Predictive Maintenance in the Context of Service

A State-of-the-Art Analysis of Predictive Models and the Role of Social Media Data in this Context

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Abstract: The aim of this study is to identify existing Predictive Maintenance methods in the context of service and the role of Social Media data in this context. With the help of a Systematic Literature Review eleven researches on notable Predictive Maintenance methods are identified and classified according to their focus, data sources, key challenges, and assets. It can be revealed that existing methods use different Prediction technologies and are mainly focused on industries with highly critical products. Existing methods provide value for B2B and B2C as well as products and services. Moreover, the majority is using heterogenous data that was generated automatically. However, it can be perceived that the consideration of Social Media data offers benefits for Prediction methods through identifying and using personal user data, the current usage is rare and only in the B2C sector recognizable. Thus, this research shows a gap in current literature as no universal Predictive Maintenance solution is available, that enables organizations to enhance their services by using the full potential of Social Media. Thus, future research needs to focus on the integration of Social Media data in Prediction methods for the B2C sector. With this it is deeply interesting how Social Media data has to be gathered and processed and if existing Predictive algorithms can be extended by Social Media data.

1 INTRODUCTION

Today successful companies do not only sell excellent products, they rather offer an overall service to customers. This service covers the customer support along the whole product lifecycle and it already starts with the idea of a product. Due to new trends like Predictive Maintenance, Digital Transformation, IoT and Big Data, companies do have a lot of opportunities. Especially the application of Predictive Maintenance technologies helps companies to detect product failures and customer dissatisfaction in an early stage. Thus, they are able to act proactively, which leads to cost savings, the reduction of product downtimes and an enhanced customer service.

An essential part of Predictive Maintenance methods and analysis consists of the collected and analyzed amount of data. A lot of companies do not only focus on the ongoing collection of new data, but the use and analyses of already collected and stored data is seen as equally important. The developments in the information technology enable companies to analyze data of different quantity, quality and format and as a result economic value of this data increases (Stockinger & Stadelmann, 2014, pp. 470–471). Generally, the data basis can be separated in homogenous (same data e.g. only log-data) and heterogenous data (different data e.g. log-data and sensor data).

With the emergence and increasing use of Social Media networks customer or user share a lot of personal information that had not been available before. For companies the shared information about products and services in Social Media represents a new data source. The Social Media data consists of highly specific information to single individuals as well as to products and services.

This new data offers possibilities to enhance Predictive methods through extending the data sources and increasing the data quality with highly customer specific data. Especially in the area of customer services companies might have huge potentials to improve profitability, customer satisfaction, product satisfaction and lifetime of the

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products and thus, enhancing their customer services through applying Prediction methods and inlcuding highly customer specific Social Media data (Olson & Wu, 2017, pp. 2–6).

Thus, this paper aims in providing a State-of-the-Art analysis of existing Predictive Maintenance methods with focus on the industries they are used in and whether Social Media data is already considered.

First the research method is outlined through presenting the research questions as well as the research strategy. Second, the collected data is presented by providing an overview of the existing Predictive methods and approaches and their main features. In the subsequent discussion section, the methods are first classified and then key findings are presented by referring back to the research questions. Finally the main aspects are summarized in a conclusion section and need for future research is stated.

2 RESEARCH METHOD

2.1 Aim and Research Questions

The aim of this study is to identify existing Predictive Maintenance methods in a service context, and the role of Social Media data within these approaches.

To guide the ongoing literature review a series of research questions have been developped:

1. Which basic approaches are using existing Predictive Maintenance methods? To be more specific, in which company sectors are they used?
2. Are the existing approaches focused on products or services and do they provide value for B2B or B2C businesses?
3. Which data basis and data format is the individual Predictive Maintenance method using? Are existing approaches already using Social Media data?
4. What are the challenges existing methods are facing?
5. Which assets can be extracted from the existing methods?

2.2 Research Strategy

A research strategy for this study had been defined, that followed a Systematic Literature Review procedure. Thus, the relevant data sources, time frame and keywords for the research had been defined in advance.

Initially a broad selection of databases for covering diverse publications (e.g. journal articles, conference proceedings and books) had been selected and the search included the data sources IEEE, ACM and JSTOR along with more traditional library cataloguing systems. In addition, an Internet search was conducted following a similar process for getting a complete picture of the research area.

Moreover, keywords had been identified, that were directly connected with Predictive Maintenance (e.g. Predictive Analytic, Predictive Model, Predictive Method). Many of these keywords had been combined with ‘Service’, ‘Social’, and ‘Social Media’ in order to ensure their relevance for this study. The set of keywords was then adjusted after having discovered relevant articles.

Furthermore, this study focused on literature published in the last three years.

A large number of articles could be discovered by browsing through the chosen databases, using the keywords and considering the selected time period. In a further analysis step, duplicates had been removed and the relevance of the single articles to this study had been checked. The abstracts of the remaining articles had been screened and appropriate publications had been fully read. Initially the research identified about 100 articles, reports and books. This had been carefully filtered to determine eleven publications, that represent Predictive Maintenance methods directly relevant to the research enquiry.

It is the analysis of these articles that forms the basis of the findings in this paper.

3 EXISTING METHODS AND APPROACHES

There has been publications of researches on Predictive Maitenance since 1986. With the digital transformation Predictive Maintenance gained increased attention from researchers. Thus, there is a significant amount of publications up from 2014 and they mainly originate in industry nations like USA and states of the EU. Based on the researches done in this area, a general understanding and definitions of the relevant terms has been established.

Thus, Predictive Maintenance can be defined as a technique which helps to predict potential defects and to plan maintenance intervals (Mobley, 2002, pp. 4–6). Predictive Maintenance does not only involve the software component - the algorithm -, it rather consists of several components (Microsoft Corporation, 2017). Important components are the IT infrastructure, the used sensors for data mining, the data itself, the availability of the data, the error-proneness, humans as well as laws and guidelines (Hashemian & Bean, 2011). Predictive Maintenance refers to the idea or procedure that aims in predicting maintenance activities (Rault & Baskiotis, 1986). Predictive Modelling is a collection of methods to analyze and to interpret data with the aim of deriving predictions. These predictions are not statements about the future, but about the probability that a specific case will happen in a defined timeframe (Gartner, 2017a; OnPage.org GmbH, 2017). Predictive Analytics refers to the analysis of data, that does not represent a prediction of the future, but rather makes a statement about the best possible calculated probability of a case (Gartner, 2017b; Olson & Wu, 2017, pp. 5–6).

During the literature review eleven researches about specific Predictive Maintenance approaches with relevance to this study could be identified. These existing methods vary in the industry they are focused on and are using different technical approaches and data. The table below summarizes main features of each method by outlining their industry and focus, giving a short description about their functionality, analyzing the data sources as well as clarifying if the method has already been validated empirically.

Table 1: Existing methods and approaches in the field of Predictive Maintenance part 1.

Method	Industry/Focus	Description	Data sources	Validation
1. Log based maintenance (Sipos, Fradkin, Moerchen, & Wang, 2014)	B2B; Medical industry; Focus on products.	Existing log data of the components as well as information from the Service Center is used for Predictive Maintenance with the aim to reduce the downtime caused by defects or to reduce maintenance. Preparation of big Logfiles with heavily unstructured text. Definition of a nomenclature for the logfiles to process the data in a most efficient way.	Heterogenous: Log data (which is itself purely homogenous text data) and Service Center data.	Used for several months on a part of the device fleet. 12 out of 31 failures could have been detected in a one-week prediction timeframe.
2. Bike Sharing System (Yang et al., 2016)	B2C; Transportation industry; Focus on services.	The method aims in calculating and predicting the optimized travel time, as well as the availability of target stations and the optimized allocation of the bicycles' parking stations. A huge amount of data, fix defined parameters (47) and weather data is included, as it has a big impact on the behavior of the user.	Heterogenous: Geodata, weather data, system data.	Tested with a data set from the city of Hangzhou, China and New York City, U.S with the same parameters and settings. Same performance results of both data sets.
3. Optimizing Life Cycle Cost (Nichenametla, Nandipati, & Waghmare, 2017)	B2B; Energy industry; Focus on products.	Data from the whole product lifecycle of Turbine blades (wind turbine) is used to enhance service (Maintenance) and to reach optimized maintenance costs. All available data of the crucial components are used as input data for the Predictive Maintenance method.	Heterogenous: Data from the whole product lifecycle as well as additional data from suppliers and manufactures.	Successful implementation for a windfarm with 300 turbine blades. In future, the operating costs shall be used as an additional parameter.
4. Smart Asset Management (Osladil & Kozubík, 2015)	B2B; Energy industry; Focus on products.	Method uses data about the raw material (coal) and whether data for being able to optimize the burning of coal through reducing exhaust gases and thus, reducing maintenance work during coke production. There is a static number of parameters that help to flexibly adjust the iterative approach.	Heterogenous: Sensor data, weather data, raw material data.	This Predictive Maintenance method was tested with sample data of a single power plant in Czech.
5. Analyzing Healthcare Big Data (Sahoo, Mohapatra, & Wu, 2016)	B2C; Medical industry; Focus on services.	Method aims in making statements about future health by grouping patients (high risk, risk). MapReduce and Intra/ Inter Data Analysis is used to make the best possible statements. Sensor data (ECG, measured values) is linked to data gained from reports (hand written). Through the development of a clear language the analytical procedure can work as efficient as possible.	Heterogenous: Data from different sensors and machines, hand written notes and reports. Very large amounts of data.	Simulation of the method based on publicly available data from clinics in Cleveland and Hungary. Data for 100 patients were evaluated.

Table 2: Existing methods and approaches in the field of Predictive Maintenance part 2.

Method	**Industry/Focus**	**Description**	**Data sources**	**Validation**
6. Predictive Analytics for Enhancing Travel time Pedestrian Mode (Amirian, Basiri, & Morley, 2016)	B2C; Navigation industry; Focus on services.	Method for improving a Navigation service (pedestrian mode) through calculating the duration for a particular route. The aim is to increase the accuracy of the forecast by taking additional data into account. Use of regression models and learning methods of the algorithms (e.g. how fast the user usually runs).	Heterogeneous: Personal data, weather data, geo data, 3rd party application data, map data.	This Predictive Maintenance method was performed with 39 test subjects. The test subjects were located on 48 different routes, which were used at least five times.
7. A Social-Network optimized taxi service (Zhang, Dong, Ota, & Guo, 2016)	B2C; Transportation industry; Focus on services.	Method aims in filling a taxi in the best possible way with people who have a relationship with each other (e. g. by gender to resolve conflicts). The approach is based on a heuristic algorithm to find the lowest cost for each passenger based on the length of the routes and the customers themselves. Linking data from social networks (e.g. relationships between users) with data from 3rd party applications.	Heterogenous: Social Media relationship data, map data, 3rd party application data.	The method was applied to 300 test subjects in Hokkaido, Japan.
8. Avionic Maintenance Ontology based (Palacios et al., 2016)	B2B; Avionic industry; Focus on services.	Method aims in identifying a cause and effect relationship for taking countermeasures and preventing product failure. Ontological approach, meaning of different language terms that mean the same. Separation of resources (physical item) and services (a function in the aircraft) and their analysis for Predictive Maintenance.	Heterogeneous: Hand-written reports, manuals, XML, sensor data.	Manual validation is possible, no more detailed description of the performed tests.
9. A universal sensor data platform modelled for real-time asset condition surveillance and big data analytics for railway systems (Lee & Tso, 2016)	B2B; Transportation industry; Focus on services.	IoT approach to monitor critical parts of a train as well as to minimize downtime and to better plan maintenance. Placement of the sensors on the right components with additional analysis and sending of data in real time.	Heterogeneous: Sensor data from different components of the train.	No more detailed description of the validation.
10. A Pro-active and Dynamic Prediction Assistance Using BaranC Framework (Hashemi & Herbert, 2016)	B2C; Software industry; Focus on services.	A framework to predict the next user interaction (Next App Prediction Service). Dynamic application which is divided into two categories: Representational (Location and Time) and Interactional (Clicks and Use). The user has full control over the data collected and shared by the BaranC framework.	Heterogeneous: User interactions on the smartphone, geodata, time data, smartphone specific data (network connection, prepaid credit, etc.).	Validation of the Predictive model with six test users. The test users used about 30% of the predicted apps in a 2-month trial period and the service received a predominantly positive feedback.
11. Social Media analysis on evaluating organizational performance: a railway service management context (Yang & Anwar, 2016)	B2C; Transportation industry; Focus on services.	Methods aims in analyzing the influence of Social Media on train traffic in NSW/AUS. Evaluation of tweets to filter and measure the performance of trains and services by five categories (reliability, safety, security, compactness, comfort and convenience). The Social Media channels are used to contact users and to publish information. Analytical framework consists of three modules: Data Collection, Feature Generation, Machine Learning.	Homogenous: Social Media data (Twitter).	31,008 tweets from 9,428 different users were used to validate the method.

4 DISCUSSION

4.1 Classification of the Individual Approaches

There are several works available which mention key parameters of Predictive methods.

Each Predictive method is facing different challenges and different factors for analyzation, prediction and visualization need to be considered (Chowdhury & Akram, 2011). Thus, the clear description of the key challenges of the methods is important (Chandola, Banerjee, & Kumar, 2009).

Rio uses a classification to describe Maintenance methods with the help of different parameters and asset attributes (Rio, 2017). According to Chandola the data has to be categorized, as data is one of the main components of Predictive methods (Chandola et al., 2009, pp. 6–7; Han & Kamber, 2008, pp. 6–15). Moreover, Haarman mentions the more data of different sources is available, the better the prediction can be done and by using available technology, as data mining, machine learning or analytics, the maturity level of a specific Predictive method increases (Haarman, Mulders, & Vassiliadis, 2017, pp. 4–9).

Thus, in order to gain a better overview of the individual methods and for being able to compare them, they had been classified along the following parameters:

- **'Focus of the Method':** This parameter will help to see, if the existing methods are more focused on B2C or B2B and whether they provide value for products or services.
- **'Data Source and Data Creation':** For this research enquiry it is especially interesting to see whether the approaches link different data formats and if they are already using Social Media data. Furthermore, it is analyzed, if the methods use exclusively automatically generated data or a combination of automatically and specifically (manually) generated data.
- **'Challenges':** The main challenges, that could be detected during the development of the method and the evaluation of the methods, are pointed out. This will help to derive important aspects, that future algorithms focused on Predictive Maintenance should consider.
- **'Assets':** Here the benefits and assets of the specific approaches are highlighted. This is especially interesting, as these assets might be applied to different sectors and industries.

The following table provides a simplified overview of the classification of the methods:

Table 3: Classification of Predictive Maintenance methods part 1.

Method	Focus	Data Source		Data Creation	Challenges	Assets
		Linking of different	Social Media			
1. Log based maintenance	B2B; Product	X		Automatically	Inclusion of the data and information from the Service Center into the nomenclature.	The success of a Predictive Analytics method must be measured from a technical and business point of view. This results in different requirements and KPI's.
2. Bike Sharing System	B2C; Service	X		Automatically	Attention should be paid to unforeseen behaviors of the users. What happens to the prediction if a station is overbooked?	The prediction can be hit in a more exact way with the help of the huge amount of data and the fix parameters.
3. Optimizing Life Cycle Cost	B2B; Product	X		Automatically	It is important to detect and reduce the error of measurements of third party data. To achieve this a Pre-processing and Data Reduction step is included in the method.	Through the consideration of the complete product lifecycle it can be detected, if the failure cause lies in the production step. This might have an impact on a defect or downtime of the wind turbine.

Table 4: Classification of Predictive Maintenance methods part 2.

Method	Focus	Data Source: Linking of different	Data Source: Social Media	Data Creation	Challenges	Assets
4. Smart Asset Management	B2B; Product	X		Automatically	Legal requirements for maintenance timeframes cannot be modified or extended.	The use of an iterative process in the clean-up of the parameters and the data provide the possibility of an evolving analytic method.
5. Analyzing Healthcare	B2C; Service	X		Automatically & Specifically	Due to the use of highly critical personal data, legal protection is important (agreement, anonymization).	Merging of data generated by machine and human hand. Processing of large amounts of data.
6. Predictive Analytics for Enhancing Travel Time Pedestrian Mode	B2C; Service	X	(X)	Automatically & Specifically	Legal protection is important since critical personal data is used (agreement, anonymization).	The more personal data is used, the more accurate the prediction can be.
7. A Social-Network optimized taxi service	B2C; Service	X	X	Automatically & Specifically	The more precise the personal data is, the better the results can be obtained between the users of a specific taxi.	Linking data from social networks with data from third-party systems and automatically generated data.
8. Avionics Maintenance Ontology based	B2B; Service	X		Automatically & Specifically	Redundant data must be filtered and cleaned.	Suggestion system with a strong focus on real-time data to provide the best possible Predictive Maintenance.
9. A universal sensor data platform	B2B; Service	X		Automatically	Identification of sources of interference during data evaluation (automatic recognition of intermediate stops at train stations).	Universal sensor data platform. The detection of component states and planning of maintenance.
10. A Pro-active and Dynamic Prediction Assistance	B2C; Service	X		Automatically & Specifically	A challenge is the influence of the human psyche, especially changes in user decisions based on suggestions.	The learning algorithm is based on heterogeneous data that predicts the next app to be used.
11. Social Media Analysis	B2C; Service	X	X	Automatically & Specifically	The challenge lies in filtering the tweets through inclusions and exclusions.	The approach tries to find out what users think about the train company. The train company can improve its service and respond directly to user criticism.

4.2 Addressing Research Questions and Key Findings

Based on the findings of the literature review and the classification of the relevant approaches, the research questions stated in the beginning are addressed and key findings are outlined.

Referring to Research Question 1, it can be concluded that there is not one single universal technical solution available that is best suited for Predictive Maintenance. The analyzed methods have selected different data mining technologies depending on their needs and industries. Overall, all methods attempt to derive patterns and connections from the existing data in order to use them for maintenance and Predictive services. Especially for industries with highly critical products and services, like aerospace and medical products and services, Predictive methods have already been developed and applied. Highly critical refers to the direct influence on humans and their well-being.

Predictive methods have either been developed for B2C or B2B industries and moreover, there is no clear tendency regarding their orientation towards product-specific solutions or services. There are methods with product- or service-orientation. Thus, referring to Research Question 2 the methods provide value for B2B and B2C as well as products and services.

Regarding the data base (Research Question 3) it can be derived, that for the majority of the evaluated methods, heterogeneous data that was generated automatically, represents the data base. Nevertheless, some methods already merge data which is generated by humans, e.g. medical reports (see method 5) and thus, involve subjective aspects. Three approaches already use Social Media data for their predictions. This data includes information about relations, posts, tweets, comments, discussions, statuses and reactions. Only one approach (see method 7) uses data from social networks and combine it with data from other sources.

One of the major challenges (Research Question 4) refers to legal aspects. It is important that the companies inform the customers about their data collection and make clear what kind of data is collected and in which way. As in Europe the users are quite skeptical about data collection (TNS Infratest, 2016), this challenge is an important success factor of a Predictive method (see method 4, 5 and 6). Moreover, user's personal data highly contributes to the quality and accuracy of the predictions. In general, the more data is available and used, especially personal information, the more accurate the predictions are. Thus, the right quantity and quality of data is highly critical for the success of Prediction methods. For reaching this, the matching data source for the specific prediction problem has to be chosen and accurate filtering with inclusions and exclusions as well as redundancy filters has to be applied (see method 3, 7, 8, 9 and 11).

The analysis revealed (Research Question 5) that not every Predictive Maintenance approach would have a significant advantage by the use of Social Media data (see method 1 and 3). Especially approaches and methods with focus on B2B are most likely the ones which will not benefit from Social Media data. This is caused by the fact, that individuals usually do not speak about highly technical B2B products and services in Social Media and thus, in most cases no or very little information is available. This is confirmed by the analysis of this paper, as only approaches with focus on B2C are currently using Social Media data (see method 6, 7 and 11).

These methods offer new ways to identify additional data, potential defects, and risks from a social view, e.g. using social profile data for gaining demographic information (see method 6), enhancing taxi services by considering social relations (see method 7), and improving train services through considering customer insights and opinions about the company (method 11). On the one hand companies will create a closer relation to their customers particularly in the B2C sector when considering Social Media data. On the other hand, customers profit from a better service, receive more information and guidance for using a product or service in the best way.

5 CONCLUSIONS AND FUTURE RESEARCH

In conclusion, there are a few Predictive methods in different industries (B2B and B2C) with focus on service-oriented topics. For most of the existing Predictive methods in the B2B sector, the enrichment with Social Media data is difficult. Thus, especially the B2C sector can profit a lot of Social Media data, as there is much more information available which is highly user specific and can be linked to specific products and services.

However, only very little approaches with focus on B2C currently link purely machine-generated data with human-made data from social networks.

With this, a major gap in existing research is identified, as so far there is no universal Predictive Maintenance solution available, that helps B2C organizations to predict and enhance their customer services by using the full potential that can be realized through integrating Social Media data and combine it with other data sources.

Thus, future research should aim in answering the following research questions:

- Which tools and keywords should be used to gather Social Media data with focus on products and services in the B2C sector?
- How has this data to be processed for its further use in Predictive Maintenance solutions? How can non-related and redundant data be excluded by using inclusion and exclusion parameters?
- Can algorithms of existing Predictive methods be extended by Social Media data? How should Social Media data be applied to?

Further research has the aim of gaining an added value for companies and customers in the B2C sector, by increasing the accuracy of predictions in a service context through the consideration of Social Media data.

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