of organizational data processing as described by Wölfl et al. (2019) (see Figure1) are listed in detail below[2]:

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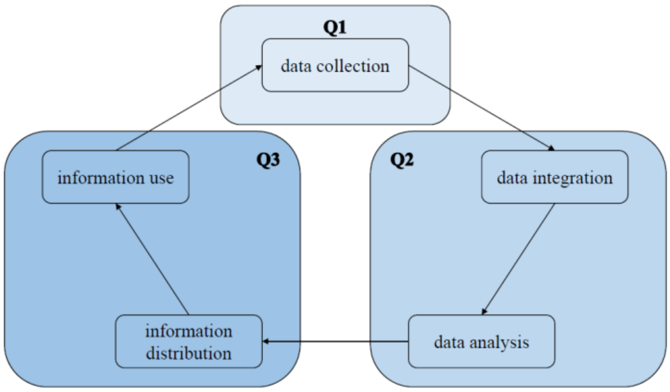

Figure 1. Research question structured based on core process of organizational data processing as described by Wölfl et al. (2019).

The press shop is a central part of the manufacturing process in the automotive industry. This is where car body parts are manufactured, formed and machined [3]. Through the use of various sensors, valuable information can be obtained about the condition of the machines and tools. This information can serve as the basis for implementing AI-supported maintenance strategies to avoid unplanned downtime and increase productivity [4]. The aim of this study is to propose an approach for handling and analyzing large volumes of productive data, specifically compressed air data from a press line, for predictive maintenance. The process involves data volume assessment, data selection, and the application of unsupervised learning techniques to identify data patterns, anomalies, and correlations. The results will determine the feasibility and effectiveness of a predictive maintenance system for the press shop. This research will assist companies in making informed decisions to enhance their predictive maintenance strategies and maximize the value of sensor data. The paper begins with a comprehensive literature review to underscore the topic's relevance and identify important prior works. It then delves into the specific case of compressed air data and presents the results. Additionally, it outlines the approach's applicability in a predictive maintenance strategy. Finally, the paper provides a summary of the findings and future research directions.

2. Literature Review – Data Analysis in Production Systems Related to Maintenance

Considering the subject of the paper, this chapter identifies and examines existing literature. The goal is to confirm the scientific relevance of the topic as well as to clarify the need for further investigation in the context of using data mining methods in relation to production data. Production data is narrowed down to production data in the context of maintenance. The procedure of the systematic literature research is mainly based on the systematics according to vom Brocke (2009) [5]. The search engines Google Scholar, IEEE Xplore and Science Direct were used for the search. The main search terms "maintenance", "production" and "data science" were linked by means of logical operators. In order not to distort the core content of the paper, the individual steps up to finding the results according to vom Brocke (2009) are not presented in detail. Instead, an overview of the procedure can be seen in Figure 2. According to this, the main search criteria are first used to search the search engines under consideration, as just described. In order to reduce the number of hits found to the essentials, duplicates are not considered, and filtering is done by year and type of literature. Subsequently, the abstract of the respective publication was screened before further filtering in the analysis phase. Specific search terms such as Condition Monitoring or Knowledge Based Maintenance were used. The remaining publications were then analyzed in more detail. The result of the analysis can be seen in Table 1. The literature was clustered into the main topics "Maintenance Strategy" and "Data Science". The "Maintenance Strategy" cluster is divided into the current trend strategies Condition Monitoring (CM), Predictive Maintenance (PM) and Knowledge Based Maintenance (KBM). The topic "Data Science" was considered with a wider spectrum. The main classification falls under Supervised Learning (S), Unsupervised Learning (US), Machine Learning (ML) as well as Deep Learning (DL). Further, the amount of data considered in the paper was separated into Database Small (DBS) and Database Large (DBL). Case studies in the papers with recorded data over multiple cycles and weeks, and/or a set of data points greater than 100,000 are assigned to DBL. Other-wise, or in cases where the amount of data is not precisely described in the papers, the assumption is made that small amounts of data were used in a case study. Thus, these papers are classified in DBS. In addition, the application domain in the considered papers was specifically added. Here, we distinguish between a case study on production data (CSPD), case study on real data (CSRD) and case study on simulation data (CSSD). It was also considered the point whether different data sources and data types were used in the papers. These were assigned to the Various Data Sources (VDS) category.

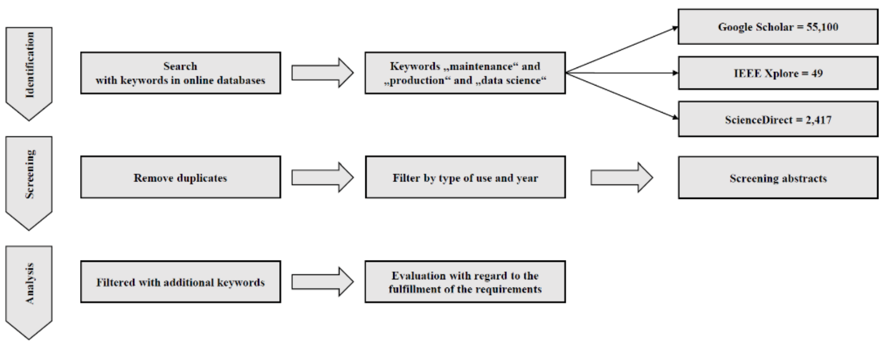

Figure 2. Outline of the stepwise approach to the literature search and filtering strategy.

In Figure 3, the authors explore maintenance strategies with a data analytics perspective. Among the 27 authors, 20 concentrate on applying data mining methods in maintenance. Out of these, 12 use production data, and 6 employ real data from outside production machines, as seen in the case study of Kammerer et al. (2020) involving the packaging industry [6]. 2 of the authors use simulated data in their case studies, such as Feng et al. (2013) [7]. Here, simulated data for gear acceleration is used to develop automatic time series models based on prediction errors and provide the proof of function. Moreover, it can be noted that 15 out of 20 authors use small data sets for the case studies. Only 5 of the papers considered use large data sets. For example, Han and Chi(2016) use about 37,000 data points and thus are attributed to DBS, while Shi et al. (2019) [8, 9] use about 32,500,000 with the considered vibration data and thus are attributed to DBL. If in addition the component VDS is considered, a total of 7 authors can be summarized, which were simultaneously attributed to DBS by means of which a case study was conducted and related to maintenance strategies. For example, Sang et al. (2021) provided a decision support model based on the use of various data sources. The data sources were mainly composed of machine, process and sensor data. These data are used to develop a LSTM model to estimate the RUL (remaining useful life). Real data from three robots and carrier plates with one bearing on the one hand and from CNC machines on the other hand were used. As a result, a sufficient statement about the planning of maintenance activities could be made, but Sang et al. emphasize the complexity of Industry 4.0. Accordingly, the aspects of domain knowledge and the limitation of the amount of data should be considered [10]. Tangible knowledge is needed especially for the KBM strategy. 8 out of 27 authors deal with this strategy, whereas only 5 authors use production data and obtain data from different sources at the same time. Furthermore, the data sets of the just mentioned authors are to be defined on DBS. This leads to the conclusion that in the field of KBM a compilation of larger amounts of data is difficult. However, it should also be noted that large data volumes are not synonymous with high data quality. Rather, the collection of, according to Compare et al. (2020), smart data is of great importance [11]. Zenkert et al. (2021) take the idea of knowledge utilization further in the context of manufacturing and highlight the importance of knowledge for manufacturing companies [12]. Complementing this, Tao et al. (2019), whose work is cited by Zenkert et al. (2021), emphasizes that the transformation of manufacturing companies from knowledge-based intelligent production to data-driven and knowledge-enabled smart production is in full swing [13]. However, challenges arise because knowledge, in particular, is often only available verbally or in documents. This complicates the integration into data-driven infrastructures that serve to build and use data analysis methods, such as supervised learning [12]. Consequently, the need for an intelligent methodology in handling large amounts of productive data (DBL) for the use of data analysis methods which lead to a predictive maintenance application results.

Table 1. Analysis of the publications.

	Maintenance Strategy			**Data Science**									
Author	**CM**	**PM**	**KBM**	**S**	**US**	**ML**	**DL**	**DBS**	**DBL**	**CSPD**	**CSRD**	**CSSD**	**VDS**
[14]	X	X	-	X	X	X	-	X	-	X	-	-	-
[15]	-	X	-	X	X	X	-	-	-	-	-	-	X
[6]	X	X	-	-	-	X	-	X	-	-	X	-	X
[16]	-	X	-	X	-	X	-	X	-	-	X	-	-
[17]	-	X	-	-	-	X	-	-	X	X	-	-	-
[11]	-	X	-	X	X	X	X	-	-	-	-	-	-
[18]	-	X	-	X	X	X	X	-	-	-	-	-	-
[10]	-	X	-	X	-	X	-	X	-	-	X	-	X
[19]	-	X	-	-	X	X	-	X	-	-	X	-	-
[12]	-	X	X	X	X	X	X	-	-	-	-	-	X
[20]	-	-	X	X	-	-	X	X	-	X	-	-	X
[21]	-	X	-	-	-	X	-	-	-	-	-	-	X
[22]	X	-	-	-	X	X	-	X	-	X	-	-	-
[7]	X	-	-	-	X	X	-	X	-	-	-	X	-
[23]	-	-	X	X	-	X	-	X	-	X	-	-	X
[9]	X	X	-	X	-	X	-	X	-	X	-	-	-
[24]	X	X	-	X	-	X	-	-	X	X	-	-	-
[25]	X	X	X	-	-	-	-	X	-	X	-	-	X
[26]	X	X	-	X	X	X	X	X	-	X	-	-	-
[27]	X	X	X	-	-	X	X	-	-	-	-	-	-
[28]	-	X	-	X	X	X	X	X	-	X	-	-	-
[8]	X	X	-	X	X	X	X	-	X	-	X	-	X
[29]	X	X	-	X	-	X	-	-	X	-	X	-	-
[30]	X	X	-	-	X	X	-	-	X	-	-	X	X
[31]	-	-	X	-	-	X	X	-	-	-	-	-	X
[32]	X	X	X	X	X	X	X	X	-	X	-	-	X
[33]	-	-	X	X	-	X	-	X	-	X	-	-	X

3. CASE STUDY – COMPRESSED AIR SYSTEM

A case study was conducted in an automotive manufacturer's press shop with a press line equipped with numerous sensors producing terabytes of data weekly. Due to storage limitations, historical sensor data isn't available, and data selection for predictive maintenance is crucial.

Predictive maintenance aims to reduce downtime by detecting component failures early. To achieve this, the root causes of unplanned downtimes must be identified. Asset and maintenance logbooks are valuable sources in this context, recording detailed information about downtime events. An analysis of these logbooks over ten years in the press shop revealed that many unplanned downtimes were linked to compressed air loss. This insight was derived from a detailed examination of textual data within technical documentation and confirmed through interviews with experienced employees. The paper's focus is on analyzing compressed air data to detect anomalies that may indicate such events, ultimately aiding in predictive maintenance. The press line in question is a transfer press responsible for automatically moving components between press stages using a bar as a carrier. Gripper arms with suction cups are used for handling components, and compressed air is created by a compressor. This air is accelerated and compressed by a special nozzle, creating a vacuum that helps lift components with the suction cups. Once a component reaches the next press stage, the vacuum is released, and the component is inserted into the press die. From a sensor data perspective, the process is illustrated in Figure 3. The data includes the compressed air flow sensor values over time and the crankshaft position of the press line. These two sets of data are then correlated, allowing the tracking of the forming process at each press line step. For instance, the graph on the right in Fig. 4 illustrates the relationship between compressed air flow sensor values and shaft positions, showing when components are picked up and released by the suction cups.

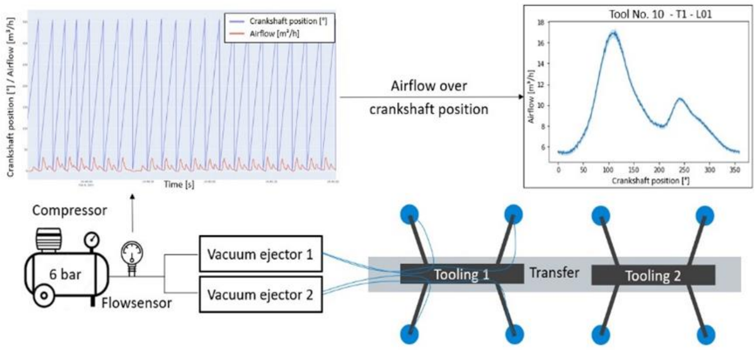

Figure 3. Transfer compressed air system.

3.1. Data Preparation

For the case study, data from 16 compressed air flow sensors, three total air consumption sensors, three compressor pressure sensors and a drive shaft sensor were recorded over a period of one month. In addition to the sensors, the tool number and crankshaft position, also called press position, were also recorded. This data is especially important to provide a reference to a specific tool and or press position. Following the CRISP-DM model, the ETL (Extract, Transform, Load) process is performed.

The data, recorded using Siemens AG's xTools software in XTS format, can only be read with xTools. To make it more accessible, the data is converted from XTS to CSV using an extended function in xTools. This conversion takes as long as the original recording time, e.g., 24 hours to convert 24 hours of data. To expedite this process, every tenth data point from the XTS file is converted, reducing the measurement frequency from 100 Hz to 10 Hz. This lower sampling rate is sufficient for analysis and mitigates Big Data issues while requiring less computing power due to the reduced data volume. The data for each sensor is stored in twelve-minute CSV packets, a result of xTools' data packet size limit setting. The case study generated a total of 81,675 CSV files, amounting to 243 GB. Each file includes a timestamp in the first column, formatted as "date:time.nanoseconds." A Python script was used to merge the CSV files by sensor and day.

To establish an initial understanding of the data and sensor data relationships, a preliminary visualization was generated using the first 3000 data points, as depicted in Figure 5. Here a cyclic characteristic of the sensor values L1-L16, as well as the press position becomes clear. The press position moves within the range of 0° and 360°, which can be attributed to the rotation of the crankshaft. From this, it can be deduced that a stroke occurs at the press line during one rotation. Likewise, a cyclical movement over timecan be seen in the compressed air flow data. In addition, it can be seen that the compressed air consumption first increases and then falls again in the course of the press position. When the respective sensor values are compared, a clear difference in the consumptions can be identified. For example, sensor 16, the front-of-line sensor, has a significantly higher consumption than all the other sensors. Between timestamp 1000 and 2100, there are no noticeable spikes in the data. This is because the press line is standing still and the crankshaft is not moving. The assumption can be made here that the compressed air consumption should decrease drastically. However, in Figure4, it can be seen that sensors L5, L9, L11 and L16 continue to have high consumption. This is an indication of leakage in the compressed air system. In addition, the tool number is constant, so no tool change has taken place in the period considered. In order to identify a dependency on the installed tool, the average amount of compressed air consumption for three different tools was considered for sensor L1. In Figure 5, a comparison of sensor L1 for tools 1, 9, and 69 reveals notable differences, which were confirmed by experts. These differences are due to varying press settings for each tool, specifying when a vacuum is generated on the suction cups at different press positions. As each press stage has unique settings, the sensors are independent of one another.

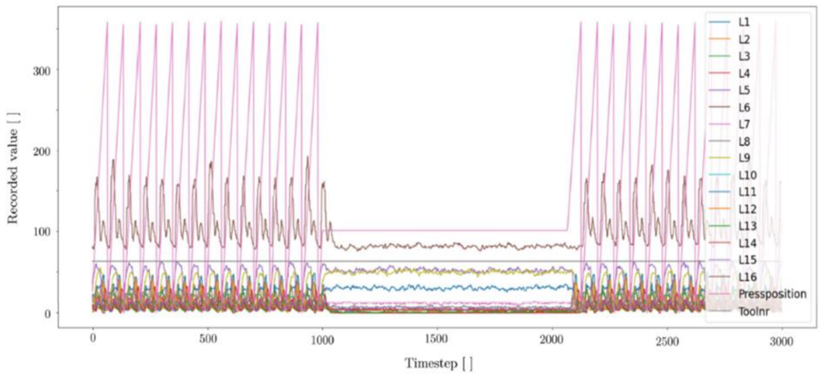

Figure 4. Plot all sensor values over time.

Therefore, the focus for further consideration in all data points was placed on the sensor L1 with the tool number 10. In addition, periods of planned downtime were filtered out of the data set, leaving a total of 1651488 data points. This data set is used for the further anomaly analysis. First, the data points were divided into the respective strokes so that the strokes of a press line can be compared with each other. The result is a data set in which each row represents a stroke and each column a press position. This results in a total of 26857 strokes for the data set under consideration. This results in a total of 26857 strokes for the data set under consideration.

3.2. Unsupervised Machine Learning

The prepared data is used in the following for the application of unsupervised machine learning models. The goal is to let the models learn patterns and correlations independently and thus identify outliers. One known algorithm is the DBSCAN (Density-Based Spatial Clustering of

Applications with Noise). This works density-based and has the ability to detect multiple clusters, where noise points are returned separately. In the following, we consider the application of DBSCAN to a time series and to a scatter plot, using DBSCAN from the scikit-learn library. The algorithm assigns the label "-1" to all data points that cannot be assigned to a cluster. Thus, these data points can be identified as outliers and the time of occurrence can be determined. For the application on a time series, the result can be seen in Figure5.

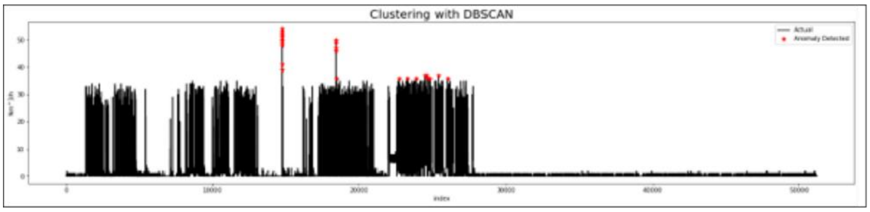

Figure 5. Clustering with DBSCAN.

Since there is a correlation between the compressed air values of a sensor and the press position, density-based clustering was further performed using DBSCAN algorithm for a scatter plot consisting of the compressed air values of a sensor and the press position. To apply the algorithm, several data preparation steps are required first. As a first step, unneeded columns are removed from the data frame so that it only consists of the columns "Press position" and "Sensor value", as well as "Datetime" as an index column. The data is then normalized using min-max normalization in order to be able to use uniform parameters. After this data preparation, the actual algorithm is performed. The algorithm forms clusters of points that are close together. Points that cannot be assigned to a cluster are marked as outliers. Figure6 shows that the algorithm can already identify the outliers clearly without perfectly optimized parameters. However, the use of the results to create added value for production needs to be discussed in more detail.

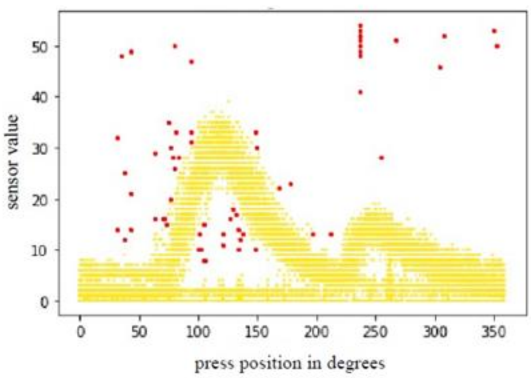

Figure 6. Clustering with DBSCAN on a scatter plot.

3.3. Predictive Maintenance Approach

The analysis reveals clear anomalies in the press rotation curve, raising the question of how to apply this information in a predictive maintenance strategy. For predictive maintenance to predict possible defects or sudden shutdowns, the analysis should signal potential damage to production machinery. The unsupervised learning analysis established a pattern using historical data and identified outliers in the same time frame. The next step is realtime monitoring of each press cycle, but manual monitoring of every cycle is impractical, and setting static alarm limits for outliers is unreliable. To address these issues, supervised learning models, developed with domain experts, can be employed to assign real-world states to outliers based on sensor data. However, this approach requires substantial effort to gather domain knowledge through interviews or text evaluation. This use case provides valuable insight for future research into AI-supported maintenance strategies.To fully implement a holistic predictive maintenance strategy, the ability to predict damage before it occurs is essential. This necessitates integrating machine knowledge, sensor data, and specialist empirical values. In essence, robust damage detection on machines requires a solid link between data analysis and domain expertise, and standalone anomaly detection in sensor data alone is not sufficient.

4. CONCLUSIONS

In conclusion, this paper has provided comprehensive guidelines for analyzing sensor data from a productive press shop in order to determine its value for a predictive maintenance database. The research questions addressed in this study revolved around the selection of sensor data, challenges in data collection and analysis, and the creation of conditions to generate knowledge from the data analyses. The analysis focused on sensor data from a production press shop in the automotive industry, with the goal of supporting AI-powered maintenance strategies to minimize downtime and increase productivity. Various data analysis techniques, particularly unsu-pervised learning, were employed to identify patterns, anomalies, and correlations in the collected compressed air data from a press line. By evaluating the results of the analysis, conclusions can be drawn regarding the feasibility and effectiveness of a predictive maintenance strategy for the press shop. The literature review conducted as part of this research highlighted the relevance of data analysis in production systems related to maintenance. It revealed the application of data mining methods in the context of maintenance strategies, including CM, PM and KBM. The review also emphasized the importance of knowledge utilization and data-driven infrastructures for effective data analysis in manufacturing companies. The case study on the compressed air system of a press line demonstrated the practical implementation of the research approach. By analyzing asset and maintenance logbooks, it was determined that a significant number of unplanned downtimes were caused by compressed air loss. This finding guided the analysis of the compressed air data, further validating the relevance of the study. The DBSCAN provided acceptable results for outlier analysis, but it didn't fully meet predictive maintenance requirements. Nevertheless, this work offers valuable insights for sensor data analysis in a press shop. The findings can aid companies in making informed decisions about maintenance strategies and maximizing sensor data potential. As Industry 4.0 evolves, future work should address the integration of knowledge and data-driven infrastructures, key challenges in this field.

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AUTHORS

M.Sc. Safa Evirgen, In his current position, he works as IT Service Manager in Volkswagen AG's IT department at the Wolfsburg plant, focusing on increasing IT security in production and standardizing processes. This position was followed by several years in the press shop, where he mainly managed IT and digitalization projects, including a project with the aim of implementing predictive maintenance in the press shop. His academic career began with a bachelor's and master's degree in industrial engineering at TU Dortmund University, including a semester abroad at California State University Long Beach. His doctorate began with a position as a doctoral student at Volkswagen AG in the Wolfsburg press shop with the aim of designing an intelligent data pipeline on which data mining methods can be applied with the aim of implementing a prescriptive maintenance strategy in production.

Prof. Dr. Maylin Wartenberg, Professor of business informatics with a focus on data science at Hanover University of Applied Sciences and Arts since 2018. Her research interests cover various topics in the field of data analytics and its interaction with computer-aided simulation, with a particular focus on sustainable mobility and logistics (see www.das-hub.de). In addition, she gives (popular) scientific lectures in the field of artificial intelligence. In teaching, she is characterized by the use of innovative concepts and the testing of new formats. Since 2023, she has been a member of the board of the Institute for Applied Data Science at Hannover University of Applied Sciences and Arts, Data|H. Her academic career led her to a degree and doctorate in mathematics at the TU Braunschweig. Prior to her position at Hanover University of Applied Sciences and Arts, she gained almost 10 years of professional experience at the Volkswagen Group, at VW Financial Services. There she held various positions, from system analyst to project and team leader to sub-department head.