PROCESSUAL BENEFITS OF PREDICTIVE MAINTENANCE IN THE MIDMARKET

Jonas Pfeffer
Comenius University
Bratislava, Slovakia
Pfeffer3@uniba.sk

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ABSTRACT.
Background: Industrialization has given rise to numerous new topics for companies. In the age of Industry 4.0, predictive maintenance represents an opportunity to reduce machines' downtime and enable companies to gain competitive advantages. For this purpose, sensors are installed in machines, and the data of individual parts is constantly monitored and evaluated. By detecting possible failure risks of individual parts at an early stage, they can be replaced before the downtime occurs, thus preventing a long downtime. A shorter downtime can bring further positive aspects in multiple terms. A lot is written in the literature about the general advantages of predictive maintenance, but there is no particular focus on the German midmarket sector. **Aims:** The aim of this paper is to find out how midsize companies perceive the processual benefits of predictive maintenance. **Methods:** A standardized questionnaire with four questions is developed. **Sample:** Answers from 104 respondents are evaluated. **Results:** The results show that a large proportion of the respondents expect added value. **Conclusion and Implications:** The research in this paper shows that the added value generated by predictive maintenance is not limited to multinational corporations but can also be realized in medium-sized companies.

Keywords: *Industry 4.0, Internet of Things, Predictive Maintenance, Value Generation*

JEL Classification*:* M20

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Introduction

Digitization in Germany is advancing rapidly, and the Corona pandemic, in particular, has given companies in Germany a boost in their progress toward digitization. However, there is still a considerable need for German midsize companies to catch up in some areas of digitization (Neuerer, 2021). Predictive maintenance is considered one of the drivers of digitization and is the subject of considerable discussion. The goal of predictive maintenance is to prevent machine failures and thus save costs. The subject of predictive maintenance was only made possible by the transformation of the industry from Industry 1.0 to Industry 4.0 and modern technologies (Haarman et al., 2017).

However, predictive maintenance also poses a number of challenges that need to be considered in greater detail during implementation. On the one hand, the technical prerequisites for monitoring machine data must be in place, and on the other hand, contractual and legal framework conditions must also be taken into account during implementation. Even though studies on predictive maintenance show promising results, companies should always consider these scenarios on a case-by-case basis and work out the appropriate implementation methodology (Roland Berger GmbH, 2017). Modern topics such as machine learning are also being combined with predictive maintenance to achieve benefits through less frequent machine downtime and improve the prediction accuracy of the algorithms (Tessaro et al., 2020).

There is a current research gap in this field, as the studies mainly focus on large enterprises rather than specifically in the German midmarket. To this end, the theoretical background and the current state of research will first be presented, followed by an explanation of the research methodology. The data basis for this measurement will be companies from German medium-sized businesses from various industries. It is important to highlight that this study‘s results are to be validated for other countries to ensure the maximum added value for international companies.

Theoretical background

Industry and production have existed for many centuries. For modern industry, however, there are mainly four relevant revolutions which have changed the way of working decisively. While in the beginning, the focus was still strongly on physical machines, the 21st century has brought data and the networking of machines to the fore (Becker et al., 2017). The following figure shows the development of the four industrial revolutions.

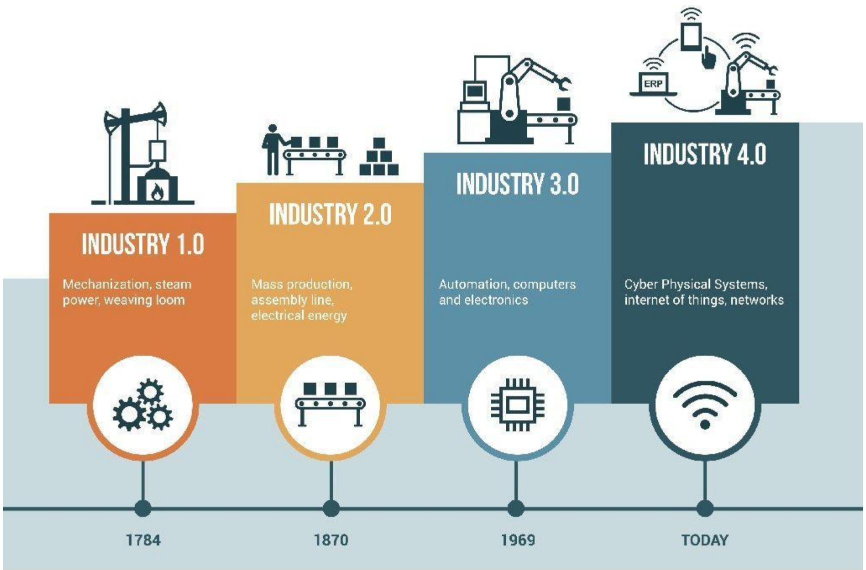

Fig. 1 – From Industry 1.0 to Industry 4.0. Source: Diaonescu, 2018

This figure shows the key points of the respective steps between Industry 1.0 and Industry 4.0. Due to the scope of this paper, the most important key points considered as fundamentals for the current application of predictive maintenance will be explained hereafter.

The mechanization and steam-powered machines were particularly important for Industry 1.0. Through them, it was possible to increase productivity enormously and generate greater output than was the case with manual activities (Bauernhansl, 2014, p. 5). The first steam-powered loom is seen as a key innovation for the textile, steel and iron industries (Siepmann & Graef, 2016, p. 19).

The second industrial revolution was characterized by the use of electrical energy and the associated mass production based on the division of labor. The assembly line developed by Henry Ford enabled workers to specialize in individual work steps and to achieve higher productivity through the division of labor. Frederic W. Taylor's work on scientific management also helped to restructure companies. With the development and use of combustion engines, petroleum became increasingly important as a fuel for mobile systems. Machines could now be operated decentrally, and automobiles became part of logistics. The developments of Industry 2.0 were signposts for today's consumer-oriented affluent society. The further development of automobile traffic, the use of airplanes and the possibility of long-distance transportation by ship made increasing globalization possible (Bauernhansl, 2014, pp. 6–13).

The third industrial revolution was triggered by the development and use of electronics and information technology. Based on the developments of Lovelace and Babbage from the first industrial revolution, Konrad Zuse developed the world's first functional computer in 1941 (Frick, 2017). It enabled progressive automation of production processes, which was one of the reasons for the economic miracle in Germany at that time. The use of information and communication technology led to rationalization, but it also enabled a varied series of production (Bauernhansl, 2014, p. 7).

The German working group Platform Industry 4.0, consisting of the associations Bundesverband Informationswirtschaft, Telekommunikation und neue Medien, Verband Deutscher Maschinen und Anlagenbau and Zentralverband Elektrotechnik- und Elektronikindustrie, focuses in its definition of Industry 4.0 on the control of the value chain over the product life cycle, which is only possible through the availability of real-time data. This working group is an association of various German industrial societies which publish recommendations and information for German and international industries. The main goal is to support companies' progress and make modern, often not widely used technologies more tangible. They define Industry 4.0 as a term that stands for the fourth industrial revolution, a new level of organization and control of the entire value chain over the life cycle of products. This cycle is oriented towards increasingly individualized customer requirements and extends from the idea, the order, through development and production, the delivery of a product to the end customer, to recycling, including the associated services. The basis for this cycle is the availability of all relevant information in real-time through networking of all instances involved in the value chain and the ability to derive the optimal value chain flow at any given time from the data. By connecting people, objects and systems, dynamic, real-time-optimized and self-organizing, cross-company value-added networks are created, which can be optimized according to various criteria such as costs, availability and resource consumption (Plattform Industrie 4.0, 2015, p. 8).

Now that the basics of industrial change have been described as a prerequisite for predictive maintenance, the topic of maintenance will be discussed in more detail next. While machine maintenance is about reducing or preventing wear and tear, repair aims to eliminate the wear and tear that has occurred. A typical repair procedure includes the decommissioning of the affected plant, decoupling it from the surrounding plant, dismantling and cleaning, damage detection, replacement or repair of the affected parts, including adjustment and adjustment of the assembly as well as functional testing and recommissioning (Hölbfer, 2014, p. 16). According to Aha, there are three different maintenance strategies in which the basic measures just mentioned are implemented. There belong the failure-related maintenance strategy, the planned preventive maintenance strategy and the condition-based maintenance strategy (Aha, 2013, pp. 19–20). Predictive maintenance is a core component of Industry 4.0 and clearly distinguishes itself from conventional maintenance approaches such as reactive or preventive maintenance. This involves installing sensors on the individual parts of a machine and monitoring whether they run faster, are noisier or get hotter than expected, for example. This data is then used to calculate the probability of a part or machine failing within a given time frame. Recognizing these patterns makes it possible to identify the faulty parts at an early stage. This can make a big difference to machine downtime, as parts that are needed can be ordered early, and production can be designed to accommodate repairs. It is necessary to collect, store and analyze a large amount of data to make reliable predictions for predictive maintenance. Due to the vast amount of data, techniques and databases from the big-data environment are used. The recorded measured values and diagnostic data are transmitted from the machines via networks to service centers or directly to the manufacturers. In many cases, the Internet of Things serves as the network technology basis (Carvalho et al., 2019). Two major challenges in the technical implementation of predictive maintenance that companies can face are the quality and quantity of the data. A distinction is made between the required data, i.e. the data that would not be possible without predictive maintenance, and additional data that improves the quality of the predictions (Schleichert et al., 2017, p. 11).

In the literature, it has not been clearly worked out at which points medium-sized companies in Germany can benefit from predictive maintenance. Authors like Shamayleh et al. highlight the benefits for specific industries like medical companies but do not focus on the German midmarket in a cross-industry approach (Shamayleh et al., 2020). In the following, therefore, a method will be presented that is intended to make this consideration possible by using a questionnaire and conducting quantitative research.

Methodology

By using a standardized questionnaire, results are to be obtained on four questions in the subject area benefits through predictive maintenance. The target group for the survey is defined as:

- Midmarket companies based in Germany. Since there is no universal definition for the term midmarket, a company size of up to 500 million euros in annual company turnover is taken as the basis for the following research
- No pre-selection based on age, gender or position in the company

To formulate the questions, a structure tree has been developed for operationalization by means of a dimension analysis. For this purpose, the construct is defined as "added value through predictive maintenance". The dimension this research focuses on is the processual dimension. Therefore, the following indicators are used:

- Maintenance duration: How long does it take to check or repair a machine?
- Duration of downtime: How long does it take a machine to stop if a part is defective?
- Lifetime of the machines: How long is a machine in use on average from the time of purchase to the time of disposal?
- Frequency of maintenance: How often do machines need to be maintained during their life cycle?
- The following questions or statements were then developed to assess the impact of predictive maintenance at the subjects' companies:
- The use of predictive maintenance would reduce the time needed to maintain our machines.
- The use of predictive maintenance would reduce the time our machines are out of operation due to maintenance or a defect.
- The life cycle of our machines would be extended by using of predictive maintenance.
- Our machines would require less frequent maintenance by using predictive maintenance.

Due to the questionnaire design, primarily closed questions are asked. Mainly a verbalized ordinal scale is used to answer the question with the possibility to assign 1-5 points with the meaning "Do not agree at all", "Do rather not agree", "Neither agree nor disagree", "Do rather agree" and "Agree completely". Additionally, there is the possibility to skip the question with the answer "No answer". This answer option can be selected if there is either no opinion on the statement or the respondent does not want to rate the statement.

The questionnaire is sent electronically via Google Forms to 192 subjects, of whom 104 participated in the survey, a rate of approximately 54%. The data is collected electronically via Google Forms. The subjects are contacted personally, but the responses are evaluated anonymously. The survey is completed using Google Forms. This ensures that the respondent's name is not requested and that no correlation can be made on the basis of other criteria.

Cronbach's alpha is used to check reliability. This measures the degree of correlation between several questions within the questionnaire in order to ensure internal consistency. Values below 0.5 are regularly considered unacceptable in science and indicate that the individual items of the questionnaire should be reviewed.

In order to check the comprehensibility and meaningfulness of the questions, a pretest was carried out in advance of the survey. For this purpose, two experts from the industry were interviewed, followed by a test subject with whom the comprehensibility of the questions was discussed. After completion of the pretest, no changes were made to the questions.

Results

104 respondents took part in the survey, and none of the answers were invalid or missing.
The following answers were given to the statement, "The use of predictive maintenance would reduce the time needed to maintain our machines":

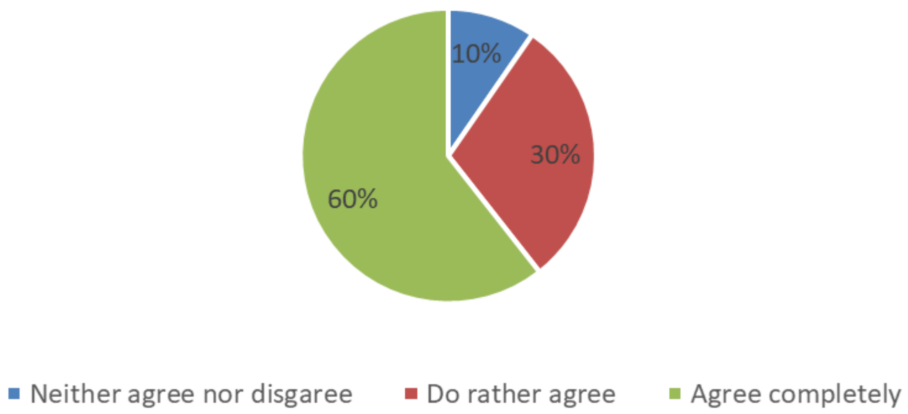

Figure 2: Pie Chart for Question 1. Source: Own research

The following answers were given to the statement, "The use of predictive maintenance would reduce the time our machines are out of operation due to maintenance or a defect":

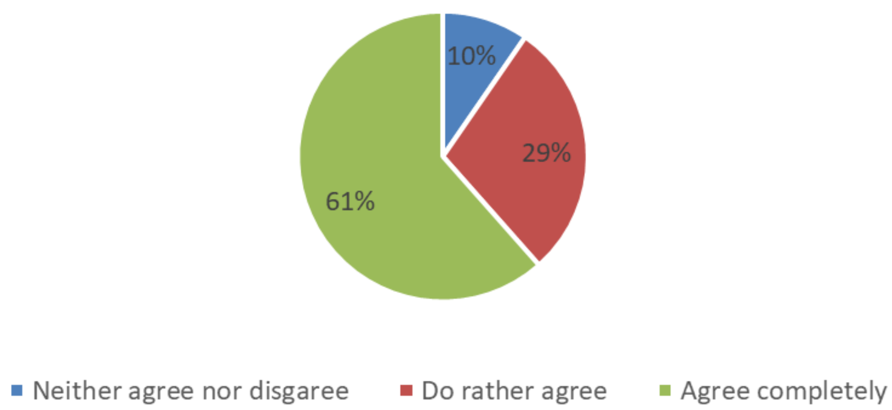

Figure 3: Pie Chart for Question 2. Source: Own research

The following answers were given to the statement “The life cycle of our machines would be extended by using predictive maintenance”:

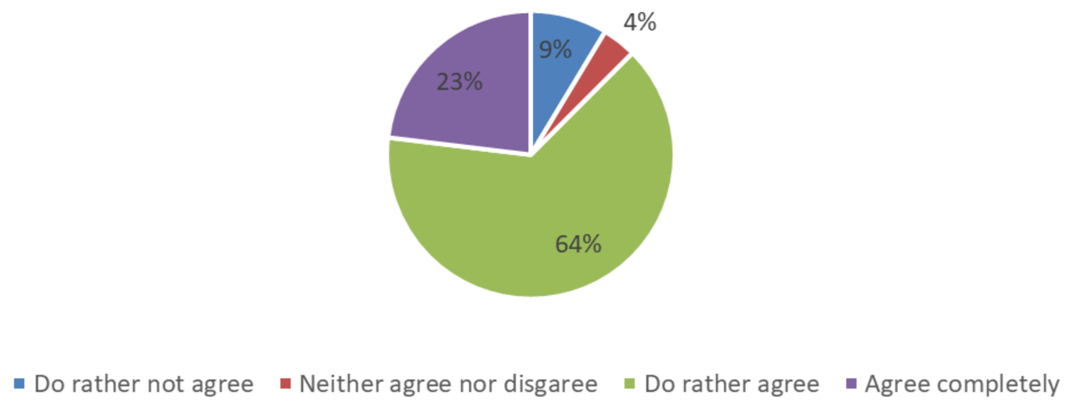

Figure 4: Pie Chart for Question 3. Source: Own research

The following answers were given to the statement “Our machines would require less frequent maintenance through using predictive maintenance”:

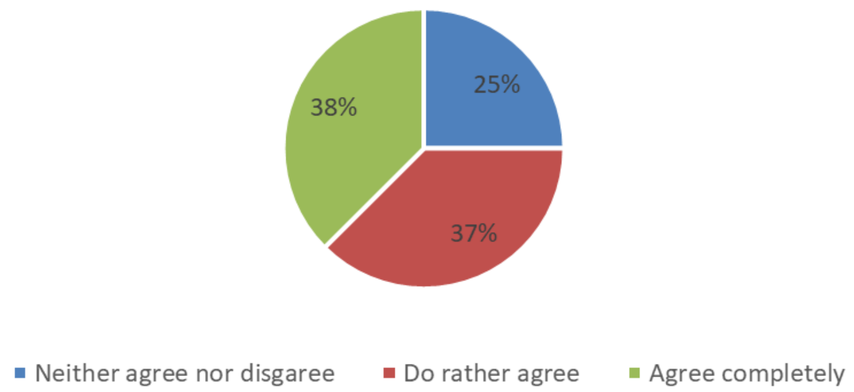

Figure 5: Pie Chart for Question 4. Source: Own research

If we consider the two categories "Do not agree at all” and "Do rather not agree" as perceptions of no added value, the category "Neither agree nor disagree" as neutral, and the two categories "Do rather agree" and "Agree completely" as perceptions of added value, the responses reveal a clear picture. Across all four questions, an average of 2,18% see no added value, 12% are neutral about predictive maintenance, and 85,82% see the added value.

Conclusion

The answers to each of the questions show that an added value of predictive maintenance is perceived by the majority of the respondents. This is consistent with the literature, which reports on the benefits and effects of predictive maintenance from a general point of view. The data collected in this study from 104 subjects came exclusively from companies belonging to the German midmarket. By combining the results of this study with the expected values through the literature research, it can be assumed that the present results can also be transferred to companies of other sizes or from other countries, provided that at least similar basic conditions exist. As identified in the literature review, there are certain prerequisites for the successful use of predictive maintenance, which can be found in the technical area, among others. Without these basic prerequisites, it is unlikely that the same added values can be achieved as expected by the subjects of this research study. For subsequent studies, it may be interesting to specify the results for the value-added consideration of predictive maintenance even more precisely regarding individual industries. It may also be interesting to validate the assumption of similar results through studies in other countries.

In the following, the three quality criteria, objectivity, reliability and validity, are considered. Objectivity is achieved by using a standardized questionnaire in combination with an anonymous survey. The results are, therefore not influenced by interpersonal interaction and should show the same results with another researcher. Reliability was calculated by Cronbach's Alpha and showed an acceptable result with a value of 0.70. Omitting individual items would not have significantly improved Cronbach's Alpha. Other methods, such as a retest or a parallel test, were not used due to the scope of this work. In terms of validity, content validity was ensured by pretesting with two experts in predictive maintenance. Construct validity was ensured by aligning and deriving the questions from the literature review.

Predictive maintenance is a topic that can generate a great deal of added value for many companies. Even though the topic has been discussed for several years, many companies have not yet used it. During this paper, the basic requirements for predictive maintenance and how the literature describes possible added values through predictive maintenance were worked out. Due to a research gap in the area of predictive maintenance in German medium-sized businesses, this paper took a closer look at this area. The majority of the 104 participating respondents see a potential added value in their company using predictive maintenance. For future research, it may be interesting to set an industry focus and to question how the added value through predictive maintenance is presented in individual sub-industries. The research results of this work can also be generalized to other countries and company sizes under similar basic conditions and are valid not only for the German midmarket.

The first applications and results of predictive maintenance are already being implemented and realized in the industry. However, the response to these possibilities is still very restrained, especially in German medium-sized companies, even though the possible results look promising. By increasing research in these areas, it may be possible to introduce more companies to predictive maintenance and convince them of the potential benefits. The research in this paper provides reliable starting points that can be elaborated in more detail in more in-depth research. Future research will show the international impact of predictive maintenance and the differences that may occur between different countries.

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