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Integration of Statistical Process Control and Artificial Intelligence to Improve Steering System Process Capability in the NANO Model

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Abstract
The high Defects per Unit (DPU) in the NANO model, mainly caused by handlebar effort problems, indicates process variation in the steering system that affects product quality. This study aims to evaluate the stability and capability of the steering system production process and identify process parameters that contribute to handlebar effort through the integration of Statistical Process Control (SPC) and Artificial Intelligence (AI). Data were collected from measurements of steering system component dimensions and assembly process parameters on the production line. The analysis used $\bar{X}$-R control charts, process capability indices, and a machine learning-based AI approach to detect abnormal patterns among process variables. The results show that the process is generally close to statistical control, but special cause variations are still found. Process capability analysis indicates that the process has not consistently met specifications, as shown by $Cp = 0.87$ and $Cpk = 0.74$. The main parameters affecting process performance are steering stem height 1 and head pipe height, both of which show high variation and low process capability. AI analysis also identified abnormal multivariate patterns related to these parameters. Therefore, improvements should focus on standardizing work procedures, calibrating measuring instruments, controlling materials, maintaining jig fixtures, and improving operator competence. The integration of SPC and AI supports more predictive quality control and helps reduce defects in the steering system production process.

Keywords: Statistical Process Control, Artificial Intelligence, Process Capability, Handlebar Effort, Quality Control.

Introduction

Quality is one of the main factors that determine the competitiveness of manufacturing companies in meeting customer needs and expectations. Quality is not only judged by the final product, but also by the ability of the production process to produce products that meet specifications consistently. Therefore, companies need to implement a Quality Management System to ensure that each stage of the process runs according to the standards that have been set. The implementation of an effective quality management system can help companies maintain product quality consistency, increase customer satisfaction, and reduce the potential for defects during the production process.

In DEF companies, one of the quality problems that is of concern is the high value of Defect per Unit (DPU) in the NANO model which is dominated by handlebar effort problems. Handlebar effort is a quality characteristic related to the comfort and performance of the vehicle's steering system.

This problem not only affects the quality of the products produced, but also has the potential to reduce customer satisfaction and increase quality costs due to rework and additional inspections. The high number of defects caused by handlebar effort is also one of the factors that cause the company's quality targets to not be achieved.

Based on internal Quality Testing data, it was found that there were process variations in the steering system area related to the dimensions of steering components and assembly process parameters. These variations cause some products to not meet the standards that have been set, affecting the conformity quality and performance quality of the product. This condition shows that there are still sources of variation in the production process that need to be identified and controlled so that product quality can be improved sustainably.

One approach that can be used to control process variation is Statistical Process Control (SPC). This method allows companies to monitor the stability of the process and identify the causes of variations that occur during the production process. As technology develops, the application of Artificial Intelligence (AI) is also beginning to be used in the field of quality control to help detect irregular patterns and relationships between process variables that are difficult to identify through conventional analysis. The integration of SPC and AI is expected to provide more comprehensive information to support efforts to improve product quality.

Although Statistical Process Control (SPC) has been widely used to monitor process stability and identify variations in manufacturing processes, this method generally focuses on statistical control limits and univariate process behavior. SPC is able to indicate whether a process is under control, but it has limitations in explaining complex relationships among several process parameters simultaneously. In the case of the steering system, handlebar effort can be influenced by the interaction of multiple dimensional and assembly variables, such as head pipe height, steering stem height, and tightening torque. Therefore, the integration of SPC with Artificial Intelligence (AI) is important because AI can support multivariate pattern recognition, detect abnormal data patterns, and provide more predictive insight into potential process deviations. Previous studies have shown that SPC is effective for quality control in manufacturing processes, but the integration of SPC and AI is still needed to strengthen data-driven decision-making and improve the accuracy of defect prevention. Thus, this study offers a more comprehensive approach by combining SPC as a process monitoring tool and AI as a pattern recognition method to improve the capability of the steering system production process.

Based on these problems, this study aims to analyze the stability and capability of the steering system production process in the NANO model using the Statistical Process Control (SPC) method and identify patterns of process variations that have the potential to cause handlebar effort problems with the help of Artificial Intelligence (AI). The results of the study are expected to provide measurable improvement proposals to reduce defect rates, improve process capabilities, and support the creation of more effective and sustainable quality control.

Method

This study uses a quantitative method with a descriptive and analytical approach to analyze process stability, process capability, and factors causing handlebar effort problems in the NANO steering system production process at DEF Company. Data were collected directly from production, measurement laboratory, and vehicle testing areas through measurements of steering component dimensions and assembly parameters, including crown nut accuracy, head pipe height, cone race position, steering stem height, steering nut torque, and crown nut torque. Measurements were carried out using precision instruments such as FARRO, height gauge, vernier caliper, inside/outside micrometer, bore gauge, and push-pull gauge, with 30 data sets collected using subgroup sampling to represent actual process conditions. The data were analyzed using Statistical Process Control (SPC), particularly the X̄–R control chart, to evaluate process stability and identify special cause variations, while process capability analysis was used to assess the ability of the process to meet specifications. In addition, an Artificial Intelligence (AI) approach using machine learning through Google Colab was applied to identify multivariate patterns, detect abnormal process conditions, and support root cause analysis. The results of the SPC and AI integration were then used as the basis for formulating improvement recommendations to reduce defects and improve the consistency of the steering system production process.

Results and Discussion

Control Map Selection Explained

The Handlebar Effort problem is one of the big problems that causes the achievement of Defect per Unit in January to not be met.

Table 1. Defects per Unit (DPU) that exceed the company's target

Responsible	Accumulative Monthly DPU by Responsible								Accumulative Monthly DPU			
	Fit Finish	Dyno	HLA	Running	Off-Line		Final Inspection		Off-Line		Final Inspection	
Defect Part	540	19	263	573			24					
Unit	352	352	352	352			352					
DpU Part	1.53	0.05	0.75	1.63	Target	2.00	Target	0.80	Target	5.0	Target	2.00
					Actual	3.96	Actual	0.07	Actual	4.15	Actual	0.09
Defect Process	66	1	0	0			8					
Unit	352	352	352	352			352					
DpU Process	0.19	0.00	0.00	0.00	Target	1.00	Target	0.40				
					Actual	0.19	Actual	0.02				
Defect Design	0	0	0	0			0					
Unit	352	352	352	352			352					
DpU Design	0.00	0.00	0.00	0.00	Target	2.00	Target	0.80				
					Actual	3.96	Actual	0.07				

Based on the table above, data can be taken in the area of quality testing that *the handlebar effort problem* dominates the defects in the NANO model.

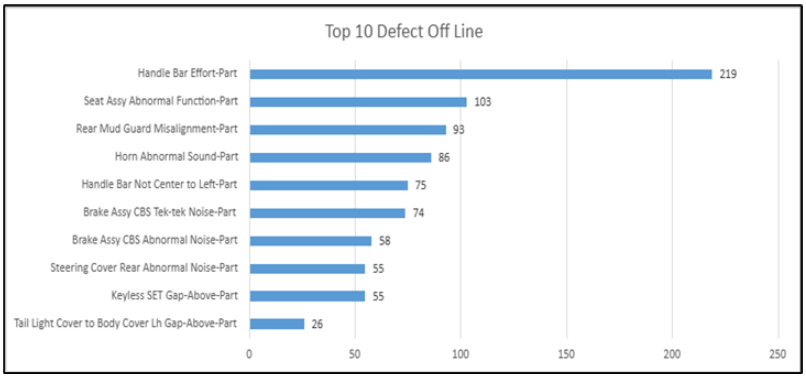

Figure 2. Data of the 10 biggest defects

This defect accounts for an NG ratio of 80% by January 2026. As a result of *the handlebar effort* problem , 219 issues were recorded out of a total of 352 units produced. This affects the division's KPIs that exceed the target set by the company, namely 2 Defects per Unit, the actual achievement in January is 3.96 DpU. This shows a significant gap in quality performance.

In addition, the variation in the value of the handlebar effort in the steering system process shows a fairly high fluctuation and is close to the specified limit that has been set. This condition indicates the possibility of a variation in the process that has not been statistically controlled.

Data Collection

Data collection in this study was carried out to obtain information on the actual condition of the process that affects the handlebar effort problem in the NANO model in DEF company. Data is collected directly from production areas, measurement laboratories, and vehicle testing areas. Measurements are made using several precision measuring instruments according to the characteristics of the analyzed components. In this study, data was taken directly from the field using several measuring instruments, such as *FARRO, Height gauge, vernier caliper, inside/outside micrometer and bore gauge.*

In this study, several precision measuring instruments were used to obtain accurate measurement data according to the characteristics of each steering system component. FARRO was used to measure the geometry and dimensional accuracy of steering system components, while a height gauge and vernier caliper were used to measure the linear dimensions of the components. In addition, inside and outside micrometers were employed to measure component diameters with higher precision, and a bore gauge was used to measure the internal diameter and fitting condition of component holes. Furthermore, a push-pull gauge was used in the vehicle testing area to measure the force or handlebar effort value on the complete bike. The use of these instruments ensured that the collected data represented the actual dimensional and functional conditions related to the handlebar effort problem in the NANO model.

The handlebar components taken in this data collection are in accordance with the initial analysis of the effect of preload on the axial force handlebar.

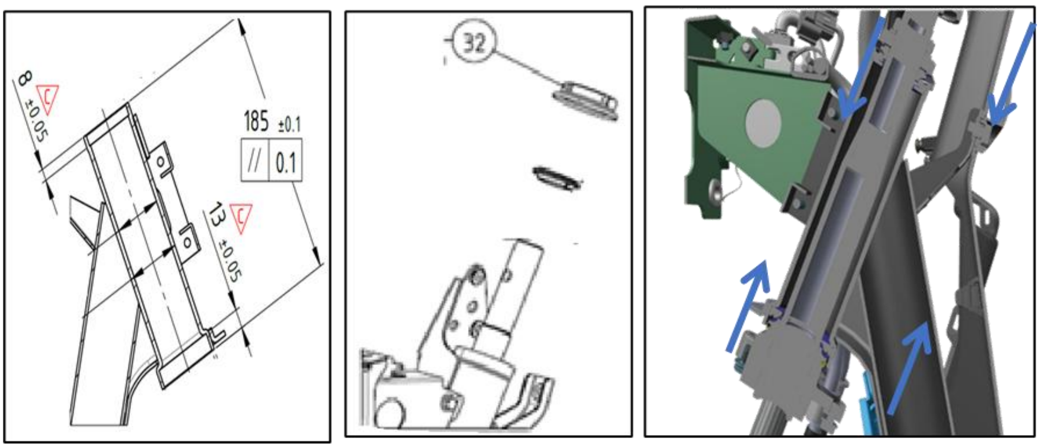

Figure 3. Steering and *axial force components*

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Data collection for this steering component is to determine the axial load acting on the steering component on the NANO model in the DEF company. The data produced is in the form of *variable data*, because it is to find the integrity of the process and the limits of the OK or NG part against the standards stated in the *drawing part*. Sampling was carried out periodically for several days before the trial on the *main production line*, using *the subgroup sampling method* to represent the actual process conditions. The measurement data is then used as the basis for *Statistical Process Control* analysis to evaluate process variations that contribute to the handlebar effort problem. The data obtained will be processed using the X – R control chart (X – R control chart).

The data presented in this study consist of several measurement variables related to the steering system components. These data include crown nut accuracy, frame data consisting of head pipe height, cone race upper holder, and cone race lower holder, as well as steering stem data consisting of cone race upper mount height and cone race lower mount height. In addition, data collection was carried out on each component using 30 data sets to provide sufficient measurement representation for further analysis. These data were then summarized to facilitate processing using the Statistical Process Control (SPC) approach.

Data has been made in the form of a data summary with the aim of making it easier to process data. The data presented is in the form of excel which is ready to be processed in the form of SPC.

Table 2. Measurement Summary of Steering System Components and Assembly Torque for SPC Analysis

VIN	Crown Nut	Height Head pipe	Cone Seat Race Lower	Cone Race Upper Stand	Steering stem Height 1	Steering stem Height 2	Torque Nut steering	Torque crown nut
VIN 698	15.03	184.701	13.15	8.00	11.01	186.53	40.04	10.1
VIN 699	15.05	184.644	13.10	8.06	10.67	186.61	40.05	10.08
VIN 700	15.12	184.731	13.18	7.98	10.39	186.20	40.03	10.05
VIN 701	15.1	184.699	13.09	8.07	10.75	186.62	40.02	10.04
VIN 702	15.09	184.496	13.11	8.09	9.83	185.63	40.08	10.09
VIN 703	15.12	184.712	13.03	8.04	10.06	186.23	40.03	10.08
VIN 704	15.07	184.653	13.08	7.98	10.36	186.31	40.07	10.07
VIN 705	15.11	184.781	13.11	8.07	10.22	186.69	40.06	10.07
VIN 706	15.09	184.598	13.05	8.00	9.79	186.39	40.05	10.06
VIN 707	15.18	184.509	13.13	7.97	10.48	186.50	40.05	10.07
VIN 708	15.02	184.735	13.12	7.97	10.19	186.49	40.03	10.05
VIN	15.11	184.621	13.05	8.02	9.90	186.46	40.04	10.07

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709								
VIN 710	15.12	184.684	13.18	8.00	10.20	186.43	40.06	10.05
VIN 711	15.05	184.552	13.10	8.02	10.22	186.47	40.05	10.05
VIN 712	15.07	184.476	13.14	8.05	10.12	186.37	40.08	10.04
VIN 713	15.12	184.693	13.12	8.03	10.04	186.43	40.07	10.05
VIN 714	15.07	184.577	13.07	8.05	10.09	186.73	40.06	10.1
VIN 715	15.11	184.74	13.18	8.09	10.44	186.43	40.05	10.09
VIN 716	15.09	184.615	13.16	8.04	10.05	185.65	40.04	10.08
VIN 717	15.18	184.502	13.20	8.00	10.07	186.61	40.07	10.07
VIN 718	14.96	184.663	13.02	8.00	10.62	186.72	40.08	10.07
VIN 719	15.11	184.728	13.06	8.09	10.53	186.17	40.1	10.04
VIN 720	15.09	184.541	13.04	7.98	10.68	186.54	40.06	10.05
VIN 721	15.03	184.692	13.01	8.08	10.21	186.28	40.07	10.04
VIN 722	15.12	184.573	13.04	8.05	10.30	186.52	40.1	10.06
VIN 723	15.12	184.781	13.13	8.09	10.26	186.52	40.05	10.04
VIN 724	15.09	184.635	13.09	8.03	10.05	186.25	40.06	10.02
VIN 725	15.09	184.508	13.02	7.96	10.21	186.80	40.04	10.07
VIN 726	15.07	184.699	13.16	8.00	10.37	186.36	40.07	10.03
VIN 727	15.00	184.754	13.03	8.03	10.17	186.54	40.03	10.02

Control Map Explained

A *Control Chart* is a statistical method that distinguishes between variations or deviations due to general and special causes. Deviations caused by specific causes are usually outside the control limits, while those caused by general causes are usually within the control limits. Usually between 80% to 85% of deviations are caused by general causes while between 15-20% are caused by specific causes.

The purpose of using this control map is to control the production process so that it can produce superior quality by detecting the causes of unnatural variations (Special Causes, Unnatural Causes) or called process shift (the occurrence of process shifts) and to reduce the variations contained in the process so as to produce a stable process.

In this study, the main components of the control map were used:

X̄ Control Map

Used to monitor the average change of processes in each subgroup. This graph shows whether there is a significant shift in the process mean over time.

This study shows that the main contribution to improving the production process of the steering system is through a structured approach that integrates Statistical Process Control (SPC), root cause analysis, and the use of Artificial Intelligence (AI) in data-based monitoring. The results of the analysis identified that the critical parameters that most affected the process performance were steering stem height 1 and head pipe height, which have high variation and low process capability. Evaluation using the X̄–R control map showed that although the process was generally close to a controlled state, there were still specific variations that required further investigation. In addition, the results of the calculation of process capabilities showed Cp and Cpk values of less than 1 (0.87 and 0.74) which indicated that the process has not been able to meet the specifications consistently and requires systematic improvement.

The root cause analysis revealed that quality problems are influenced by human, machine, method, and material factors, both in terms of the cause of defects and the exit of defective products to the next process. Based on these findings, various technical improvement efforts were formulated which included calibration of measuring instruments, repair and replacement of jig fixtures, standardization of sampling methods, control of material changes, and enforcement of standard operating procedures for operators. In addition, the integration of AI in quality control systems provides added value in detecting anomalous patterns in a multivariate manner and supports early identification of potential process nonconformities.

In order for the improvements to be implemented effectively and sustainably, a comprehensive control system is needed, including process standardization, implementation of calibration and preventive maintenance systems, strengthening production control plans, improving operator competence, controlling material changes, and implementing data-based monitoring through the integration of SPC and AI. In addition, periodic audits and the implementation of continuous improvement cycles are important elements in maintaining process quality consistency.

Overall, this study emphasizes that the success of process improvement is highly dependent on consistent statistical control, disciplined operational standardization, and support for digitally and manually integrated monitoring systems. The combination of SPC, root cause analysis, control plan, and AI monitoring has been proven to be able to push the production process towards a more stable and capable state, as well as improve the ability to detect variations, identify sources of nonconformity, and support data-driven decision-making in a sustainable manufacturing steering system.

X Bar R Chart of Torque Crown Nut

On the X̄ control map it can be seen that the average value of each subgroup is around the middle line of the process and does not cross the control limit. On the control map R, it can be seen that the variation in each subgroup is relatively consistent and is within the set control limit.

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Hypothesis and Statistical Testing

The statistical testing in this study did not use parametric hypothesis tests such as ANOVA, t-test, or p-value testing, because the purpose of the study was not to compare the mean between groups or treatments. The analysis focused on evaluating the stability of the production process using *the Statistical Process Control (SPC) approach*. In the SPC method, statistical decisions are determined based on the position of the data against the control limits and patterns of process variation, rather than on the value of inferential probability. Thus, statistical testing is carried out through the interpretation of the control map to detect any *special cause variation* or process shift.

Interpretation of data from statistical test results

Based on the results of the X̄–R control map analysis obtained through Minitab software, an evaluation was carried out on the stability of the production process of steering system components that affect the handlebar effort in the NANO model. On the X̄ control map, all the mean values of the subgroup are within the upper control limit (UCL) and the lower control limit (LCL). This shows that in general the average process does not experience significant shifts and is still around the middle line of the process.

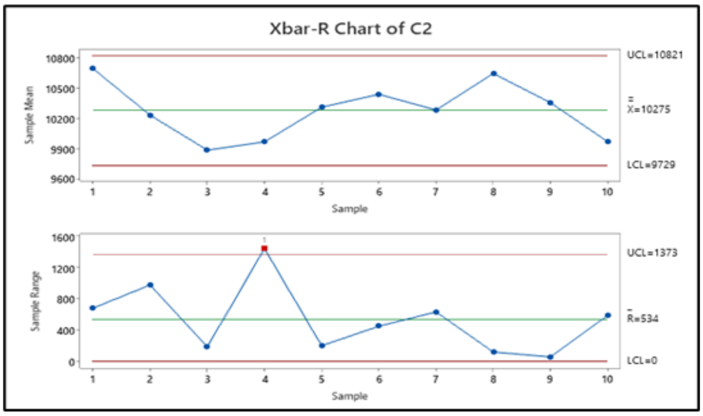

Figure 4. R chart deviation

This condition suggests that the variation in the subgroup exceeds the natural variation of the process. The occurrence of observation points outside the control limits on the control map R indicates a **special cause variation**, which is a variation caused by non-random factors that affect the consistency of the production process. This abnormal variation indicates that in the observation period there is a change in process conditions or certain disturbances that cause irregularities of variation in one subgroup. Although the average value of the process is still within the control limit, the instability on the control map R indicates that the process is not yet fully statistically controlled. This is due to the fact that the stability of the process is determined not only by the average position, but also by the consistency of the variation in each subgroup of observations. In practical terms, excessive variations within one subgroup can indicate inconsistencies in process conditions, such as differences in assembly conditions, variations in tightening torque, irregularities in component positions, or other factors that affect the uniformity of the steering system.

Thus, it can be concluded that the production process of steering system components is generally in a near-stable condition, but there are still indications of specific variations that need to be investigated further to ensure that the process is truly statistically controlled. Abnormal variations within one subgroup have the potential to affect the mechanical interactions between steering system components, which can ultimately affect the value of the handlebar effort felt in the vehicle. Therefore, the identification and control of *special cause variations* is an important step in efforts to reduce defects and improve the consistency of the performance of the steering system.

Analysis of Quality Concepts to Operational Processes Using *Artificial Intelligence (AI)*

ML is the domain of Artificial Intelligence (AI), which consists of automated programming algorithms from data and experiences or through interaction with the environment. There are three main branches: supervised/guided learning, unsupervised learning, and reinforcement learning. One of the main contributions of the application of ML techniques in designing control diagrams is that modern processes (production, insurance, healthcare, etc.) generate enormous data sets with great levels of diversity using modern measurement systems such as sensors that traditional statistical monitoring methods fail to do. to handle the process monitoring procedures.

The development of digital technology in the manufacturing industry has driven the transformation of quality control systems from an inspection-based approach to a predictive and optimization approach. In this study, the concept *of Artificial Intelligence (AI)* is used as a follow-up approach to support quality analysis in the steering system that affects handlebar effort. The AI approach is applied using **the Google Colab** platform, which enables Python-based data processing and machine learning computationally. The integration of AI in Quality Engineering aims to improve the system's ability to understand the complex relationships between process variables and predict potential mismatches before a defect occurs.

The results of using Google Colab are as follows:

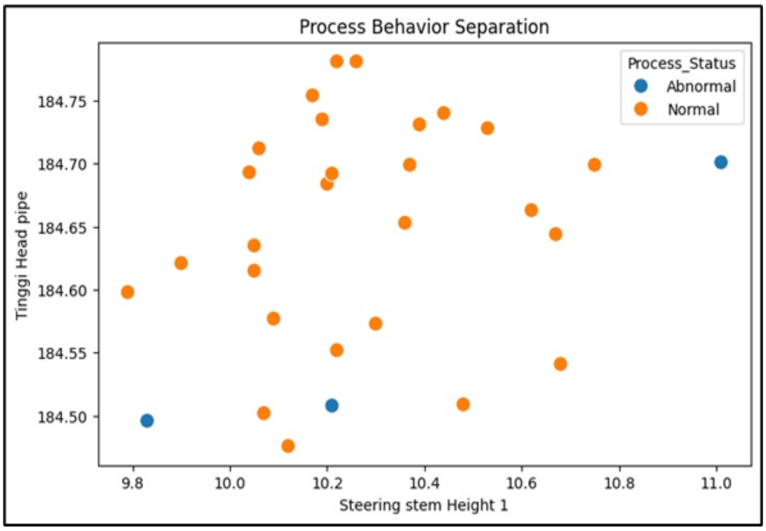

Figure 5. Google Colabs

Correlation between headpipe height and steering stem Height 1

Based on the results of the visualization of process behavior separation, the observation data of the steering system is divided into two main categories, namely normal process conditions and abnormal process conditions identified using unsupervised learning algorithms. Most of the observational data reside in the normal process group that forms the main distribution pattern. This shows that the majority of production units have consistent process parameter characteristics and are within a stable operating range. However, there are several observation points that are classified as abnormal conditions. These points are outside the main pattern of data distribution, indicating a combination of significantly different process parameters than normal conditions.

Specifically, process deviations were identified at a specific combination of head pipe height and steering stem height 1 values that did not follow the general pattern of process distribution. This suggests that the interaction between the two parameters has the potential to affect the stability of the steering system.

The existence of this abnormal point indicates a special cause variation, which does not originate from the natural variation of the production system. This condition can be caused by factors such as inaccuracies in component dimensions, misalignment of the steering system, or variations in assembly conditions. The Artificial Intelligence approach allows the identification of process irregularities in a multivariate manner, i.e. by considering the simultaneous relationships between process parameters. This provides an advantage over conventional methods that only monitor one variable separately.

The data distribution shows that small changes in the combination of steering component dimensions can result in significant changes in system behavior. This confirms that the steering system is sensitive to multivariate variations and requires more comprehensive process control.

The results of the AI analysis showed that the steering system had a stable dominant operating pattern, but there were certain process conditions that deviated from the normal pattern. These deviations represent a potential source of special variation that can affect the quality of handlebar effort.

In this study, the roles of Statistical Process Control (SPC) and Artificial Intelligence (AI) complement each other in supporting quality control analysis. SPC is used as the main approach to monitor the stability of the production process, determine whether the process is under statistical control, detect special cause variations, and provide control limits consisting of the upper control limit (UCL), center line (CL), and lower control limit (LCL). When the R chart shows data points outside the control limits, this indicates that the process is unstable and that abnormal variation occurs in the production process. Therefore, SPC plays an important role in monitoring and detecting process deviations.

Meanwhile, Artificial Intelligence (AI) is used to analyze the relationship patterns among process parameters, identify abnormal data in a multivariate manner, predict potential process instability, and support faster root cause analysis. The use of the Isolation Forest algorithm helps detect abnormal observation points, while the scatter plot visualization shows the separation of process behavior between normal and abnormal conditions. Thus, AI contributes to pattern recognition and prediction by providing a deeper understanding of process variations that cannot be fully explained through conventional SPC analysis.

Overall, the integration of SPC and AI provides a more comprehensive quality control approach. SPC serves as a fundamental method for monitoring process stability and detecting abnormal variations, although it mainly indicates the presence of irregularities without fully explaining the complex relationships among process parameters. In contrast, AI acts as an advanced analytical approach that can identify multivariate patterns, detect abnormal data, and help interpret the causes of process instability more comprehensively. Therefore, the combination of SPC and AI enables quality control to move beyond reactive detection toward more predictive and data-driven process improvement.

Thus, the integration of SPC and AI allows quality control systems to be not only reactive in detecting deviations, but also proactive in understanding process patterns and supporting predictive defect prevention.

Conclusion

This This study concludes that the integration of Statistical Process Control (SPC) and Artificial Intelligence (AI) provides a more comprehensive approach to improving the quality control of the steering system production process in the NANO model. The SPC analysis using the $\bar{X}$–R control chart indicates that the process is generally close to a controlled condition; however, the presence of special cause variations shows that the process has not yet achieved full statistical stability. The process capability results, with Cp and Cpk values below 1, further indicate that the process is still unable to consistently meet the required specifications. The analysis also identifies steering stem height 1 and head pipe height as critical parameters that contribute to variations in handlebar effort. Meanwhile, the application of AI supports the detection of abnormal patterns and multivariate relationships among process parameters, allowing potential process deviations to be identified more effectively. Therefore, improvements should focus on measurement instrument calibration, jig fixture maintenance, work method standardization, material control, and operator competence enhancement. Overall, the integration of SPC and AI can support more predictive, data-driven, and sustainable quality control to reduce defects and improve production process capability.

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