MIC 2024
Management International Conference
Trento, Italy • 5–8 June 2024

Preliminary Results of Processes Monitoring: The Case of a Company in the Automotive Industry

Aleksander Janeš
University of Primorska, Faculty of Management, Slovenija
aleksander.janes@upr.si

Robert Pavlin
University of Primorska, Faculty of Management, Slovenija
robert.pavlin@outlook.com

Abstract.
Rationale: The study is dedicated to an automotive company that faces the challenge of improving the quality of its products while simultaneously reducing production costs. New methods for monitoring and analysing Key Performance Indicators (KPIs) are developed to overcome this challenge.

Research question: What is the relationship between technological process indicators and return on investment (ROI)?

Purpose and Aim: The purpose of the research was to improve the understanding and management of key performance indicators in the case of a selected automotive company. The research aims to develop a management tool to accurately monitor the Business and technological processes (BTP) including the analysis of the preparation and assembly processes.

Methodology: The theoretical framework relies on measuring process technology performance and its correlation to financial results. The research relies on a case study that involved data analysis, the use of a critical process capability (Cpk) measurement system, and event tracking and logging.

Main Findings: In the third optimisation, significantly improved indicators were recorded, including higher KPI values (e.g., Cpk, OEE, and ROI). These improved indicators led to compliance with end-product specification requirements while increasing the operational efficiency of manufacturing.

Added Value of the Paper: The preliminary results of the survey are an important contribution to the automotive company by highlighting the key role of business and technology processes performance measurement and automation in improving operational efficiency. This can support improved process management and add value to social responsibility and environmental protection.

Originality: This research makes an important contribution to the understanding of the complex correlations between technology indicators, financial performance, and overall efficiency in the automotive company.

Limitations and further research: The limitations of the research relate to the approach of the single case study application and to time and financial constraints. For further research, it is recommended to delve deeper into the correlations between process technology performance indicators and financial outcomes and to extend the research to other automotive cases and industries.

Keywords: measurement, business processes, process technology, performance indicators, process capability, overall equipment efficiency, return on investment, monitoring system, automotive company.

https://doi.org/10.26493/978-961-293-323-4.9-21

1 Introduction

The automotive industry faces the challenge of improving the quality of its products while reducing production costs. New methods for monitoring and analysing Key Performance Indicators (KPIs) are developed to overcome this challenge. To this end, we have been developing an integrated business and technological process measurement system (BTP) that enables the effective monitoring and control of technological processes, thereby improving the efficiency and quality of production. The present preliminary research aims to provide an organisation with a tool for accurate monitoring of BTP, which integrates technological processes and enables the analysis of the preparation and assembly processes with their sub-processes. In the development of the BTP system, special attention was paid to the definition of measurable and verifiable performance indicators that allow effective control of the technological processes in the organisation.

2 Theoretical backgrounds

Measuring the performance and effectiveness of BTP is crucial for manufacturing organizations. However, there are shortcomings in current measurement systems, which do not have properly integrated technology processes (Neely, Gregory and Platts, 1995).
The theoretical background of the problem focuses on the management of technological processes by measuring their efficiency and effectiveness (Melnyk, Bititci, Platts, Tobias and Andersen, 2014, p. 175). The dynamic business environment requires performance measurement systems (PMS) to keep pace with constant changes in strategies and measurement methods. In addition to traditional methods, new methods are emerging, such as Business Activity Monitoring (BAM) (Janiesch, Matzner, and Müller, 2012, p. 626) and Service Oriented Architecture (SOA) (Malatras, Asgari, Baugé, and Irons, 2008, p. 133). New artificial intelligence methods are also being developed to monitor technological processes. A technological process can be defined as a series of activities carried out in a specific order to achieve a specific goal. To effectively manage a technological process, it is important to use appropriate methods and tools to control and monitor the process and to detect and correct errors.
These approaches include business process analysis and diagnosis (Horenbeek and Pintelon 2013, p. 34), selection of KPIs (Neely, Gregory and Platts 1995, p. 108), process monitoring and control (Das, Maiti, and Banerjee 2012, p. 721), fault detection and correction, and change management (Hyötyläinen 2015, p. 3; Janiesch, Matzner, and Müller, 2012, p. 627). Hyötyläinen, (2015, p. 163) and vom Brocke and Schmiedel (2015, p. 194) also deal with issues such as relational capital, absorptive capacity, process reliability and maintenance management. Their findings point to the importance of measuring the performance of technological processes to achieve competitive advantage. Durivage (2014, p. 143) and Horenbeek and Pintelon (2013, p. 36) further discuss different approaches such as modelling and simulation, analytic network process (ANP) and balanced scorecard (BSC) used to measure and monitor the performance of technological processes.
The technological processes include assembly of Daytime Running Lights (DRLs) parts and assembly processes, which include bolting, glueing and final inspection. The bolting process uses various tools such as automatic bolting machines to achieve the appropriate torque, bolting time and number of turns. Durivage (2014, p. 115) discusses processes of primary importance in the automotive industry and presents an example of statistical methods for process evaluation and improvement. The bonding process in the automotive sector requires precise measurement of various parameters such as adhesive temperature, component temperature and adhesive mass, and bonding time, which is important to balance the overall technological process with other operations. This represents an important step to balance the overall technological process with other operations in production (Agostini, Nosella, and Soranzo, 2017, p. 1151). The final inspection process is the last operation in the technological process considered in the study. This process is crucial to ensure the quality of the product. Different methods and tools are used to inspect and test the product. These approaches include the use of an ANP to select performance indicators and a systems approach to diagnose the current state of quality management

systems and business processes (Garza-Reyes, 2017, p. 22; Horenbeek and Pintelon, 2013, p. 34). In the automotive sector, assembly, bolting, bonding, and final inspection are key processes that require precise monitoring of parameters to ensure quality and production efficiency. Authors such as Durivage (2014, p. 93), Agostini, Nosella, and Soranzo (2017, p. 1147), Garza-Reyes (2017, p. 4), Horenbeek and Pintelon (2013, p. 45), and several others have presented different approaches and methods that include statistical methods, measurement of parameters (torque, time, number of revolutions, temperature, mass, and timing), and the use of tools to inspect and test the product. From the literature review, we identified an opportunity for a scientific contribution to the development of an integrated business and technological process measurement (BTP) system in the automotive company, which would enable better alignment of technological processes, measurement of KPIs, and improvement of production quality and efficiency. The research is based on a case study and conducted to understand the correlations between the technology indicators Critical Process Capability (Cpk), Overall Equipment Effectiveness (OEE) and the financial indicator Return on Investment (ROI) and the relevance of this correlation to the overall performance of the organisation. Within the conceptual research model (Figure 1), we placed Cpk on the left-hand side and OEE and ROI on the right-hand side.

The research question that guided research is: "What is the relationship between the technology indicators Cpk and OEE and the financial indicator ROI?", during the preliminary research we tested the following two hypotheses:

H1: Cpk is statistically significantly related to OEE.
H2: ROI is statistically significantly related to Cpk.

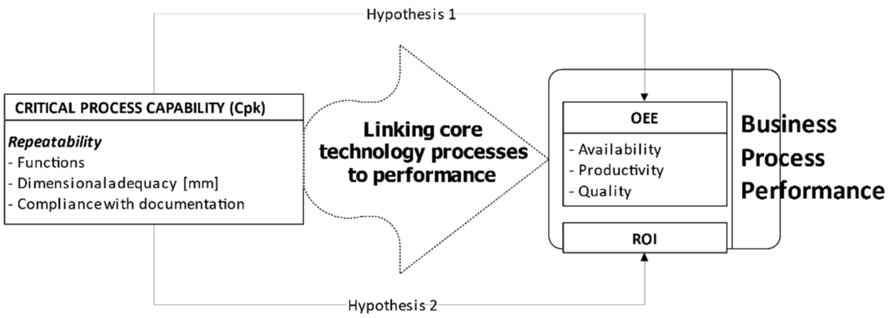

Figure 1: Conceptual model of the survey.

Based on the analysis, decisions were taken on improvements and follow-up actions to achieve the defined process objectives.

3 Methodology

For the study, we collected data on the technological processes using a measurement process that allowed us to obtain objective and reliable data for analysis. We used several tools and methods, ranging from simple ones such as gauges and scales to complex devices such as a coordinate measuring machine and a photometer.
In carrying out the measurements, we closely followed the ISO 22514-7:2012 standard (ISO 2012), which specifies a minimum number of measurements for each operation. Our approach to measurement involved many considerations and careful planning (Kaplan, 2010, p. 28). For operations where the assembly process deviated from the specified tolerance range during the commissioning phase, we carried out an extensive assembly analysis involving at least 700 measurements. For the measurement of the technological assembly process with 15 operations, we measured at least 750 pieces. For the analysis of the final assembly operation, where function, dimensional adequacy and quality were checked, 250 measurements were taken. We used specialised measurement devices such as a

screwdriver and a glueing machine, which enabled the automated recording of key data, including torque, number of turns, temperature, glue mass and screw-driving or glueing time. The accuracy of the measurements was ensured using control tools such as a balance, thermometer, and stopwatch. The analogue indicators were measured using a simple cycle measurement procedure, recording the time taken to complete each step in the process. Each measurement was repeated several times to obtain accurate data. This challenging measurement process took one year and involved several thousand measurements. In cases where the optimisation showed that the process was not stable, the measurements and optimisation were repeated several times. All the measurements made were key to the Cpk analysis, which covered three key indicators: function, dimensional adequacy, and compliance with documentation (Figure 1). This comprehensive approach ensured the highest quality of the manufacturing process and product. For the study, we developed a conceptual model (Figure 1), which included a narrower set of indicators for analysis. To calculate the performance of the business process, we used the OEE, which consists of three indicators: availability, productivity, and quality. In addition, we used the ROI indicator, which together with the OEE represented the business process performance. Two software packages, i.e., Minitab and SPSS, were used for the statistical analysis. To test hypotheses, we focused on the Cpk indicators, which were determined using Minitab. To validate the hypotheses, we had to achieve a Cpk value of at least 1.67, which is derived from the Six Sigma methodology. This value was crucial to validate the hypotheses as stated in Pyzdek (2003, p. 475), Aized (2012, p. 251) and Pojasek (2003, p. 4). Cpk is an indicator of a process's compliance with specifications and measures how well a process is managed against the requirements of the product or service specification. The Six Sigma methodology aims to reduce process variability and ensure high product quality (Pyzdek, 2003). In the text, we use labels, such as "_L3", which are key to understanding certain properties in analytical process. Each tag consists of a letter (e.g. L for the left-hand side and D for the right-hand side of the assembly line) and a number indicating the sequence number of the optimisation of the technological process, for example "_L3" for the left-hand side and the third optimisation. To test H1, we used regression analysis, including in the model the indicators measured after the third optimisation. All Cpk indicators were included as independent variables, and on the other hand, we used OEE, represented by the availability, productivity and quality indicators, as the dependent variable (see Figure 1).

Based on H1, a regression model equation to predict the value of OEE_L3 based on the indicators (Cpk) Functions_3L, Dimensional Adequacy_3L, and Documentation Compliance_3L was designed.

$$OEE\_L3 = b\_0 + b1*Functions\_3L + b2*Dimensional\_Adequacy\_3L + b3*Documentation\_Compliance\_3L + \varepsilon \quad (3.1)$$

Based on H2, a regression model equation to test the relationship between ROI_3L and Functions_3L, Dimensional Adequacy_3L, and Documentation Compliance_3L was designed (3.2):

$$ROI\_3L = b0 + b1*Functions\_3L + b2*Dimensional\_Adequacy\_3L + b3*Documentation\_Compliance\_3L + \varepsilon \quad (3.2)$$

H2 was used to test whether there is a correlation between ROI and Cpk. To test hypothesis 2, we compared ROIs between groups with different Cpk. We compared the statistical indicators and calculated a p-value which shows how likely it is that the differences between the indicators are random. Validation is crucial to demonstrate the ability of processes to deliver the intended results. However, we sometimes find ourselves in situations where we doubt our ability to generate a reliable assessment that would convince us of the substantive validity of validation, as described by Carder and Ragan (2004, p. 129).
According to ISO 9001:2015 (ISO 2015), every organisation must validate its BTP processes when the compliance of the processes cannot be ensured by subsequent monitoring and measurement. This

includes all processes where deficiencies are only revealed at the stage of use of the product or service. Validation or checking the integrity of the measurements can be carried out based on previous analyses, measurements, reflection on the problem and knowledge of the circumstances.

4 Empirical Findings

To test the hypotheses, Cpk analysis in Minitab was used. At the same time, a regression analysis in SPSS, which provides a basis for verifying the scientific assumptions in the study was performed.

4.1 Analysis of Indicators using Minitab

The analysis shows the results of the gradient function of the Daytime Running Lights (DRLs). The purpose of the analysis with the Minitab software was to check the functionality of the daytime running lights.
The functions labelled Function_2L, Function_2D, Function_3L and Function_3D are presented in Table 1. The labels "2L" and "2D" represent the measurements after the second optimisation for the left and right DRLs. The number "3" refers to the third optimisation. The function indicator represents the gradient, a mathematical concept that allows an understanding of changes in the DRL function in different contexts. The gradient represents the rate of change of this function depending on the different factors.
Analysis of the data for Function_L3 and Function_3D shows that the target values for this indicator have also been set at the midpoint between the lower specification limit (LSL) and the upper specification limit (USL). The results of the analysis show that the target values for Function_2 were achieved, but the standard deviations for Function_2D were higher than for Function_2L. Function_L3 and Function_3D showed very low standard deviation, indicating high precision of the measurements (Table 1).

Table 1: Process data for the functions indicator

Indicator	LSL	Target	USL	Sample Mean	Sample N	StDev(Within)	StDev(Overall)
Function_2L	152	*	168	160.090	50	1.96692	1.95691
Function_2D	152	*	168	159.888	50	2.04022	2.02984
Function_3L	152	*	168	160.116	50	1.00621	1.00109
Function_3D	152	*	168	160.194	50	0.99799	0.99292

Note: LSL (Lower Specification Limit) represents the lower specification limit set by the customer or designer. The USL (Upper Specification Limit) represents the upper limit. Sample Mean represents the average value. N represents the number of measurements.

Table 2 shows the calculation of the potential capability and within the capability for each of the variables relating to the functions (Function_2L, Function_2D, Function_L3 and Function_3D). The potential capability reflects the full alignment of the process with the product specifications, while the within capability assesses the actual performance of the process concerning the variability of the data within the specification range. Each variable has two values for the performance within the range: the CPL for the lower specification limit and the CPU for the upper specification limit. The within-range performance is calculated as the ratio of the distance between the specification limit and the within-range standard deviation. In addition, Table 2 also shows Cpk, which is an indicator of the compliance of the process with the specifications. A Cpk value below 1.33 indicates that the process is not compliant with the specifications, while a value above 1.67 indicates that the process is compliant with the specifications.
According to the data in Table 2, the values of potential capacity and in-range capacity for the functions after optimisation 3 are higher than after optimisation 2.

Table 2: Potential and in-scope capacities for the functions indicator

Indicator	Cp	CPL	CPU	Cpk
Function_2L	1.356	1.371	1.341	1.341
Function_2D	1.307	1.289	1.325	1.289
Function_3L	2,650	2.689	2.612	2.612
Function_3D	2.672	2.737	2.607	2.607

Note: Cp indicates the ratio of the process standard deviation to the tolerance (the difference between the upper CPU and lower CPL specification limits). The specification requires Cpk to be greater than 1.67 (6 Sigma).

Figure 3 illustrates the improved Cpk indicators of Function_L3 and Function_3D compared to Function_2L and Function_2D. After the third optimisation, we achieved Cpk values that met the requirements of the specifications, and we achieved this on both the left and right sides. This figure provides a clear visual comparison and makes it easier to understand the analysis results.

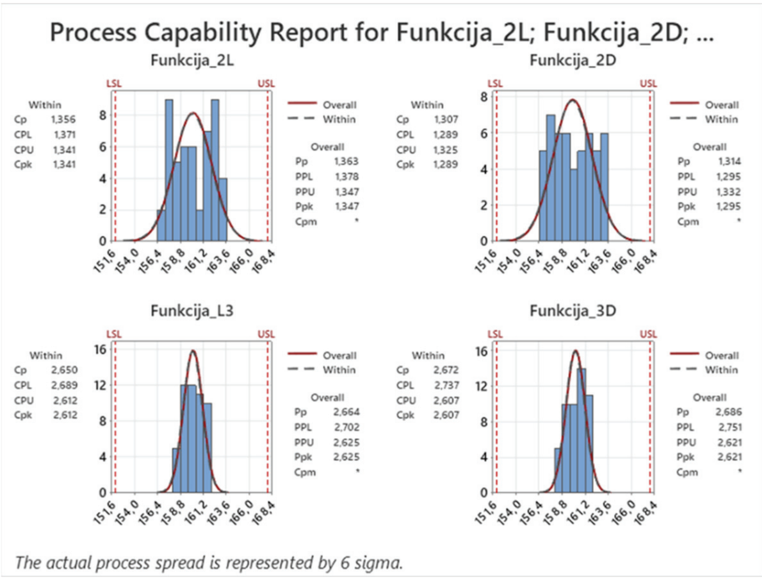

Figure 3: Cpk report for functions

The results (Table 3) show that for optimisation 2 on the left-hand side (Dimensional_fit_2L), the within-sample standard deviation is 4.27897, which exceeds the required specification. This means that Optimisation 2 did not meet the technical requirements for dimensional adequacy. Similarly, the result on the right-hand side (Dimensional_Adequacy_2D) shows a within-sample standard deviation of 3.99365.

On the other hand, optimisation 3 achieves sufficient dimensional adequacy, as the within-sample standard deviations for Dimensional_Adequacy_3L and Dimensional_Adequacy_3D are only 0.82414 and 0.70193, respectively. In addition, the values for both sides are consistent with the technical specification.

The within-sample standard deviation values measure how well the samples are distributed around the mean value. The smaller the standard deviation, the better the dimensional fits.

StDev(Overall) measures the overall variability of the process and is similar to the standard deviations within a sample. The results show that optimisation 2 was unsuccessful in achieving sufficient dimensional adequacy, while optimisation 3 achieved the required standards.

Table 3: Process data for the Dimensional Adequacy Indicator

Indicator	LSL	Target	USL	Sample Mean	Sample N	StDev(Within)	StDev(Overall)
Dimensional_Adequacy_2L	132.05	*	145.95	138.300	50	4.27897	4.25719
Dimensional_Adequacy_2D	132.05	*	145.95	138.720	50	3.99365	3.97333

Dimensional_Adequacy_3L	132.05	*	145.95	139.044	50	0.82414	0.81995
Dimensional_Adequacy_3D	132.05	*	145.95	139.062	50	0.70193	0.69836

Table 4 shows that the process indicator of dimensional adequacy for 2L and 2D optimisation (left- and right-hand side) is too low. The values of the 3L and 3D optimisation indicators are very high and exceed 2. This indicates that the product dimensions are in line with the technical specifications and that the process is well-compliant.

Table 4: Potential and in-area capacities for the Dimensional Adequacy Indicator

Indicator	**Cp**	**CPL**	**CPU**	**Cpk**
Dimensional_Adequacy_2L	0.541	0.487	0.596	0.487
Dimensional_Adequacy_2D	0.580	0.557	0.603	0.557
Dimensional_Adequacy_3L	2.811	2.829	2.793	2.793
Dimensional_Adequacy_3D	3.300	3.330	3.271	3.271

Note: Cp value represents the ratio of the tolerance interval to the standard deviation of the process, while the CPL and CPU indicators show how well the process meets the specification at the lower and upper end of the tolerance range. The specification requires Cpk to be greater than 1.67 (6 Sigma).

From Figure 4 it can be seen that the values of Cp, CPL, CPU, and Cpk for optimisation 3L and 3D are much higher compared to optimisation 2L and 2D, which means that optimisation 3 has better met the technical specifications.

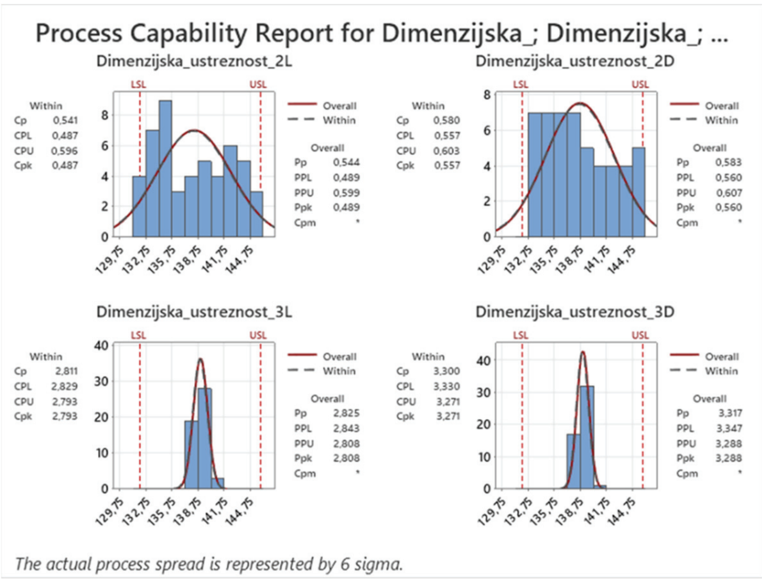

Figure 4: Cpk Dimensional Adequacy Report

A smaller standard deviation within the sample means the products are within tight tolerances and meet the technical requirements.

The conformity indicator assesses how well products meet the prescribed specifications according to UNECE R87 (UNECE 2010). This indicator helps to understand how often differences occur between actual products and their specifications.

Table 5 shows that Optimisation 2 is not compliant with the technical requirements, as all compliance indicators (Compliance_2L and Compliance_2D) exceeded the upper limit of the technical specification (USL). The within-sample standard deviations are relatively high for both functions, indicating high product variability. On the other hand, the Compliance_3L and Compliance_3D functions achieved much higher values of the compliance indicators, indicating that the 3 optimizations are compliant with the technical requirements prescribed by UN/ECE R87 (UN/ECE 2010). The within-sample standard deviations for the Compliance_3L and Compliance_3D functions are quite low, indicating more compliant products.

Table 5: Process data for the compliance indicator

Indicator	LSL	Target	USL	Sample Mean	Sample N	StDev(Within)	StDev(Overall)
Compliance_2L	142.12	*	157.08	149.314	50	1.93578	1.92593
Compliance_2D	142.12	*	157.08	149.102	50	2.17079	2.15974
Compliance_3L	142.12	*	157.08	149.580	50	0.63374	0.63052
Compliance_3D	142.12	*	157.08	149.628	50	0.62243	0.61926

Table 6 shows the results of the compliance indicator for the four variables (Compliance_2L, Compliance_2D, Compliance_3L and Compliance_3D). The value of Cpk focuses on the compliance of the process to the specifications. For a process to be considered compliant, the Cpk must be at least 1.67. If the value is lower, it indicates a higher variation.

From Table 6 for Compliance_2L and Compliance_2D the Cpk does not reach 1.67, which means that the process is not conformant and there are larger variations. This required improvements in the technological process. After the third optimisation, the Cpk for Compliance_3L and Compliance_3D exceeded 1.67, indicating a compliant process and less than 0.6% of products not meeting the specifications according to UN/ECE R87 (UN/ECE 2010).

Table 6: Potential and in-scope capacities for the compliance indicator

Variable	Cp	CPL	CPU	Cpk
Compliance_2L	1.288	1.239	1.337	1.239
Compliance_2D	1.149	1.072	1.225	1.072
Compliance_3L	3.934	3.924	3.945	3.924
Compliance_3D	4.006	4.021	3.991	3.991

Note: Cp indicates the ratio of the process standard deviation to the tolerance (the difference between the upper CPU and lower CPL specification limits). The specification requires Cpk to be greater than 1,67 (6 Sigma).

From Figure 5 it is seen that the values of Cp, CPL, CPU, and Cpk for Compliance_3L and Compliance_3D are much higher compared to Compliance_2L and Compliance_2D, which means that optimisation 3 has met the technical specifications.

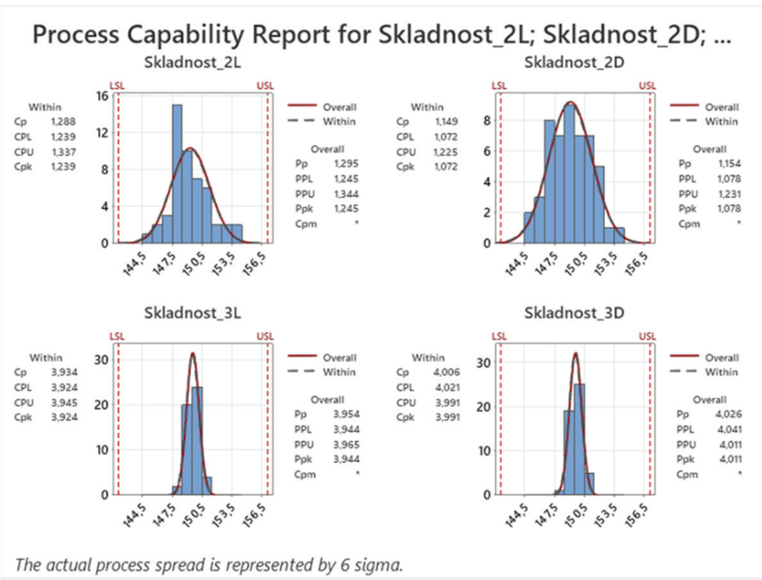

Figure 5: Cpk Compliance Report

Optimisation 3 achieved significantly higher Cpk and OEE values, resulting in a higher ROI than Optimisation 2. In calculating ROI, various costs including development, tooling, preparation, industrialisation, start-up, operational and non-quality have been considered. After optimisation2 we spent another €15.000 on improvements. This reduced the operating costs and the cost of product defects, justifying the higher investment.
Optimization 3 cost just over €1.5 million, including upgrades and improvements to production facilities through testing. Despite the initial costs, the investment has paid off in terms of increased efficiency and improved quality and ROI=7.978.259,00 €. This has led to higher revenues and lower operating costs. Analysis shows a high ROI after the third optimization compared to the ROI=2.915.182,27 € of the second optimization, confirming that the initial costs were justified. To calculate the ROI, we considered the development costs, the cost of the preparation tools, the cost of the complete assembly line, and the project start-up costs. These were compared with the total selling price, a methodology that allows a clear quantification of the correlations between the resources invested and the revenue generated. In this way, we ensure the reproducibility and transparency of the calculation.
The analysis used data collected in the first year, which included the start-up of the production line before the start of the series production (SOP). During this period, optimization of the production processes took place. After the optimization, the same production parameters were maintained for the whole period from the SOP to the end of the production period (EOP). The number of units produced in the analysis, corresponds to the actual number of products delivered to the customer. This approach allows for verifiability and a comprehensive assessment of the production process.

4.2 The H1 Verification's outcomes

Based on the results of the linear regression analysis, we found that there is a statistically significant relationship between Cpk and OEE. A higher Cpk means better OEE, which is crucial for the automotive industry, as regular monitoring of Cpk improves OEE (Baciarello and Schiraldi, 2015, p. 3). In addition, other factors, such as employee education (Neely, Gregory, and Platts, 1995, p. 84), have been shown to have an impact on OEE in this industry. Quality management, approach to maintenance, and use of technology are also important (Scagliarini, 2018, p. 2).
H1 assumes a statistically significant association between Cpk and OEE. To test this hypothesis, we used the indicators after the second and third optimisation. In regression model, we included all Cpk indicators. The dependent variable was OEE. The same regression model was used for the indicators after the third optimisation, as these indicators were consistent with the specification (Equation 3.1).

Table 7 shows the results of the regression analysis for the dependent variable OEE_L3, which measures operational efficiency, and the independent variables Documentation Compliance_3L and Dimensional Adequacy_3L. The variable Functions_3L was excluded from the model as it did not show a statistically significant relationship with OEE_L3.

Table 7: Regression analysis of the independent variables Cpk and the dependent variable OEE

Model Summary[b]										
					Change Statistics					Durbin-Watson
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change	
1	0,328[a]	0,108	0,070	8,04053	0,108	2,841	2	47	0,068	2,032

a. Predictors: (Constant), Documentation Compliance3L, Dimensional Adequacy 3L
b. Dependent Variable: OEE_L3; Method Stepwise

The Adjusted R Square coefficient of determination by including the number of predictor variables in the model confirms the low explanatory power of our model (0.070). This means that the current predictor variables are not sufficient to explain the variability in OEE_L3 satisfactorily.

Moreover, the correlations between the predictor variables and OEE_L3 are low, indicating that there is a weak correlation between them. It could suggest the need to look for other factors or better predictors for OEE_L3. The low correlations indicate the stability of the technological process as well as the insensitivity of the process to minor changes and support the findings of the Cpk analysis with Minitab, which is important for consistent future results.

The results of the Cpk and regression analyses clearly show that it is crucial to optimize technological process to achieve an appropriate level of Cpk indicators, which must be at least 1.67 (VDA 2011) as required by the UN/ECE R87 technical specification (UN/ECE 2010), and a high level of OEE, which should ideally be as close to 100 as possible. Although the already achieved value of OEE=85,41% (Availability=91.98%, Productivity=92.10%, Quality=98.60%) is indicative of excellent production performance, we aim to achieve the highest possible value of the OEE, while guaranteeing the adequacy of the dimensionality and compliance with the documentation.
H1, which claims that there is an association between Cpk and OEE, has been confirmed.

4.3 The H2 Verification's outcomes

H2 argues that there is a statistically significant relationship between ROI and Cpk. The analysis was based on the indicators after the second and third optimisation and included all Cpk indicators (functions, dimensional and documentation compliance) and ROI in the regression model (equation 3.2).
Through regression analysis, was found that there are weak correlations between ROI3 and Functions3, Dimensional Adequacy3 and Documentation Compliance3. However, there are no statistically significant correlations between these variables. Based on these results, there is insufficient evidence to support the H2 hypothesis with regression analysis alone. This is to be expected as we have deliberately chosen indicators that are expected to have very low or even absent correlations, which confirms the correct choice of indicators for analysis.
These results support the assumption that improving product functionality, dimensional fit and compliance with documentation has a positive impact on an organisation's ROI. Based on these findings, it can be concluded that hypothesis 2 is supported. This means that there is a relationship between ROI and Cpk, as a higher Cpk indicates a higher ROI.
Starting from the results (Table 8), an important fact is the extremely low coefficient of determination (R Square), which is only 0.006. This means that only 0.6% of the variability in ROI3 can be explained by the selected independent variables. At the same time, the Adjusted R Square is negative.

Table 8: Regression analysis of independent variables Cpk and dependent variable ROI3

Model Summary[b]										
					Change Statistics					
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	0.075[a]	0,006	-0,037	79,89634	,006	0,133	2	47	0,875	2,344

a. Predictors: (Constant), Documentation Compliance3, Dimensional Adequacy 3
b. Dependent Variable: ROI3; Method Stepwise

Although Dimensional Adequacy3 and Documentation Compliance3 have a statistically significant impact on ROI3, they explain only a small percentage of its variability, suggesting the presence of other important factors not captured by this model.
The analysis of Cpk and its correlation with ROI3 in our study revealed interesting findings. Although the correlation coefficients between Cpk and ROI3 showed a weak association between these variables, this does not mean that there is no association. Further analyses (analysis for the processes of screwing, glueing and final inspection; Critical Machine Capability-Cmk), used in the framework of the Six Sigma methodology to improve the quality of processes in organizations (Pyzdek, 2003) carried out, confirmed

that the relationship between Cpk and ROI3 is distinctly strong and visible. This successfully confirmed hypothesis H2, which predicted a relationship between Cpk and ROI3.
This fact leads to an important conclusion: although the correlation coefficients may be small and insignificant, they do not necessarily imply the absence of a relationship between the indicators. It is important to understand that a weak correlation does not exclude the possibility that the variables are related, but they may not be linearly related. In our case, despite the weak correlation between ROI3 and Cpk, we could confidently confirm hypothesis 2, as Cpk is significantly associated with ROI (see 4.2).
In this research work, regression analysis is not the main method of analysis, but one of the complementary techniques. The main approach is based on the Six Sigma methodology, which includes specific analyses of processes such as screwing, gluing and final inspection, and the use of indicators such as Cpk to assess quality. Regression analysis was used to further test the relationship between Cpk and ROI, but due to the very low R-squared (0.006) it was not sufficient to draw clear conclusions. Nevertheless, the analyses carried out within the Six Sigma framework confirmed a strong association between Cpk and ROI, supporting hypothesis H2.
For our analysis, we have used absolute values of the net return in EUR, as these allow us to assess more clearly the financial correlation of the investment over time (from the SOP to the EOP). Although ROI is usually expressed as a ratio, we have chosen absolute values as they better reflect the overall financial correlation of the project. This approach allows us to measure performance more accurately at a monetary level, which is crucial for our analysis.

5 Conclusion

The survey's initial findings demonstrate how important the BTP monitoring system is to enhancing organizational performance. By measuring indicators such as ROI, OEE and Cpk, we have optimized BTP and observed positive changes in performance and production quality.
A lack of research dealing with technical indicators of BTP was noted. Findings of several authors such as Kaplan and Norton (2006), Neely, Gregory and Platts (1995), and Santori and Anderson (1987) confirm that financial indicators alone are not sufficient and that it is also crucial to measure technological processes to improve production and business performance.
Hypothesis H1 was confirmed by Minitab, demonstrating a relationship between Cpk and OEE. Higher Cpk values indicated improved consistency of features, dimensions, and overall product quality, resulting in increased production efficiency. The low correlations in the regression analysis indicated the stability of the technological process and its insensitivity to minor changes, which supports the findings of the Cpk analysis using Minitab.
Hypothesis H2 systematically investigated the correlation between Cpk and ROI, confirming a correlation between these two indicators. Despite the low correlation coefficients resulting from the regression analysis, it is crucial to understand that a weak association does not exclude the possibility of a correlation between the variables. Further analyses and the application of the Six Sigma methodology confirmed the existence of a correlation between Cpk and ROI. An increase in Cpk contributed significantly to an increase in ROI.
By validating the hypotheses during the study, we have provided a concrete answer to the research question " What is the relationship between the technology indicators Cpk and OEE and the financial indicator ROI?". Our findings clearly show a positive correlation between higher values of Cpk and OEE and the financial indicator ROI.
There are limitations in the survey that affect the generalizability of the results to other organisations. One limitation is that the research focuses on only one manufacturing organisation (Ivanko, 2007). A potential area for further research is the in-depth analysis of the correlations between production process indicators and the financial performance of an organisation.

References

Agostini, L., A., Nosella, and B. Soranzo. 2017. ‘Measuring the impact of relational capital on customer performance in the SME B2B sector: The moderating role of absorptive capacity.’ *Business Process Management Journal* 1144–1166.

Aized, T. 2012. *Total Quality Management and Six Sigma*. Rijeka: InTech.

Baciarello, L., and M. M. Schiraldi. 2015. A Proposal for a Management-oriented Process Capability Index. *International Journal of Engineering Business Management* 7, 7–26.

Bititci, U. S., F. Ackermann, A. Ates, J. Davies, P. Garengo, S. Gibb, J. MacBryde, D. Mackay, C. Maguire, R. van der Meer, F. Shafti, M. Bourne and S. Umit Firat. 2011. ‘Managerial processes: business process that sustain performance.’ *International Journal of Operations & Production Management* 31(8): 851–891. https://doi.org/10.1108/01443571111153076

Brocke, J. vom in T. Schmiedel. 2015. *BPM–Driving Innovation in a Digital World*. Heidelberg: Springer International Publishing Switzerland.

Carder, B., and Ragan, P. 2004. Measurement Matters; How Effective Assessment. Drives Business and Safety Performance. ASQ Quality Press, Milwaukee, WI.

Das, A., J. Maiti and R. N. Banerjee. 2012. ‘Process monitoring and fault detection strategies: a review.’ *International Journal of Quality & Reliability Management* 29(7): 720–752. https://doi.org/10.1108/02656711211258508

Durivage, M. A. 2014. *Practical engineering, process, and reliability statistics*. Milwaukee: Quality Press.

Economic Commission for Europe of the United Nations (UN/ECE). 2010. *Regulation No 87: Uniform provisions concerning the approval of daytime running lamps for power-driven vehicles*. Available at https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX%3A42010X0630(03).

Garza-Reyes and J. Arturo. 2017. ‘A Systematic Approach to Diagnose the Current Status of Quality Management Systems and Business Processes.’ *Business Process Management Journal* 24(1): 216–233. https://doi.org/10.1108/BPMJ-12-2016-0248

Hair, J. F., W. C. Black, B. J. Babin in R. E. Anderson. 2014. *Multivariate Data Analysis*. Harlow, Essex: Pearson Education Limited.

Horenbeek, A. Van and L. Pintelon. 2013. ‘Development of amaintenance performance measurement framework – using the analytic network process (ANP) for maintenance performance indicators election.’ *Omega* 42(1): 33–46.

Hyötyläinen, T. 2015. *Steps to Improved Firm Performance with Business Process Management: Adding Business Value with Business Process Management and its Systems*. Wiesbaden: Springer Gabler.

International Organization for Standardization (ISO). 2012. ISO 22514-7:2012 *Statistical methods in process management–Capability and performance Part 7*. First edition. Geneva: ISO.

International Organization for Standardization (ISO). 2015. ISO 9001:2015 *Quality management systems - Requirements*. Geneva: ISO.

Ivanko, Š. 2007. *Raziskovanje in pisanje del: metodologija in tehnologija raziskovanja in pisanja strokovnih in znanstvenih del*. Kamnik: Cubus image.

Janiesch, C., Matzner, M. and Müller, O. 2012. ‘Beyond process monitoring: a proof□of□concept of event□driven business activity management’ *Business Process Management Journal* 18(4): 625–643. https://doi.org/10.1108/14637151211253765

Kang, B., D. Ki in S.-H. Kan. 2012. ‘Periodic performance prediction for real□time business process monitoring.’ *Industrial Management & Data Systems* 112(1): 4–23.

Kaplan, R. S. 2010. *Conceptual Foundations of the Balanced Scorecard*. Boston, Massachusetts: Harvard Business School, Harvard University.

Kaplan, R. S. in D. P. Norton. 2006. *Alignment*. Boston, Massachusetts: Harvard Business School Publishing Corporation.

Malatras, A., A. Asgari, T. Baugé and M. Irons. 2008. 'A service-oriented architecture for building services integration.' *Journal of Facilities Management* 6(2): 132–151.

Melnyk, S. A., U. Bititci, K. Platts, J.Tobias and B. Andersen. 2014. 'Is performance measurement and management fit for the future?' *Management Accounting Research* 25(2): 173–186.

Neely, A., M. Gregory, and K. Platts.1995. 'Performance measurement system design: A literature review and research agenda.' *International Journal of Operations & Production Management* 15(4): 80–116.

Pojasek, R. B. 2003. 'Lean, Six Sigma, and the Systems Approach: Management Initiatives for Process Improvement.' *Environmental Quality Management* 13(2): 85–92.

Pyzdek, T. 2003. *The Six Sigma Handbook*. New York: The McGraw-HIll Companies.

Santori, P. R., and A. D. Anderson. 1987. 'Manufacturing Performance in the 1990s: Measuring for Excellence.' *Journal of Accountancy* 164 (5): 141.

Scagliarini, M. 2018. A sequential hypothesis testing procedure for the process capability index Cpk. *Quality and Reliability Engineering International* 34(5): 791–806.

VDA. 2011. *VDA 5 Quality Management in the Automotive Industry-Capability of Measurement Processes*. Berlin: Verband der Automobilindustrie e.V. (VDA), Qualitäts Management Center (QMC).