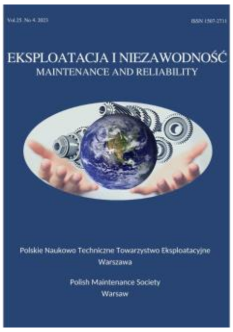

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Application of Principle Component Analysis and logistic regression to support Six Sigma implementation in maintenance

Katarzyna Antosz[a,*], Małgorzata Jasiulewicz – Kaczmarek[b], Jose Machado[c], Marcin Relich[d]

[a] Rzeszow University of Technology, Faculty of Mechanical Engineering and Aeronautics, Powstańców Warszawy 8, 35-959 Rzeszów, Poland
[b] Poznan University of Technology, Faculty of Management Engineering, Rychlewskiego 2, 60-965 Poznań, Poland
[c] University of Minho, MEtRICs Research Centre, Campus de Azurem, Guimarães, Portugal
[d] University of Zielona Góra, Faculty of Economics and Management, 65-417 Zielona Gora, Poland

Highlights

- A review of maintenance management's importance.
- A review of traditional and advanced analytical tools used in the DMAIC cycle.
- The literature review related to the improvement of maintenance processes using the Six Sigma approach.
- A Six Sigma methodology with PCA and logistic regression in maintenance processes.

Abstract

Improving the efficiency of maintenance processes is one of the goals of companies. Improvement activities in this area require not only an appropriate maintenance strategy but also the use of a new approach to increase the efficiency of the process. This article focuses on using Six Sigma (SS) to improve maintenance processes. As an introduction, the generations of SS development are identified, and traditional and advanced analytical tools that can be useful in SS projects are reviewed. As part of the research, an example of the implementation of the SS project in the maintenance process using the DMAIC and selected advanced analytical methods, such as PCA and logistic regression, was presented. The PCA results showed that it was enough to have seven main components to keep about 84% of the information on variability. In developed logistic regression explained the impact of the individual factors affecting the availability of the machines. The identified factors and their interactions made it possible to define maintenance activities requiring improvements.

Keywords
maintenance management, Six Sigma generation, DMAIC, PCA, logistic regression

1. Introduction

One of the most important issues in achieving high efficiency of manufacturing processes and timely deliveries of products in accordance with customer specifications is to ensure the availability and reliability of machines and devices. Companies are increasingly realizing that they can improve their efficiency and reliability by planning and implementing maintenance activities more effectively. Today, maintenance plays a strategic role in generating an organization's revenue, and improving the efficiency and effectiveness of maintenance processes through continuous improvement is one of the main goals of any company. According to [53] maintenance expenses can reach up to 40% of the operational costs. Failures of industrial equipment result not only in financial losses but can also cause problems related to safety and environmental protection [3]. This makes the maintenance function the center of attention of managers [65, 103].

(*) Corresponding author.
E-mail addresses: K. Antosz (ORCID: 0000-0001-6048-5220) katarzyna.antosz@prz.edu.pl, M. Jasiulewicz - Kaczmarek (ORCID: 0000-0002-8332-3192) jasiulewicz-kaczmarek@put.poznan.pl, J. Machado (ORCID: 0000-0002-4917-2474) jmachado@dem.uminho.pt, M. Relich (ORCID: 0000-0003-1193-432X) m.relich@wez.uz.zgora.pl

Various approaches have been implemented to increase the reliability and availability of manufacturing equipment [17, 87, 44]. Six Sigma is one of them [47, 83, 100, 111]. Six Sigma is a popular and often used methodology by companies to improve processes [55, 77]. Examples of SS projects can be found in various sectors, such as the automotive industry [51, 76, 86], food industry [23], glass industry [107], and vehicle fleet [91] among others. Six Sigma is an approach that can complement the concepts of Lean [34, 64], TQM [6], ecology/sustainable development [98, 108], and thanks to the process-oriented approach can be used in various industries and areas of the company to increase efficiency system and ensuring a culture of continuous improvement.

In recent years, many authors have pointed to the need and advantages of using I4.0 technology in Six Sigma projects [19, 37]. Technologies such as Big Data (BD), Internet of Things (IoT), AI offer resources to expand and complete the SS structure and strengthen the improvement system, and intensify statistical analysis [56, 57, 89, 97]. According to [61], by incorporating more advanced data analysis technologies, I4.0 strengthens the SS/DMAIC approach and allows for improved flexibility when solving complex problems.

That is why, the main purpose of this paper is to incorporate more advanced data analysis tools into the classic Six Sigma approach in order to improve the efficiency of the maintenance process. This paper is a continuation of the previously undertaken work presented in [11].

The main contributions of this article are:

1. The generations of development of the Six Sigma methodology are shown.
2. The systematic review and categorization of the traditional and advanced analytical tools that can be used in DMAIC methodology in Six Sigma projects is shown.
3. The literature review related to the improvement of maintenance processes using the Six Sigma method is presented.
4. An example of Six Sigma project implementation in the maintenance process using the DMAIC methodology and selected advanced analytical methods such as PCA and logistic regression is presented.

The graphical abstract of the paper is presented on Figure 1.

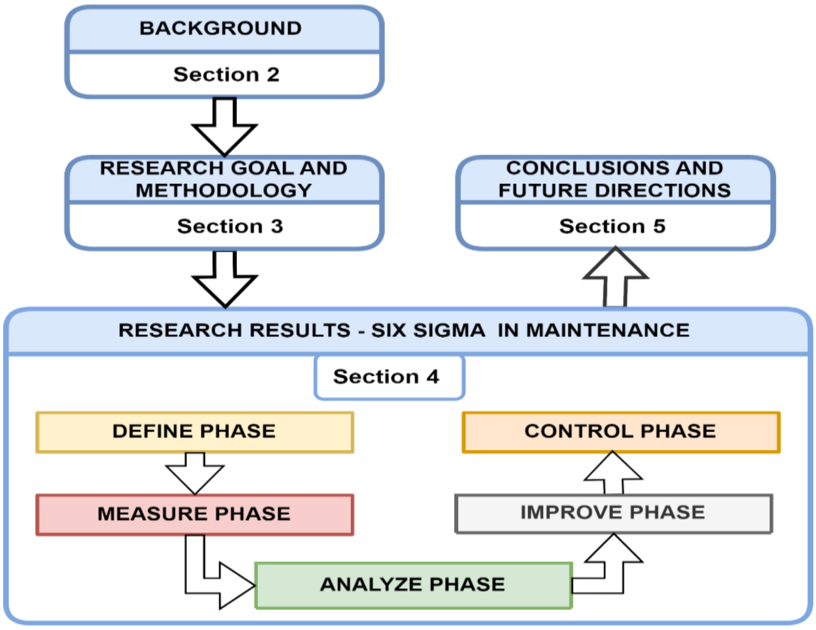


Fig. 1. Structure of the paper.

In Section 2 the background of maintenance and Six Sigma implementation in manufacturing companies are presented. The research methodology used is shown in Section 3. In Section 4 the research results of Six Sigma project implementation in the maintenance process using the DMAIC methodology and selected advanced analytical methods are presented. Finally (Section 5), the conclusions and directions of future research are discussed.

2. Background

2.1 Maintenance importance in manufacturing

Maintenance is a critical issue in achieving excellent industrial performance [60] European Standards [28] define maintenance as "the combination of all technical, administrative and management activities during the life cycle of a facility, aimed at maintaining it or restoring it to a condition in which it can fulfill the required function". The aim of maintenance is to guarantee that machines and devices will operate in accordance with the expectations of users, maintaining a high level of operator safety along with quality, reliability, and energy efficiency [59]. Maintenance is a set of complex activities covering the entire structure and organization of a production company, and the management of maintenance activities has changed from a functional to a process orientation. In the early 20th century, the "fix when equipment breaks" approach was used. From the 1950s to the 1980s, maintenance was recognized as a key manufacturing function, and the perception of "fix when equipment breaks" shifted to a planning and control approach - preventive maintenance. In the 2000s, maintenance management began to be seen as an integral part of the company's strategies. In recent years, the need to manage the various areas of maintenance more effectively has gained additional importance due to changing operational technologies and new market demands [7, 39, 113].

Traditionally, only technical and economic aspects were taken into account when making maintenance decisions. Over the past few years, increasing attention has been paid to the role of maintenance in contributing to sustainability [35, 43, 104]. From an economic perspective of sustainability, Syan and Ramsoobag [92] indicate that by optimizing maintenance activities, savings of 20-30% of total operating costs can be achieved. From the social perspective of sustainability, many authors indicate the positive impact of maintenance on the creation of a safe and healthy working environment [33]. As far as environmental issues are concerned, maintenance activities are aimed, among others, at reducing the energy consumption of machines and devices, minimizing the production of toxic waste, and effective use of spare parts and consumables [32, 46, 73].

In addition, the fourth industrial revolution, also known as Industry 4.0 (I4.0) has increased the expectations of enterprises in terms of productivity, high efficiency of manufacturing equipment, and increased automation of production systems. However, in order for automated production systems to perform their functions, it is necessary to effectively manage machine failures [31, 40].

I4.0 and its key technologies are influencing and transforming both manufacturing processes and maintenance management. Today, maintenance practices can benefit from the technological development of I4.0, and maintenance based on I4.0 technologies is gaining popularity as Maintenance 4.0 (M4.0) [50]. M4.0 can be defined as an innovative and optimized maintenance strategy that integrates a traditional approach with I4.0 technologies. This combination of traditional maintenance management concepts with I4.0 technologies is transforming current maintenance practices [20]. The development of sensor techniques makes it possible to extract more and more accurate data on industrial machines/components in real time and continuously monitor the state of the operating system [78]. The resulting system health data and data analytics technologies provide the ability to better understand data and predict failures long before they occur. The application of data-driven approaches such as machine learning (ML) is increasingly becoming a norm in maintenance solutions [24, 63, 68, 95].

Today, maintenance relies on powerful mathematical and statistical models to detect, diagnose, and forecast, equipment problems that can help managers make better decisions and adopt a new paradigm in maintenance, called "data-driven maintenance" [105]. According to [38] data-driven maintenance and the application of advanced analytical tools "enable not only an increase in availability but also an increase in product quality and a stabilization of production processes".

Given the increasing complexity of the manufacturing environment, new requirements and opportunities resulting from I4.0 technology force managers to constantly look for ways to improve maintenance processes. To support improvement, various methodologies, techniques, and tools have been developed that combine traditional maintenance approaches with new ones [62, 79, 81]. One of the methods focusing on process improvement is the Six Sigma methodology, referred to as the data-driven approach.

2.2. Six Sigma and maintenance

In manufacturing industries, SS is one of the most popular approaches for systematic and continuous process improvement. Six Sigma was invented by Bill Smith of Motorola in the 1980s. Since then, the concept of SS has attracted the attention of scientists, researchers, and practitioners and has been widely adopted in many enterprises from various industries [15, 72, 94]. Schroeder et al. [84] defined Six Sigma as "an organized, parallel-mesostructured to reduce variation in organizational processes by using improvement specialists, a structured method, and performance metrics with the aim of achieving strategic objectives".

In order to better understand processes and their interactions with the environment, this method uses both qualitative and quantitative methods. In general, Six Sigma projects follow the DMAIC cycle with five phases: Define, Measure, Analyze, Improve, and Control. According to [58] DMAIC "is one of the well-known manifestations of the scientific method applied to problem-solving". DMAIC cycle includes a number of different statistical and management tools used in each phase such as Voice of the Customer (VOC) tools, Critical to Quality (CTQ), Quality Function Deployment (QFD), SIPOC (Suppliers-Inputs-Process-Outputs-Customers), Failure Mode and Effect Analysis (FMEA), Root Cause Analysis (RCA), Measurement System Analysis (MSA), and statistical process control (SPC) [65, 69, 91, 99]. Guidance on how to use the tools in certain phases is described, among others, in the standard ISO 13053 [49].

Due to the company's experience in implementing improvement actions and the nature of the problems that companies want to solve with SS, the way in which this approach is implemented may vary [26]. This also applies to the benefits [94]. Literature analysis indicates benefits in areas such as finance (cost reduction), quality (defect reduction), production (efficiency improvement, cycle time reduction), customer satisfaction, and increase in market share [70, 72, 94, 99, 109].

Analyzing the literature [8, 10, 67, 74] four generations of the development of the SS concept can be noted. (Figure 2).

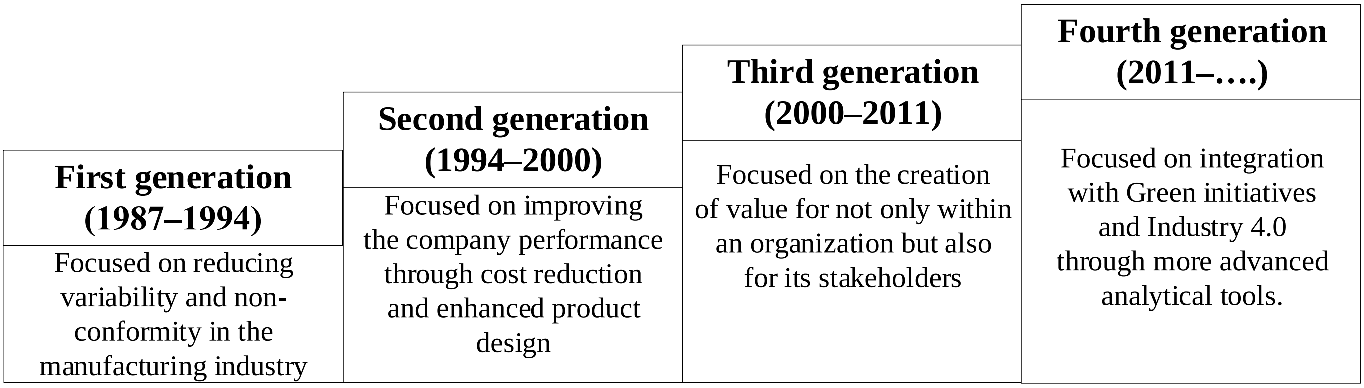


Fig. 2. Generations of development of Six Sigma methodology.

The fourth generation of SS is aimed at supporting enterprises in solving problems in the new digital reality. Based on a survey of experts, in [9] Six Sigma emerging trends were identified.

The first emerging trend is focused on SS and green /sustainability initiatives. This direction concerns the assessment and reduction of the impact of the company's processes and products on the environment [13, 29, 52].

The second trend related to SS is its integration with Big Data (BD) / Big Data Analytics (BDA) [56]. Six Sigma has proven its effectiveness in the field of traditional statistical methods, providing a structured approach to identifying the root causes of manufacturing defects. However, these methods are less effective for larger and more complex datasets [114]. Modern production data is characterized by the four/five/seven V's of BD (e.g. 7 V's – Volume, Velocity, Variety, Variability, Veracity, Visualization, and Value), and it is difficult to analyze them using the traditional Six Sigma approach. If we have a lot of data, we can find new relationships, dependencies, and patterns. Therefore, practitioners need a new approach and support in solving problems [79]. The integration of BDA and SS tools is analyzed by many authors [42, 74]. For example [42] indicates, that Text and Video Mining (BDA techniques), can provide valuable input for VOC. In addition, the authors suggest that for better optimization of parameters and better results, the Improve phase of SS projects should closely consider AI, ML, and predictive analytics. According to [82], traditional Six Sigma tools such as the "Cause and Effect Matrix" or "Ishikawa Diagram" can be replaced by e.g. classification and regression trees, which could help identify variables with a significant impact on a given product feature. Giannetti and Ransing [36] used Bootstrap, a regression tree algorithm, and principal component analysis (PCA) to deal with the complexity caused by noise factors that traditional regression analysis could not handle. In [74], the authors indicate that in the context of real-time process prediction and monitoring, digital technologies can be used to support traditional process mapping techniques. Literature analysis conducted by [61] indicates that the inclusion of BD/BDA in the SS project has a positive impact on company performance by reducing the number of non-compliances, increasing process efficiency, and customer satisfaction, and reducing costs.

The third emerging trend focuses on SS and the challenges of Industry 4.0 [27, 61]. Citybabu and Yamini [21] based on a survey conducted by [70] defined Six Sigma 4.0 as “a synergy of Industry 4.0 and Six Sigma that provides a competitive advantage, appropriate decisions, problem-solving abilities and the ability to anticipate process defects through the effective integration of Six Sigma’s DMAIC framework with Industry 4.0 technologies to improve the quality of the product, process and services”.

The integration of SS with I4.0 is becoming more and more popular in the academic community [41]. In [71] the authors indicate the possibility and potential benefits of integrating AI, Big Data, and IoT tools. By collecting data using sensors and interconnected machines, the second phase of the DMAIC cycle - Measure - can be significantly accelerated [74]. Analyzing, for example, the work [93] it can be assumed that DT technology will be useful in the Improve phase. According to [2, 14] simulation is an appropriate tool for most steps of the DMAIC methodology due to its ability to understand differences in processes or products and thus identify and test potential improvements. In [101] authors present the selection and utilization of ML techniques, such as artificial neural network (ANN), k-nearest neighbors (k-NN), random forests (RF), gradient boosting machines (GBM), and multiple linear regression (MLR) in the Analyze and Improve phases of DMAIC cycle.

The literature review, conducted above, indicates that the authors suggest different traditional and advanced analytical tools that can be used in DMAIC methodology in Six Sigma projects (Figure 3).

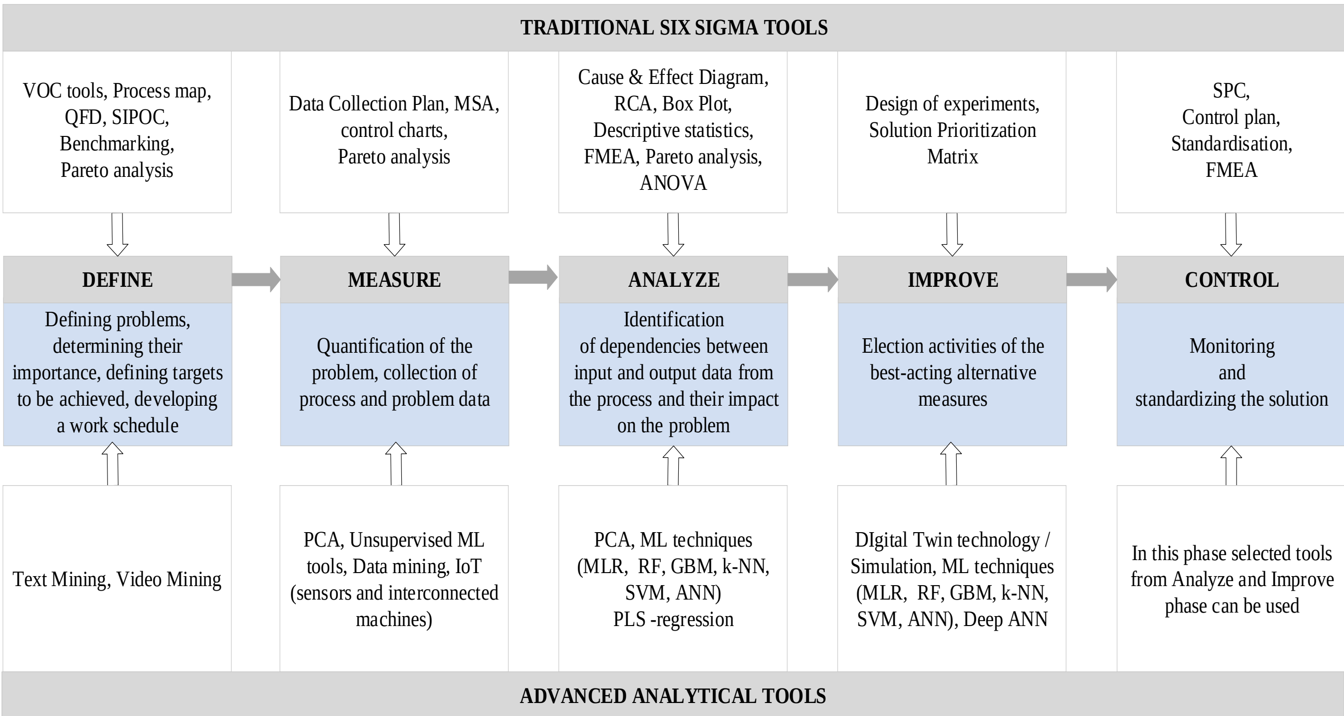


Fig. 3. Traditional and advanced analytical tools that can be used in DMAIC methodology in Six Sigma projects.

To improve maintenance processes the SS/DMAIC approach is proposed [4, 12, 48, 54, 83, 96, 110, 112]. Some of these propositions integrate SS with the Total Productive Maintenance (TPM) and Reliability Centered Maintenance (RCM) concepts [4, 5, 88]. In [85], the authors proposed a model combining SS and TPM concepts for SMEs. The developed model was validated in the papermaking industry, and its results were, among others, improved availability and efficiency of production equipment use, reduction of rework and defect rate, and reduction in maintenance cost. However, in the article [75] the authors explored the possibility of increasing the effectiveness of maintenance practices by using Six Sigma techniques. According to [4] the integration of Six Sigma and RCM, it is possible to mitigate many of the shortcomings and weaknesses of RCM. In [54] authors proposed the use of Six Sigma methodology in predictive maintenance IoT projects. Recently [100] investigated the usefulness of using the SS method and the RAM method (Reliability, Availability and Maintainability) to determine inspection intervals, plan maintenance activities and select the appropriate maintenance strategy.

3. Research Methodology

3.1. Research goals and methodology

The main objectives of the presented research was to present the possibilities of using:

• DMAIC methodology to improve the maintenance process.

• PCA and logistic regression for better results in Six Sigma maintenance projects.

To achieve the assumed goals, the research methodology presented in Figure 4 was used. The research was carried out using the DMAIC methodology extended in the Analyze phase with the use of advanced analytical tools such as PCA and logistic regression. The presented methodology presents the individual stages of the research and the activities carried out within the individual stages. In addition, Figure 4 shows the section in which the results of the study from individual stages are presented.

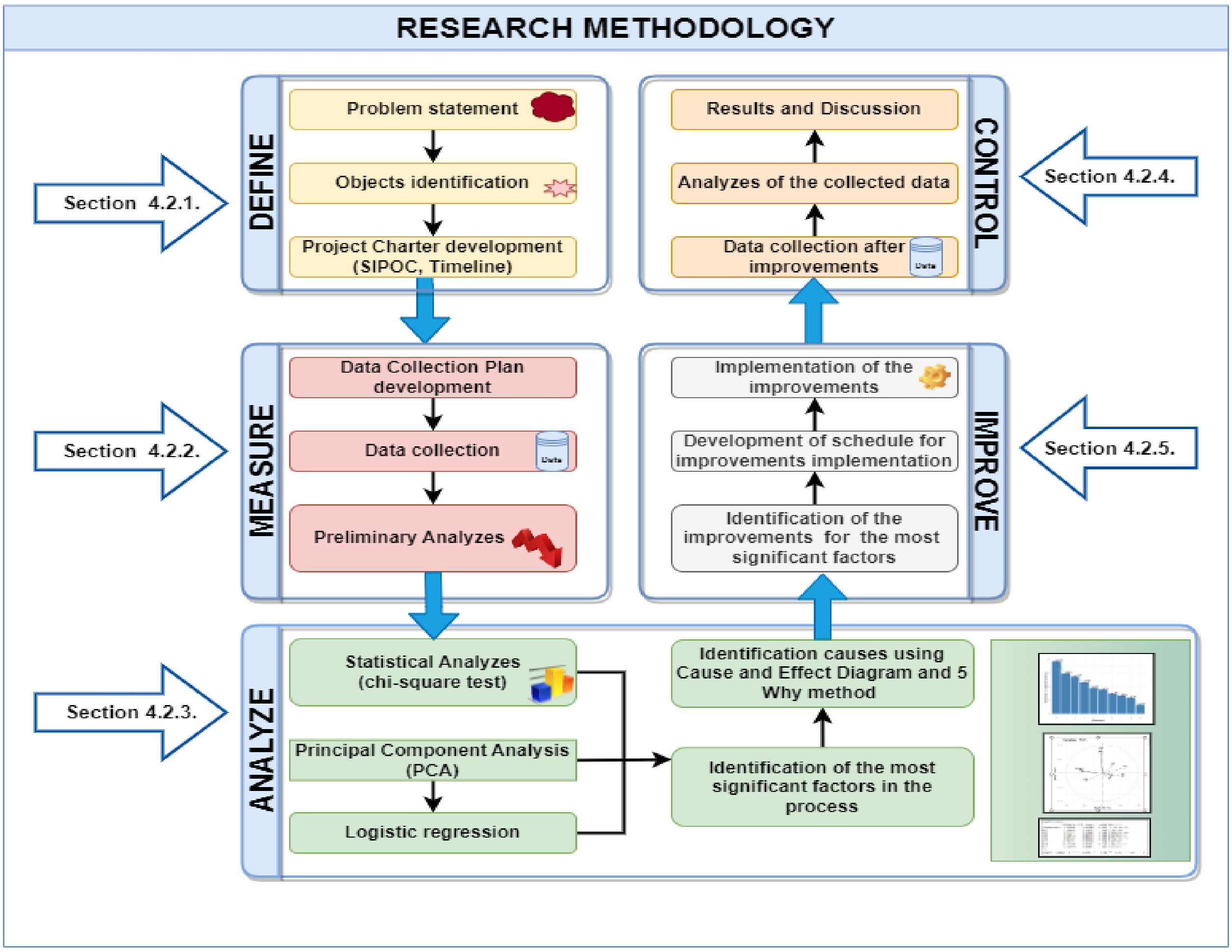


Fig. 4. Research methodology.

The brief descriptions of the DMAIC, PCA, and logistic regression methods used in this research are presented below.

3.2. Six Sigma – DMAIC methodology

The DMAIC methodology is a structured approach to process improvement, ensuring a comprehensive understanding of the problem and a systematic improvement process. As part of the research carried out in the various stages of the Six Sigma project, the following activities were carried out:

1. Define the phase of the SS project:

• Key project leaders assumed responsibility for outlining the purpose, scope, and Critical to Quality (CTQ) aspects of the project, facilitating a clear roadmap for improvement.

• The expectations of the customers relating to the process were identified, aligning the project objectives with customer needs.

• An assessment of the timeline and costs associated with the SS project was undertaken, providing a basis for resource allocation and project planning.

2. Measure phase of the SS project:

• To understand the process comprehensive data collection was conducted.

• Preliminary analysis of the gathered data was performed, enabling an initial understanding of the process dynamics and areas of concern.

3. Analyze phase of the SS project:

• Various quality management methods and tools were employed to precisely identify process bottlenecks and potential issues, while determining their root causes.

• A range of statistical analyses and advanced analytical tools such as PCA and logistic regression were conducted to identify factors with the greatest influence on the CTQ, enhancing the focus of improvement efforts.

4. Improve phase of the SS project:

• Innovative process enhancements were thoughtfully proposed, drawing from the insights gained during the previous phases.

• A well-structured implementation plan was devised, outlining the sequence and timeline for executing the identified improvements.

5. Control phase of the SS project:

• Re-collection of data from the process allowed for a comprehensive evaluation of the outcomes resulting from the implemented improvements.

• Measures for ongoing monitoring of process outcomes were established, ensuring a sustained level of performance and facilitating timely corrective actions if needed.

The using of the DMAIC methodology not only enabled a systematic approach to problem-solving but also ensured that the enhancements made were grounded in data-driven insights and aligned with the needs of both the process and its stakeholders.

3.3. Principal Component Analysis - PCA

In the statistical analyses, it often turns out that the study area is influenced by many factors. In such circumstances, the links between the individual variables are often not obvious and can be challenging or even impossible to see. As a result, attempts to construct a model may yield results that are difficult to analyse. Factor analysis can be very useful in such scenarios. One approach suitable for such analyzes is PCA.

PCA aims to reduce the number of variables used to describe phenomena, and to reveal regularities between these variables [25]. The procedure consists in identifying components that are linear combinations of the analyzed variables. Careful analysis of these principal components facilitates the identification of the primary variables that have a significant influence on the formation of distinct principal components, namely those responsible for the formation of a coherent cluster [106]. The main component variance is equal to the matrix's eigenvalue in terms of magnitude Coordinate variances in the new space are calculated by the formula: $\lambda_i = \frac{d_i^2}{n-1}$, where d_i, $0 \leq i \leq k$ are singular values of the diagonal matrix. The proportion of variance explained by *i–th* principal component is equal to $\frac{\lambda_i}{\sum_{j=1}^{m}\lambda_j}$, while the proportion of variance explained by k principal components is equal to $\frac{\sum_{j=1}^{m}\lambda_i}{\sum_{j=1}^{m}\lambda_j}$ for $1 \leq k \leq m$. Each principal component explains some part of the variability of the input variables. Principal components are a synthetic measure of information. Often, PCA is used for classification. In addition, PCA allows to identify difficult-to-find relationships between output variables [1, 18, 30].

The primary purpose of using the PCA method in this study was to decrease a number of variables used to characterize the process under study and to discover the interrelationships between these variables. The procedure consisted in identifying the components being linear combinations of the analyzed variables. By carefully examining the principal components, it has become possible to identify the original variables that have a significant impact on the construction of the separate principal components that actually form a cohesive group. The main component, characterized by the greatest variance, emerged then as a representative of this group. The subsequent components, however, showed independence from each other, as they were designed to maximize variability that remained unexplained by the previous component.

PCA was started by determining the axis that retained the largest value of variance in the dataset. These components were derived as linear combinations of the studied variables. The rationale for the creation of the following components was as follows:

- They remain uncorrelated.
- They are designed to maximize variability that was not accounted for in previous components.

A matrix factorization technique called singular value decomposition (SVD) was used to discover the main components of the dataset. This technique decomposes the data matrix into an inner product. Before PCA analysis:

- The dataset was standardized (mean = 0, variance = 1) to ensure uniform scaling of variables.
- Outliers in the sample were eliminated as their presence could potentially distort the results.
- Missing data was adjusted to the requirements of the algorithm.

The entire analysis was carried out using the R software.

3.4. Logistic regression - LR

LR is a mathematical model that allows to determine the influence of several variables $x_1, x_2, x_3, .., x_k$ on a dichotomous variable Y [45]. The LR model is based on a logistic function in the following form [15]:

$$f(z) = \frac{e^z}{1+e^z} = \frac{1}{1+e^{-z}} \qquad (1)$$

This function takes values from 0 (as x goes to - ∞) to 1 (as x goes to + ∞). Let's define the dichotomous variable Y, as the values [0 and 1], so the LR model defines the equation:

$$P(Y = 1 \mid x_1, x_2, \dots, x_k) = P(x) = \frac{e^{a_0 + \sum_{i=1}^{k} a_i x_i}}{1+e^{a_0 + \sum_{i=1}^{k} a_i x_i}} \qquad (2)$$

where: a_i, $I = 0, \ldots k$, are the regression coefficients; $x_1, x_2, x_3, .., x_k$ are independent variables. The left side of the equation is the conditional probability that the variable Y will take a value equal to 1 for independent values $x_1, x_2, x_3, .., x_k$. In this regression model (2), the regression coefficients should be estimated in order to fit the best model based on the values of a certain group of data. A condition for applying regression the logistic sample is sufficiently large, which in this case means that the sample size is $n > 10(k+1)$ where k is the number of parameters [22, 90]. To find in logistic regression coefficients $a_0, a_1, a_2, .., a_k$ the Maximum Likelihood Method (MLM) is applied in this context. MLM operates by maximizing either the likelihood function or its square. It operates under the assumption that all observations are mutually independent. In this framework, the likelihood, or probability, is computed as the product of the probabilities corresponding to the occurrence of individual observations from the sample, given the model parameters [102].

4. Research Results

4.1. Description of the research objective – case study

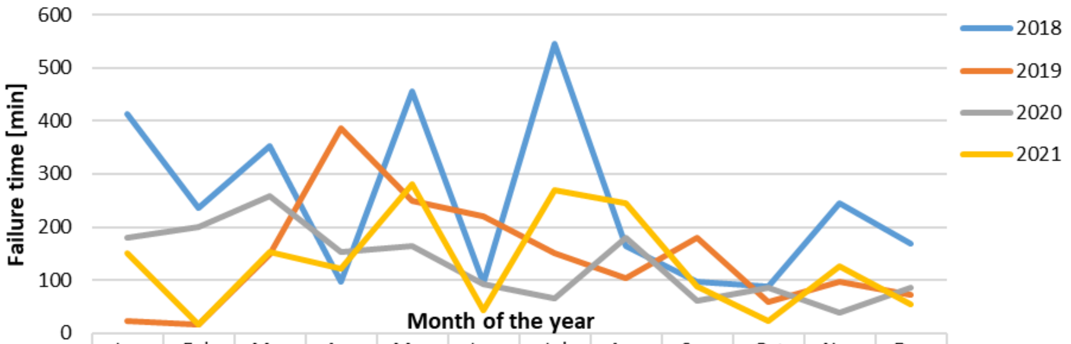
The investigation was performed in a leading factory specializing in the manufacture and distribution of flooring materials. An analysis was conducted in a production area with 70 machines. These machines ranged from simple transport devices to sophisticated precision equipment controlled by automated systems.

Maintenance processes were supervised by maintenance departments. The maintenance strategy includes both: corrective and preventive maintenance (CM and PM) and) as required for the machines. Notably, the company has also introduced a TPM system for the majority of manufacturing equipment. Each machine operator is responsible for executing autonomous maintenance (AM). The operators verify the completion of AM procedures at their respective stations. Furthermore, PM activities are regularly performed on the manufacturing equipment.

4.2. DMAIC methodology implementation - case study

4.2.1. Define Phase

The main problem of the analyzed company is low machine's availability, because of the high failure rate. Figure 6 shows the duration of the recorded failures in the years 2018-2021 in the company. Of all failures recorded in the analyzed period, the largest percentage were mechanical failures (55%), then automation failures (28%) and electrical failures (17%).



	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2018	412	235	352	98	456	95	546	165	98	89	245	168
2019	22	16	148	385	250	220	150	103	180	58	98	72
2020	180	200	258	154	165	93	66	180	61	85	39	85
2021	150	16	154	121	280	44	270	245	88	22	126	55

Fig. 6. Duration time of the recorded failures in 2018 – 2021 in the case study company.

Analyzing the results presented in Figure 6, it can be notice the significant variability in the results between individual years and months. For some months, such as May, July, and August, can observe an increase in the failure time in 2021 compared to previous years. However, for other months, such as February 2021 show a significant decrease compared to previous years. In addition, in some cases, such as March 2019, April 2019 and May 2021, there are sudden changes in values, which may suggest the impact of certain events or factors. Moreover, these results show variation in amounts between years and months, but there does not appear to be a clear trend. Therefore, it may be important to further understand the context of this data and the possible factors that may influence such variability.

Identification of factors affecting the availability of machines and determination of actions to be taken to improve the maintenance activities. For that purpose the company decide to implement Six Sigma methodology for improvement the process.

The main objective of the SS project was to reduce the failures rate by 40% within 6 months. Reducing the failure rate will increase the availability of the machine at a given time. Firstly, the SIPOC diagram was developed. Then, the following data from the process were collected: x_1 – production worker, x_2 – operation time, x_3 – week day, x_4 – check points of AM, x_5 – range of AM, x_6 – AM duration time, x_7 – PM timeliness, x_8 - employee performing PM, x_9 –reported problems after AM, x_{10} – reported problems after PM. To identify the critical factors affecting on increasing the availability of the machine at a given time the CTQ (Critical to Quality) measure was used. The following CTQ was selected for problem analysis: CTQ (Y) – machine availability at the required time. CTQ (Y) was defined on two levels: as OK - a machine's availability in the required time, and NOK - a machine's unavailability in the required time.

4.2.2. Measure Phase

The Measure phase was a key part of the Six Sigma project that focused on data collection and measurement to accurately understand the current state of the process. The main goal of this phase was to provide reliable process information on which the further actions in the next phases of the Six Sigma project can be taken. 1130 data were collected for all key process parameters and CTQ from 2018 to 2021 The data was initially analyzed, missing data were removed and outliers were eliminated. The collected data were subject to further analysis.

4.2.3. Analyze Phase

The goal of the next phase - Analyze was to thoroughly analyze the collected data to understand the causes of problems and identify potential solutions. Firstly, based on collected data the sigma level has been considered. The calculated sigma level for this process is 3.60. The value is low, so it is important to find, which of defined factor impact of machine's availability.

The main goal of data analysis was to transform the collected data into specific information and knowledge. For this purpose, statistical tools were used, such as e.g. *chi*-square test. The *chi*-squared test is a statistical test used to determine whether there is a significant relationship between two categorical variables in a dataset. This is a frequently used test in data analysis, especially in studies of relationships between two qualitative characteristics. The *chi*-square statistic (asymptotic distribution χ^2 *with* $(k-1)(p-1)$ degrees of freedom) was considered using formula (3):

$$\chi^2 = \sum \frac{(O-E)^2}{E} = \sum_{i=1}^{k}\sum_{j=1}^{p} \frac{\left(n_{ij}-E_{ij}\right)^2}{E_{ij}} \tag{3}$$

where: O – observed values; n_{ij}; E_{ij} – theoretical values. For the depended variable (Y) the *chi*-square test with null hypothesis: $H_0: x_1 = x_2 = \ldots = x_n$, *and* $H_1: x_1 \neq x_2 \neq \ldots \neq x_n$ and $H_0: x_1 = x_2 = \ldots = x_n$, *and* $H_1: x_1 \neq x_2 \neq \ldots \neq x_n$ with confidence level $\alpha=0.05$ was performed.

Table 1 presents the results of *chi*-square test for CTQ.

Table 1. Chi – square test results for CTQ (Y).

CTQ (Y)	x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8	x_9	x_{10}
p-value	< 0.05	0.038	0.182	0.048	0.0153	< 0.05	0.0124	0.0582	0.451	0.751

The *chi-square* test results indicate that the CTQ value is statistically affected by the following factors: x_1, x_2, x_4, x_5, x_6 and x_7 (p - *value* < 0.05). These factors are related to the operator and the autonomous maintenance (AM) carried out by him. This means that for these factors the improvements should be established. These improvements will allow to increase the efficiency of the analyzed process. In addition, a detailed analysis of these factors allows for a more precise determination of the causes of irregularities in the machines availability, and thus identification of detailed directions for improvements. The distribution of CTQ(Y) values for the statistically most significant factors x_1 and x_2 is shown in the Figure 7.

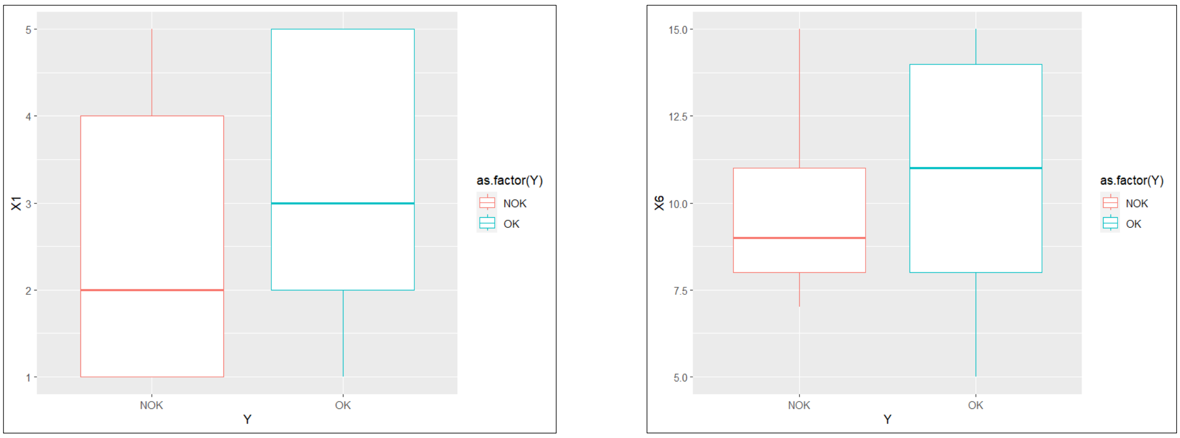


Fig. 7.Distribution of CTQ values for factors x_1 and x_6.

A detailed analysis of the results presented in Figure 7 shows that the largest number of CTQ - NOK values were identified for operators 1 and 2. Moreover, the largest number of CTQ - NOK values were recorded for machines for which the AM range was from 8 to 11 activities.

The provided analysis enabled the identification of factors that influence the machine's availability in the production process. Furthermore, the analysis demonstrated which factors did not affect the machine's availability in the production process such as: x_3 – day of the week, x_7 – PM timeliness, x_8 - employee performing PM, x_9 –reported problems after AM and x_{10} – reported problems after PM Despite the analyzed single factors their influence on machine's availability in the manufacturing process was found not to be significant.

However, when these factors interact with each other, they might have impact on the machine's availability in the production process. Therefore, in the next stage of the study, the concept of using PCA and logistic regression to search for relations between the studied factors, and thus their significant impact on the CTQ(Y), was proposed.

PCA in analyzed process

Table 2 shows the obtained principle components (nine principle components) and their relationship with the analyzed variables in maintenance process.

Table 2. Principle Components (PC's) - matrix of eigenvectors.

Rotation (n x k) = (10 x 10):

	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9	PC10
X1	-0.14887362	0.19960852	-0.18538350	0.66518961	-0.28271286	-0.32904034	-0.04305761	0.4238884	0.30201056	0.0144583
X2	-0.17972876	0.11801498	-0.54364314	-0.26674621	-0.58215477	-0.06745009	0.12268534	-0.1785753	-0.24541024	-0.3693886
X3	0.03921573	-0.57982397	-0.08025097	0.38490921	-0.06317307	0.12760262	0.42594525	0.1144804	-0.52147376	0.1446641
X4	-0.41329984	0.10887431	-0.20213416	-0.16791249	0.30613058	0.43799946	0.47990770	0.3831503	0.26989167	-0.1129615
X5	-0.45373563	-0.15047854	0.30895876	-0.17649224	-0.29753253	-0.29989555	0.35067513	-0.2769342	0.26641935	0.4424560
X6	0.33975677	0.24609749	0.33986182	0.30552515	-0.25769814	0.33820738	0.41862559	-0.3413572	0.22120613	-0.3060275
X7	-0.20920273	-0.21115758	0.54295640	-0.15320023	-0.41117271	0.22458541	-0.27879353	0.4466556	-0.08540812	-0.2989173
X8	0.02766492	-0.67950964	-0.20826035	0.04239687	0.05833284	-0.02310534	-0.14385698	-0.1996085	0.54773116	-0.3575571
X9	0.41591509	-0.04860148	0.12943820	-0.31546728	0.08233973	-0.57275330	0.41703668	0.3610205	0.02975645	-0.2615563
X10	0.48409958	-0.07930135	-0.23853052	-0.24644878	-0.38637159	0.30938101	-0.02815855	0.2561674	0.27511125	0.5046034

When analyzing the above results, it can be noticed, inter alia, that the variable x_{10} has the greatest contribution to the creation of the first principle component (PC1). On the other hand, the greatest contribution to the creation of the second principle component (PC2) is the variable x_8. Based on the above results, the dependencies between principle components and analyzed variables for PC1, PC2 and PC3 can be written as follows:

$$\mathbf{PC1} = -0.15 * x_1 - 0.18 * x_2 - 0.04 * x_3 - 0.41 * x_4 - 0.45 * x_5 + 0.34 * x_6 - 0.21 * x_7 + 0.03 * x_8 + 0.41 * x_9 + 0.48 * x_{10} \quad (4)$$

$$\mathbf{PC2} = 0.20 * x_1 - 0.12 * x_2 - 0.58 * x_3 + 0.11 * x_4 - 0.15 * x_5 + 0.25 * x_6 - 0.21 * x_7 - 0.68 * x_8 - 0.05 * x_9 - 0.08 * x_{10} \quad (5)$$

$$\mathbf{PC3} = -0.18 * x_1 - 0.54 * x_2 - 0.08 * x_3 - 0.20 * x_4 + 0.31 * x_5 + 0.34 * x_6 + 0.54 * x_7 - 0.21 * x_8 + 0.13 * x_9 - 0.24 * x_{10} \quad (6)$$

In the same way, the other principal components can be written.

Table 3 and Figure 8 show the percentage of explained variance by each of the principle components.

Table 3. Percentage of explained variance by each PCs.

Importance of components:

	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9	PC10
Standard deviation	1.3826	1.2091	1.1625	1.0734	0.97268	0.93333	0.85696	0.81129	0.76580	0.57148
Proportion of Variance	0.1912	0.1462	0.1351	0.1152	0.09461	0.08711	0.07344	0.06582	0.05864	0.03266
Cumulative Proportion	0.1912	0.3374	0.4725	0.5877	0.68233	0.76944	0.84288	0.90870	0.96734	1.00000

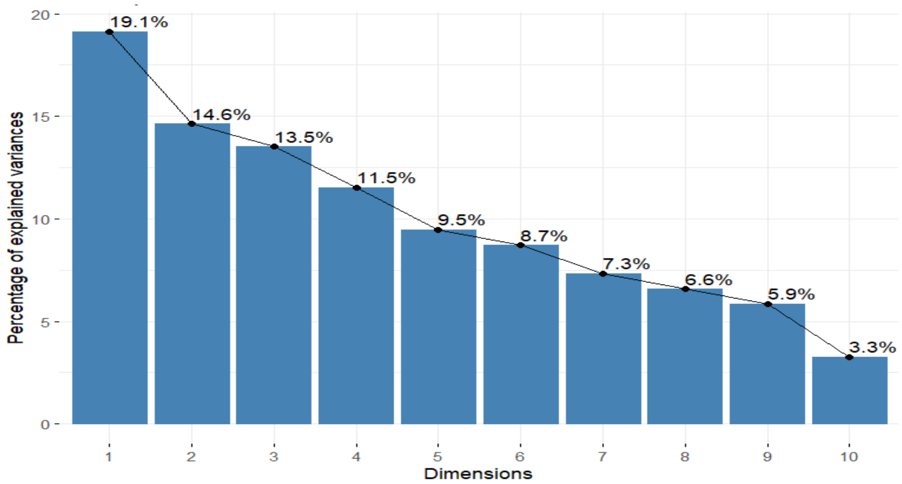


Fig. 8. Percentage of explained variance by each PCs.

Based on the percentage criterion of the explained variance, 7 components are sufficient and explain more than 80% of the original variance (Table 3). Based on the Keiser criterion, the first four components should be selected because their eigenvalue exceeds 1.

Figure 9 shows the initial variables and their correlation to the first two principle components. The directional arrows associated with the variables indicate the extent and direction of their influence on the respective principal components. Moreover, their relative positions allow for the interpretation of inter-variable correlations:

- Perpendicular vectors suggest no correlation between variables.
- Small angles between vectors indicate a strong positive correlation.
- An angle close to 180 degrees signifies a negative correlation.

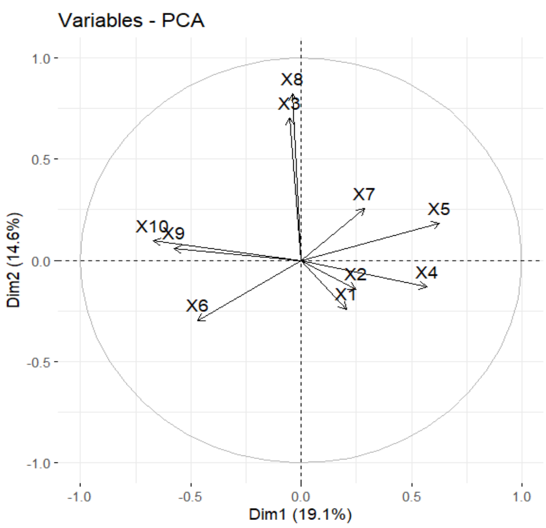


Fig. 9. Percentage of explained variance by each PCs.

The results shown in Figure 9 that the primary variable x_3 and x_8 are the most correlated with PC1. However, for PC2 it is the variable x_9 and x_4.

Logistic regression in the analysis of factors influencing the machines availability

The main purpose of using logistic regression was to identify factors of the maintenance process that affect the availability of the machines in production process. Principle components from PC1 to PC7 were used for the studies. The availability (A) of the machines was assessed as: OK=1, NOK=0. From the process 1130 observations were collected and then analyzed. The observations set for analysis was divided into two observations sets: the learning set (80%) and the validation set (20%)

Figure 10 presents the values of the coefficients in the developed regression model.

```
Coefficients:
(Intercept)        PC1        PC2        PC3        PC4        PC5        PC6
     2.0500     0.1066     0.3324    -0.3854     0.6344    -0.2035    -0.3360
        PC7
     0.2104
```

Fig. 10. Values of the coefficients in the developed regression model.

Based on the values of the coefficients, the regression model can be presented as equation:

$$LOGISTIC\ (A) = 2.05 + 0.10 * PC1 + 0.33 * PC2 - 0.38 * PC3 + 0.63 * PC4 - 0.20 * PC5 - 0.33 * PC6 + 0.21 * PC7 \quad (7)$$

The significance analysis for individual PC’s in Figure 11 is presented.

```
Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)  2.04998    0.10986  18.660  < 2e-16 ***
PC1          0.10656    0.08395   1.269 0.204339
PC2          0.33244    0.09015   3.688 0.000226 ***
PC3         -0.38540    0.13339  -2.889 0.003863 **
PC4          0.63445    0.09498   6.680 2.39e-11 ***
PC5         -0.20351    0.12568  -1.619 0.105387
PC6         -0.33598    0.10463  -3.211 0.001322 **
PC7          0.21039    0.11687   1.800 0.071827 .
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Fig. 11. Coefficients and the results of the significance analysis.

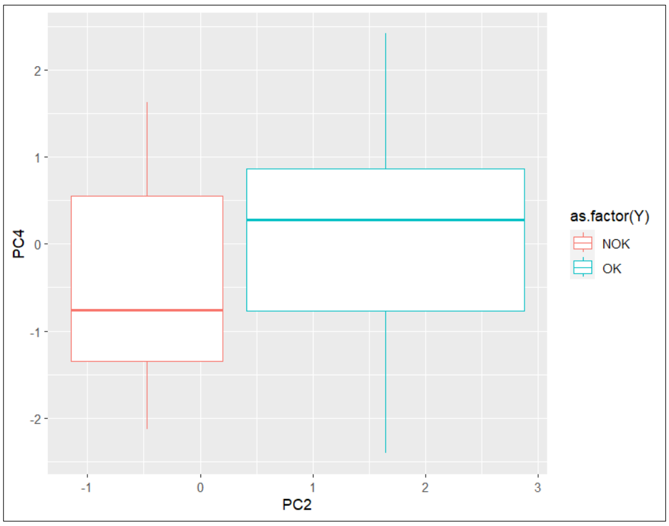


Fig. 12. Availability distribution of machines Y depending on principle component PC2 and PC4.

The presented regression results show, that components PC2 and PC4 are the most significant factors influencing the machines availability (p-value< 0.001). What's more, they are positively correlated with the machines availability. Moreover, the main components in PC2 is x_3 and x_8. It can be observed from the Table 1, that for factor x_8 the p-value was close to 0.05 (0.0582). Additionally, Figure 12 shows the availability distribution of machines Y depending on principle component.

In order to evaluate quality of the model (the model error) of the developed LR model the confusion matrix (CM) has been developed. Based on the CM Accuracy of the model for the training data was 0.92 and for test data was 0.89. Which means, that the model error for the training data was 0.08 and for the test data 0.11. The value of Accuracy demonstrates the good quality ability of developed model.

The conclusions from the analyzes carried out as part of this stage of the SS project were used to identify improvement activities for the process. Firstly, the detail analyses of the defined most significant factors show that the most frequent errors occurred on work station with the following parameters:

- with operators having less than 1 year of work experience,
- with operating time during night operation time,
- TPM implemented in less than half the year on the machines,
- the machines with the highest production load,
- the largest range of AM,
- the shortest AM duration time,
- the most reported problems on the machine post-AM.

Secondly, for further analysis, the Ishikawa diagram and 5 Why method were performed. These methods enabled to identify the root causes for the primary problem identified: the incorrect implementation of AM activities. By uncovering potential causes influencing the problem, strategies for enhancing maintenance implementation were determined, with a special focus on inadequate autonomous maintenance. Key causes of the improper maintenance implementation included:

1. No comprehensive operator training in AM procedures.
2. Insufficient specialized training for individual AM control points.
3. Overloading of machines, leading to insufficient time for AM.
4. Various standards of AM for similar machines.
5. No procedure for removing and analyzing problems after PM and AM.

In Table 4 the key causes linked to relevant identified significant factors are presented.

Table 4. Key causes linked to relevant identified significant factors.

No.	Key causes	Link to relevant significant factors
1	No comprehensive operator training in AM procedures	x_1, x_2, x_8
2	Insufficient specialized training for individual AM control points	x_1, x_2
3	Overloading of machines, leading to insufficient time for AM	x_4, x_6
4	Various standards of AM for similar machines	x_4, x_5, x_6
5	No procedure for removing and analyzing problems after PM and AMs	x_9

4.2.4. Improve Phase

The aim of the improve phase was to develop solutions aimed at removing the identified problems in order to achieve the project goals. Table 5 presents the proposed improvement actions. The proposed solutions focused on eliminating the causes of the problems identified in the Analyze phase. In addition, for the proposed solutions, the person responsible for their implementation and the time of their implementation [month] was specified.

Table 5. Improvement actions.

Lp.	Improvement actions	Responsible person	Time [month]
1	Creation of an employee training program	SS Leader	1
	Execution of employee training sessions	Maintenance Supervisor	3
2	Establishment of a method of monitoring AM performance	SS Leader	2
3	Formulation of a protocol for addressing post-AM and PM issues	Maintenance Supervisor	6
4	Assessment and implementation of revisions to PM practices	Maintenance Supervisor	6
5	Review and implementation of adjustments to production planning	Production Supervisor	6
6	Standardization of AM processes across machines of identical types	Maintenance Supervisor	3
7	Integration of scheduled audits into the workflow	SS Leader	6

The above proposed solutions were implemented to the analyzed process.

4.2.5. Control Phase

The key purpose of the this SS phase was to assess the degree to which the suggested and implemented actions have generated the planned results. At present, within the context of the studied company, four out of the seven proposed initiatives have been implemented: the creation and realization of an employee training program, the establishing a method for monitoring AM performance and formulation of a protocol for addressing post-AM and PM issues. Moreover, the final stages of developing a protocol for addressing issues post-AM and PM are underway.

Even though not all improvements have been fully realized, the company is already observing certain advantages. Notable among these is a reduction in the number of reported issues following AM, noticeable improvements in the consistent application of standardized AM procedures, and increased awareness among production personnel concerning maintenance process. A comprehensive evaluation of the usefulness of these executed measures will be conducted after all improvements have been implemented. In addition, periodic audits were conducted to check the continuity of the implementation of implemented activities.

5. Conclusions And Future Directions

Analyzing the current literature on SS, one can see the authors' growing interest in using the new I4.0 technologies in the DMAIC improvement cycle. In the face of the availability of large data sets, the traditional methods used so far in the SS methodology are no longer sufficient, which is why the authors of the publication emphasize the legitimacy of using new, advanced analytical methods that increase the effectiveness of SS projects. New I4.0 technologies affect not only the methods of obtaining and data, but also their collection and advanced analysis.

That's why the main aim of the paper was to present the possibility of the application of the SS project in the maintenance process using the DMAIC methodology and selected advanced analytical methods, such as PCA and LR. The goal of using the PCA method was to decrease the number of variables describing the analyzed process and to discover the relationship between the variables. The main purpose of using logistic regression was to identify additional factors of the maintenance process that affect the availability of the machines in production process. Firstly, the scope of the SS project and needed information from the process was defined. Then, the combination of qualitative and quantitative research methods used in the first phase of the study allowed to identify the individual factors affecting the availability of the machines. Then, the use of advanced analytical tools, such as PCA and logistic regression, allowed for the identification of relationships between the analyzed factors, as well as to discover the new, additional factors affecting the effectiveness of the analyzed process. The identified factors and their interactions made it possible to define activities in maintenance process requiring improvements. As a consequence, the implemented improvement activities significantly increased the efficiency of the process, and thus the machine's availability in the manufacturing process.

Due to the fact that mechanical failures predominated in the analyzed company, the analyzes carried out concerned this type of failures. In further stages of research, when conducting a more in-depth analysis, it is worth considering carrying out similar research for other types of failures, i.e. automation and electricity. The results of such analyzes may reveal further important factors influencing their occurrence and thus indicate additional actions to improve the maintenance process in the company.

Analyzing the literature, one can notice a growing interest in the use of I4.0 technology in SS projects. The reasons for this interest can be seen in the very fast progressing automation and computerization of production processes, and thus in access to large data sets. On the one hand, such amount of data and their structure is a challenge for traditional analysis methods used in SS, on the other hand, it creates new opportunities to discover new knowledge about processes, and thus, to make more effective decisions as to the direction of process improvement. Reviewing publications on the use of advanced methods of data analysis in SS projects, the authors indicate the possibility of using, for example, BDA, IoT and show the potential benefits of their implementation. However, there is still not much research, especially practical examples of their applications. Since the technological progress in the field of data acquisition and collection is very fast, there is a need, primarily from a practical point of view, to extend the SS methodology with new advanced analytical tools and to build a road map for SS project managers. In this aspect, it would be interesting to assign new analytical tools to individual phases of the DMAIC cycle and to build a guide for their use.

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