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Intelligent Quality Control in Manufacturing Using Integrated Statistical Process Control and Machine Learning

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Abstract*— This paper presents an integrated framework combining Statistical Process Control (SPC) and Machine Learning (ML) to enhance quality monitoring and productivity in CNC manufacturing processes. The study focuses on a shaft diameter machining process using a dataset of N production batches, where diameter is considered as the critical quality characteristic and tool wear, pressure, and temperature are treated as input variables. SPC techniques, specifically Individuals and Moving Range (I–MR) control charts, are applied to evaluate process stability and identify variations such as mean shifts and abnormal fluctuations. Process capability analysis is performed using Cp and Cpk indices to assess conformance with specification limits. To enable predictive analysis, a multiple linear regression model is developed to establish relationships between process parameters and output quality, followed by a Random Forest model to improve prediction accuracy and determine feature importance. The results indicate that the process is partially capable and that tool wear is the most significant factor influencing diameter variation. The proposed SPC–ML integration provides both statistical monitoring and predictive insights, enabling early detection of deviations, root cause identification, and data-driven decision-making. This approach supports improved process control, reduced variability, and enhanced production efficiency in modern manufacturing systems.

Keywords*— CNC Manufacturing, Machine Learning, Process Capability, Predictive Quality Control, Statistical Process Control.

I. INTRODUCTION

Manufacturing industries continuously strive to achieve high-quality products, reduced waste, and improved process efficiency. Statistical Process Control (SPC) has long been recognized as an effective methodology for monitoring process performance and identifying sources of variation. By using control charts and statistical indicators, SPC enables manufacturers to maintain stable processes and ensure product quality. However, traditional SPC techniques rely on assumptions such as normality, independence, and univariate data structures. In today's advanced manufacturing systems, processes are often complex, multivariate, nonlinear, and influenced by multiple interacting parameters. These complexities reduce the effectiveness of conventional SPC methods in detecting process shifts and predicting quality issues. Machine learning techniques provide a data-driven approach capable of learning complex patterns from historical process data. When integrated with SPC, machine learning can enhance fault detection, predict future process behavior, and support intelligent decision-making.

This study focuses on a CNC-machined shaft diameter process and combines SPC with Machine Learning to strengthen both monitoring and prediction. The project uses 500 production batches and treats diameter as the quality response, while tool wear, pressure, and temperature are considered as process inputs.

A. Problem Statement

The problem addressed in this work is the lack of an integrated framework that can simultaneously detect process instability, evaluate process capability, and identify the dominant process variables influencing shaft diameter variation. In the CNC process studied here, dimensional drift and short-term variability can lead to rejects, rework, and reduced production efficiency. A combined SPC and ML approach is therefore required to support early intervention and better decision-making.

B. Objectives

The study aims to monitor process stability using I-MR control charts, quantify capability through Cp and Cpk indices, develop a regression-based baseline prediction model, apply a Random Forest model for feature ranking, and demonstrate how SPC and ML together can provide more actionable quality control information than either method alone.

II. RELATED WORK

Recent studies show that combining AI methods with SPC can improve anomaly detection and quality monitoring. Parashare [1] reported improved detection accuracy in semiconductor manufacturing by combining time-series learning with SPC baselines. Iftikhar et al. [2] showed that machine learning can strengthen predictive maintenance and abnormality detection in manufacturing systems. Guha et al.

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[3] proposed virtual metrology for long batch processes, demonstrating that partial sensor data can still support early quality prediction. Tayalati et al. [4] and Mascha [6] both showed that hybrid SPC-ML frameworks improve robustness when process behavior becomes nonlinear or unstable.

Broader reviews also emphasize the need to select the right ML model for the task and to evaluate more than one performance metric. Jourdan et al. [5] highlighted the value of standardized datasets, while Qiu [7] discussed ML strategies tailored to SPC problems. Kausik et al. [8] further concluded that model choice should depend on whether the target is interpretability, prediction accuracy, or operational deployment. These findings support the present project, which uses SPC for monitoring and ML for diagnosing the key causes of variation.

III. DATA AND METHODOLOGY

The study used a dataset of 500 consecutive production batches from a CNC machining process. Shaft diameter was measured in millimetre and treated as the critical quality characteristic. Tool wear, pressure, and temperature were recorded as process variables. The specification limits were set at LSL = 49.2 mm and USL = 50.8 mm.

Table I. Dataset and Process Summary

Item	Description / Value
Observations	500 batches
Quality characteristic	Shaft diameter (mm)
Process inputs	Tool wear (mm), pressure (bar), temperature (°C)
Specification limits	LSL = 49.2 mm, USL = 50.8 mm
Pass count	479 / 500
Fail count	21 / 500

A. Statistical Process Control

Individuals and Moving Range charts were used because the data represent single measurements from consecutive batches. The Individuals chart monitors shifts in the process mean, while the Moving Range chart tracks short-term variability. The control limits were computed from the average diameter (X-bar) and the average moving range (MR-bar) using standard I-MR formulas: UCL = X-bar + 2.66(MR-bar), CL = X-bar, and LCL = X-bar - 2.66(MR-bar). For the Moving Range chart, UCL = 3.267(MR-bar), CL = MR-bar, and LCL = 0.

B. Process Capability Analysis

Capability was evaluated after the process behavior was understood. The capability indices were calculated using the sample standard deviation and also using the moving-range based sigma estimate, sigma = MR-bar / d2 with d2 = 1.128. The indices used were Cp = (USL - LSL) / 6sigma and Cpk = min {(mu - LSL)/(3sigma), (USL - mu)/(3sigma)}.

C. Machine Learning Models

A multiple linear regression model was developed as a baseline predictor with diameter as the dependent variable and tool wear, pressure, and temperature as independent variables. A Random Forest regressor was then trained to capture nonlinear relationships and rank the relative importance of the process variables. Model interpretation focused on coefficient direction, residual behavior, and feature importance.

IV. RESULTS AND DISCUSSION

A. Process Stability

The Individuals chart shows several out-of-control points and a distinct mean shift around batches 200-220, indicating special-cause variation. The Moving Range chart shows spikes around batches 400-410, which suggests increased short-term variability and possible tool-wear-related instability. These patterns confirm that the process is not consistently stable across the full production run.

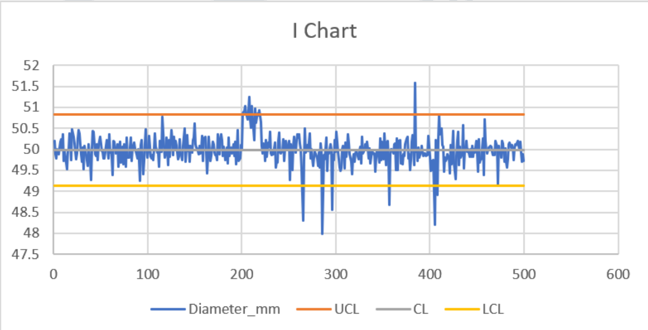

Figure 1. Individual chart for shaft diameter

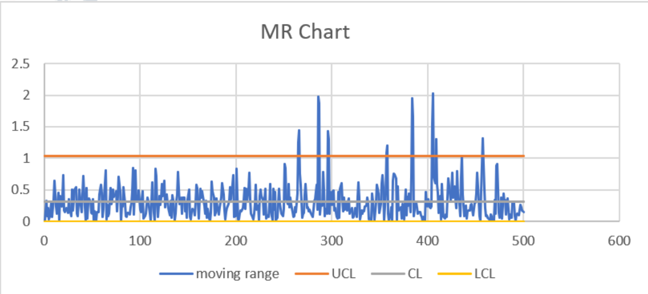

Figure 2. Moving Range chart for shaft diameter

B. Capability Results

The process mean was 49.9824 mm with sample standard deviation 0.3535 mm and moving-range sigma 0.2815 mm. The capability indices were Cp = 0.7544 and Cpk = 0.7377 using the sample standard deviation, while the moving-range estimate gave Cp = 0.9472 and Cpk = 0.9264. The within-specification count was 479 batches, or 98.8%. Although most parts were within tolerance, the capability indices show that the process still needs centering and variability reduction to achieve stronger long-term

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performance.

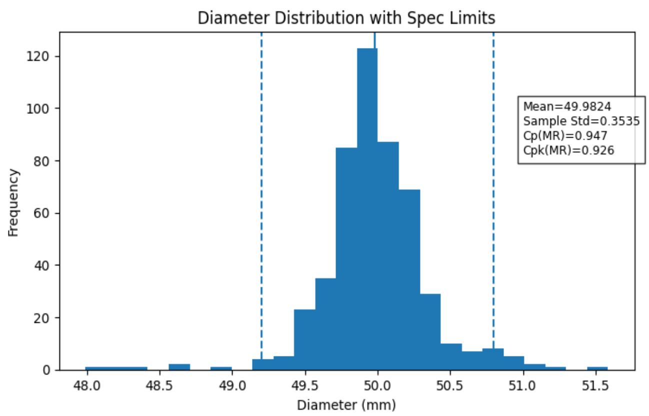

Figure 3. Diameter distribution with specification limits

C. Predictive Modeling

Linear regression was used as a baseline prediction model. The actual-versus-predicted plot shows that the predictions cluster around the process mean, which means the model captures the general level of the response but does not fully track extreme deviations. The residual distribution is centered close to zero, indicating that the model is broadly unbiased and that the linear assumption is acceptable as a first approximation.

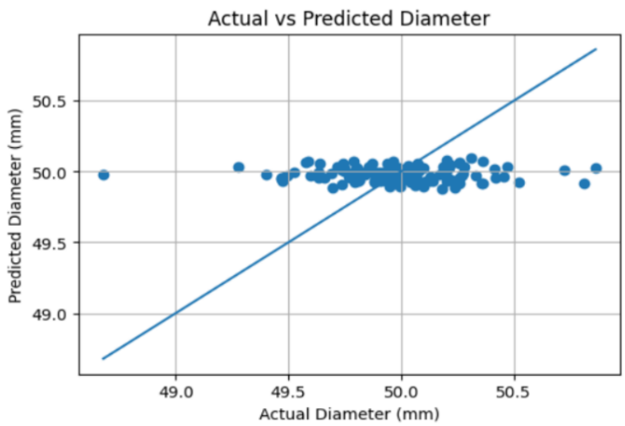

Figure 4. Actual versus predicted diameter using linear regression

Random Forest feature importance confirms the same practical message from the SPC charts: tool wear is the dominant cause of diameter variation. Temperature and pressure matter as well, but their influence is smaller than that of tool wear. This result is useful because it translates process monitoring into an actionable improvement direction: maintain tool condition more aggressively, then fine-tune pressure and temperature settings.

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          Feature  Importance
0     ToolWear_mm    0.446234
2  Temperature_degC  0.293264
1    Pressure_bar    0.260501
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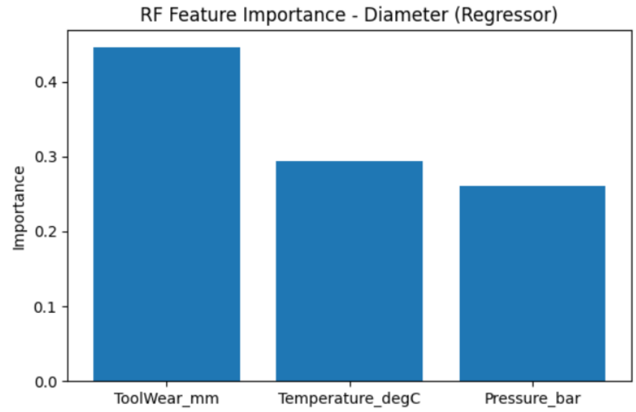

Figure 5. Random Forest feature importance for diameter prediction

Table II. Summary of Key Analytical Results

Metric	Value
Mean diameter (mm)	49.9824
Sample standard deviation (mm)	0.3535
MR-based sigma (mm)	0.2815
Cp (sample sigma)	0.7544
Cpk (sample sigma)	0.7377
Cp (MR sigma)	0.9473
Cpk (MR sigma)	0.9264
Random Forest tool-wear importance	0.446234

V. CONCLUSION

This study demonstrated that combining SPC with Machine Learning provides a stronger quality-control framework than using either method alone.

The I-MR charts identified instability and special-cause variation, while capability analysis showed that the process was only partially capable and required improved centering and reduced variability.

The regression model and Random Forest model provided predictive insight into the process, with tool wear emerging as the most important driver of diameter variation.

The proposed workflow is practical for CNC machining environments and can support earlier intervention, better process understanding, and more consistent product quality.

VI. FUTURE SCOPE

The work presented in this paper can be further extended by applying the same Statistical Process Control and Machine Learning approach to a larger dataset or to data collected over a longer production period.

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Additional process parameters can be included to better understand their influence on product quality and improve prediction accuracy. Advanced control charts such as EWMA and CUSUM can be implemented to detect small and gradual process shifts more effectively.

The machine learning analysis can be expanded by testing additional models and tuning existing models to enhance performance.

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