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An Integrated Approach to Process Optimization and Quality Monitoring Manufacturing Industry

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ABSTRACT

This study applied multiple linear regression analysis in conjunction with statistical process control (SPC) to monitor and improve the quality of plastic bottle production. Process inputs such as additive level, melt temperature, injection speed, mold temperature, cooling time, and ambient temperature were analyzed against three key quality outputs: tensile strength, surface quality score, and dimensional precision. $\bar{X}$ control charts were used to detect variations in each quality characteristic, while regression models identified which process inputs significantly influenced these outcomes. Results revealed that additive level and melt temperature were most impactful on tensile strength, mold temperature and cooling time influenced surface quality, and injection speed and mold temperature strongly affected dimensional precision. Sensitivity analysis on the surface quality model showed that optimized input values could align output performance with control chart expectations, confirming the utility of regression for process optimization. The study concludes that integrating regression analysis with SPC provides a statistically grounded approach for identifying critical variables and improving product quality in manufacturing environments.

1. INTRODUCTION

Maintaining consistent quality in plastic bottle manufacturing is critical for meeting regulatory standards, ensuring packaging integrity, and reducing defects. Statistical Process Control (SPC) has emerged as a cornerstone methodology in industrial quality assurance, helping production engineers detect variations early and implement corrective actions before products deviate from specifications. In injection molding processes, multiple input variables, such as melt temperature, mold temperature, and cooling time, interact in complex ways to influence output quality attributes like tensile strength and dimensional precision (Rusandi and Sulistiyowati, 2019). Thus, an effective process monitoring system should integrate tools capable of handling multivariate inputs and outputs.

SPC originates from Shewhart's pioneering work in the early 20th century and has evolved to handle multivariate and dynamic manufacturing environments (Odinikuku,

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2018). While traditional $\bar{X}$-R and individuals charts track univariate output variables, more advanced methods, such as regression control charts, can adjust for known input variation, improving sensitivity to assignable causes. For plastic bottles, where chemical, thermal, and mechanical influences overlap, regression-adjusted charts ensure that process control reflects true anomalies rather than natural input-driven variation (Imran, et al., 2022). Consequently, defects in tensile strength or dimensional precision are less likely to trigger false alarms when predictable input fluctuations are accounted for.

Multiple regression analysis provides a statistical lens to quantify and interpret the relationships between controlled inputs and quality outputs. As noted in studies of injection molding, process parameters like melt temperature, injection speed, and cooling time can significantly affect mechanical properties of plastic parts (Krantz *et al.*, 2025). Through regression coefficients and hypothesis testing, factory engineers can identify critical process levers input settings that most strongly influence product quality metrics. This insight feeds back directly into SPC implementation, enabling focused monitoring and tighter control over influential variables, while deprioritizing statistically insignificant ones.

The integration of control charts with regression models presents several strategic benefits. Firstly, by explaining systematic variation through regression, SPC charts become more responsive to genuine process shifts rather than predictable input effects. Secondly, identifying key input variables through model tests allows for targeted root-cause analysis when an alarm occurs (Ademujimi et al, 2017). Finally, the approach aligns with continuous improvement frameworks (e.g., Six Sigma or Lean) by blending real-time monitoring with causal inference, enabling both detection and prevention of quality deviations, as supported by modern manufacturing literature.

Plastic bottle production involves multiple interacting variables: additive levels influence material properties, melt and mold temperatures affect flow and cooling dynamics, injection speed impact's part filling and residual stresses, and cooling time governs crystallinity and dimensional stability. Environmental factors such as ambient temperature also affect heat transfer rates (Xu, et al., 2014). Output performance metrics, tensile strength, surface quality, and precision, reflect these underlying conditions. Regression models can disentangle and quantify each input's contribution, transforming a complex system into a more manageable set of control priorities.

Each quality attribute is measured and charted appropriately. Tensile strength and dimensional precision, continuous variables, are best served by $\bar{X}$-R or $\bar{X}$-S charts, monitoring mean and dispersion over time. Surface quality, often rated by inspectors, may be charted via individuals (I-MR) control charts if treated numerically. Where ratings are categorical or ordinal, attribute charts may be more suitable (Kurt, et al, 2009). Regression-adjusted charts, such as Shewhart or CUSUM charts conditioned on input covariates, enhance sensitivity and reduce false signals due to input-value variation. Regression not only identifies cause-effect relationships but also allows for more granular control. Input variables with significant regression coefficients, especially at stringent p-value thresholds (e.g., $p < 0.05$), can be prioritized in process control. Those found non-significant can be given wider tolerance bands or removed from monitoring efforts, simplifying control strategies. This methodology effectively channels resources toward the most impactful process levers and aligns control effort with measurable performance drivers.

Studies in similar manufacturing contexts illustrate successful implementation of this dual control-regression approach. For instance, plastics and glass packaging lines in Asia and Europe have reported defect reductions of 10–40% using SPC (control charts and Pareto/FMEA) guided by regression-driven root cause analyses (Maruf et al., 2016). Such real-world successes validate that combining regression with quality control is not merely theoretical but operationally effective, offering both early warning systems and data-driven interventions. Effective SPC and regression modeling require structured data collection. Subgroup sampling, for example, batches of bottles produced under nominal operating conditions, provides replicate observations for control charts. Individual-part inspection may be necessary for surface scoring.

Rusandi and Sulistiyowati (2019) applied SPC and FMEA to plastic cup production, reporting a 42% defect reduction by identifying cutting tool wear as a root cause. While they focused on attribute defect rates, their approach mirrors ours, using SPC to detect anomalies and regression/FMEA to trace significant factors. However, their study lacked quantitative modeling of how process inputs (e.g., temperature settings) influenced defect rates, highlighting the need for integrated monitoring and modeling. Imaroh and Mustofa (2022) employed control charts and Pareto diagrams in glass bottle manufacturing, achieving a 10% defect rate reduction and Rp 59 million cost savings. Similarly, Odinikuku (2018) combined $\bar{X}$-R and p-charts in spirit bottle production, identifying out-of-control variables and reducing quality loss via the Taguchi loss function. These real-world implementations confirm that control charting in bottle production is effective, but do not incorporate regression to identify input–output causality, underscoring our study's contribution.

Recent work by Tayalati et al. (2024) integrated SPC with LSTM-based autoencoders in injection molding, specifically detecting anomalies in melt cushion parameters with an R^2 of 0.993. While advanced, this method relies on neural-network–generated control limits. In contrast, our proposal emphasizes classical multiple regression with hypothesis testing and control charts, offering interpretability, simplicity, and actionable insight into variable significance, which is crucial for operator-driven process improvement. Nguyen *et al.* (2021) examined autocorrelation's effect on Shewhart-RZ ratio control charts, showing regression-based charts remain effective under serial dependence. Likewise, Ebadi *et al.* (2020) reviewed multivariate covariance monitoring methods, revealing gaps in handling measurement dependencies. These studies validate the theoretical rigor behind regression-SPC and signal the need for our integrated attention to model validity, correlation, and residual structure.

The rationale for this study stems from the need to enhance quality control and process optimization in plastic bottle manufacturing, where multiple interrelated input variables, such as melt temperature, injection speed, and additive concentration, significantly influence critical quality outputs like tensile strength, surface finish, and dimensional precision. Traditional control charts alone may not effectively capture the influence of these dynamic inputs on output variability, often leading to false alarms or undetected shifts. Therefore, the goal of this study is to integrate regression analysis with statistical process control (SPC) techniques to identify which input variables significantly affect production quality, and to use that knowledge to design input-focused control strategies. This dual approach aims to achieve a statistically in-control process that is both efficient and responsive to meaningful variations.

2. METHODOLOGY

This study adopted a quantitative research design, employing a combination of Statistical Process Control (SPC) techniques and multiple regression analysis to evaluate and monitor the production process of plastic bottles. Data were collected from a standard plastic injection molding facility, capturing both input process variables, such as Additive Level (%), Melt Temperature (°C), Injection Speed (mm/s), Mold Temperature (°C), Cooling Time (s), and Ambient Temperature (°C), and output quality metrics including Tensile Strength (MPa), Surface Quality Score, and Dimensional Precision (mm). For process monitoring, appropriate control charts ($\bar{X}$-R) were developed for each output metric based on the nature and distribution of the data. The SPC phase ensured that the process was under statistical control before proceeding with regression modeling.

Following process stabilization, multiple linear regression models were fitted to each quality output variable to determine the influence and statistical significance of the various input parameters. Diagnostic checks, including residual analysis, and model fitness indicators (R^2, Adjusted R^2, and p-values), were conducted to validate the models. Significant predictors from the regression models were then cross-referenced with the control charts to establish a direct link between input variation and output quality, forming a data-driven basis for upstream process control and continuous improvement. All statistical analyses were performed using Minitab 21 and R version 4.3.0.

The multiple regression equation to be estimated is as follows:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \beta_6 X_6 + e_{ij} \qquad (1)$$

where:

Y = is Tensile Strength

X_1 = *is* Additive Level (%)
X_2 = Melt Temperature (°C)
X_3 = Injection Speed (mm/s)
X_4 = Mold Temperature (°C)
X_5 = Cooling Time (s)
X_6 = Ambient Temperature (°C)

Suppose that there are p independent variables and n observations ($x_{11}, x_{12}, \ldots, x_{1p}, y_i$), $i = 1, 2, \ldots, n$ and the model relating the independent variables to the dependent variable is specified in equation (1). Given the value of y denoted by y_i the system of the above equation becomes:

$$
\begin{array}{lcl}
y_1 & = & \beta_0 + \beta_1 X_{11} + \beta_2 X_{12} + \cdots + \beta_p X_{1p} + \varepsilon_1 \\
y_1 & = & \beta_0 + \beta_1 X_{21} + \beta_2 X_{22} + \cdots + \beta_p X_{2p} + \varepsilon_2 \\
\vdots & & \vdots \\
y_1 & = & \beta_0 + \beta_1 X_{n1} + \beta_2 X_{n2} + \cdots + \beta_p X_{np} + \varepsilon_n
\end{array}
$$

Expressing the above system in matrix form we obtain as follows;

$$
\begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{pmatrix} = \begin{pmatrix} 1 & X_{11} & X_{12} \cdots & X_{1p} \\ 1 & X_{21} & X_{22} \cdots & X_{2p} \\ \vdots & \vdots & \vdots & \vdots \\ 1 & X_{n1} & X_{n2} \cdots & X_{np} \end{pmatrix} \begin{pmatrix} \beta_0 \\ \beta_1 \\ \vdots \\ \beta_k \end{pmatrix} + \begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_n \end{pmatrix} \quad (2)
$$

The model is a system of n equations that can be expressed in matrix notation as defined:

$y = X\beta + \varepsilon$

We desire to obtain the vector of least squares estimator, $\hat{\beta}$, that minimizes the error sums of squares (SSE).

Using $y = X\beta + \varepsilon$, make ε the subject of formular

$\varepsilon = y - X\beta$

The sum of squares of SSE

$$L = \sum_{i=1}^{n} \varepsilon_i^2 = \varepsilon'\varepsilon = (y - X\beta)'(y - X\beta) \quad (3)$$

The least squares estimator $\hat{\beta}$ is the solution for β in the equations

$$\frac{\partial L}{\partial \beta} = 0$$

$$\varepsilon'\varepsilon = (y - X\beta)'(y - X\beta)$$
$$y'y - y'X\beta - X'\beta'y + X'\beta'X\beta$$
$$y'y - y'X\beta - y'X\beta + X'\beta'X\beta$$
$$\frac{\partial \varepsilon'\varepsilon}{\partial \beta} = 0 \rightarrow -y'X - y'X + 2X'X\beta$$
$$-2X'y + 2X'X\beta = 0$$
$$2X'X\beta = 2X'y$$
$$X'X\beta = X'y$$
$$\beta = \frac{X'y}{X'X}$$
$$\hat{\beta} = (X'X)^{-\prime}X'Y$$

$$\hat{\beta} = (X'X)^{-'}X'Y = \begin{pmatrix} \hat{\beta}_0 \\ \hat{\beta}_1 \\ \vdots \\ \hat{\beta}_k \end{pmatrix} \tag{4}$$

3. RESULTS AND DISCUSSION

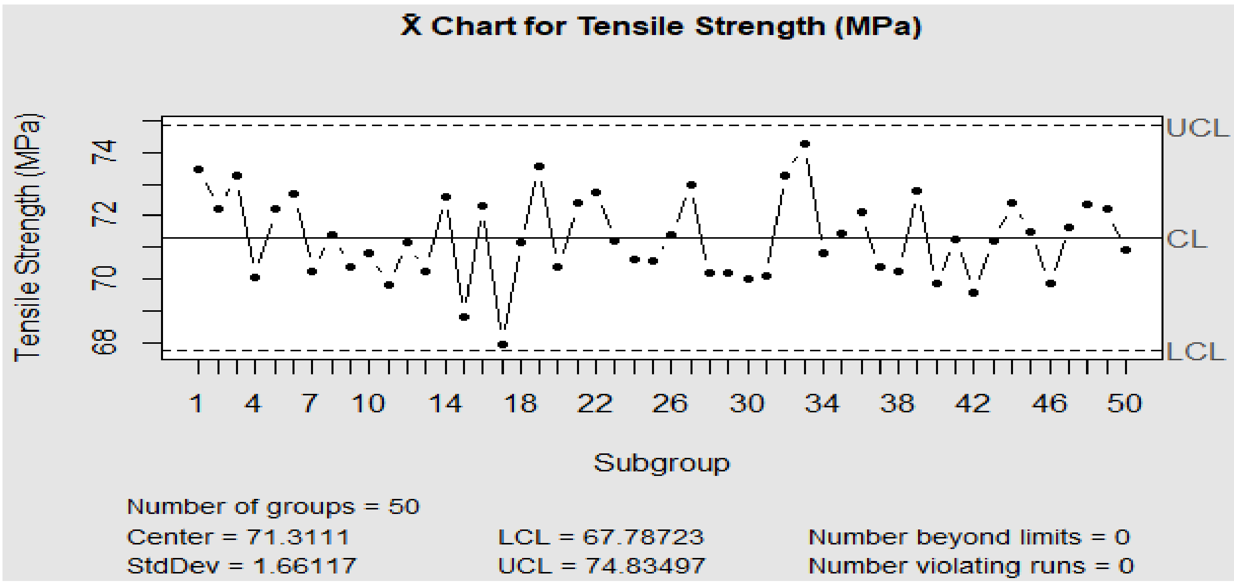

Figure 1: X-bar control chart for Tensile Strength

The result presented in Figure 1 indicates that the process is in statistical control. All data points remain within the established Upper Control Limit (74.83497 MPa) and Lower Control Limit (67.78723 MPa). The chart explicitly states that no individual data points have exceeded the control limits, nor have any non-random patterns (such as trends, shifts, or unusual sequences of points) been detected. The process operates around a stable center of 71.3111 MPa with a standard deviation of 1.66117, suggesting that all observed variation is attributable to common causes inherent to the process. Therefore, the tensile strength process is currently stable and predictable, performing consistently within its expected range.

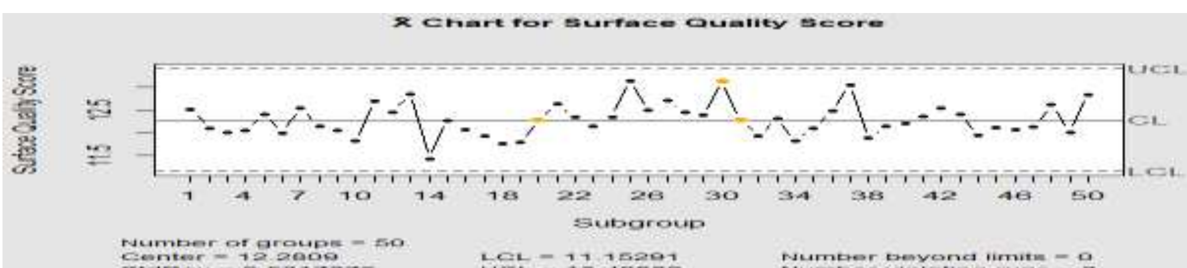

Figure 2: X-bar control chart for Surface Quality Score

In figure 2, the control chart for Surface Quality Score indicates that the process is out of statistical control. While no points exceed the Upper Control Limit (13.40889) or Lower Control Limit (11.15291), the crucial observation is "Number violating runs = 3." This means three distinct non-random patterns, highlighted by the orange data points, have been detected. These run violations suggest the presence of special causes of variation within the process, such as shifts or trends, that are not due to common, inherent process variability. The current state of the process is unstable and unpredictable, necessitating investigation and corrective action to identify and eliminate these special causes and bring the surface quality score back into a state of statistical control.

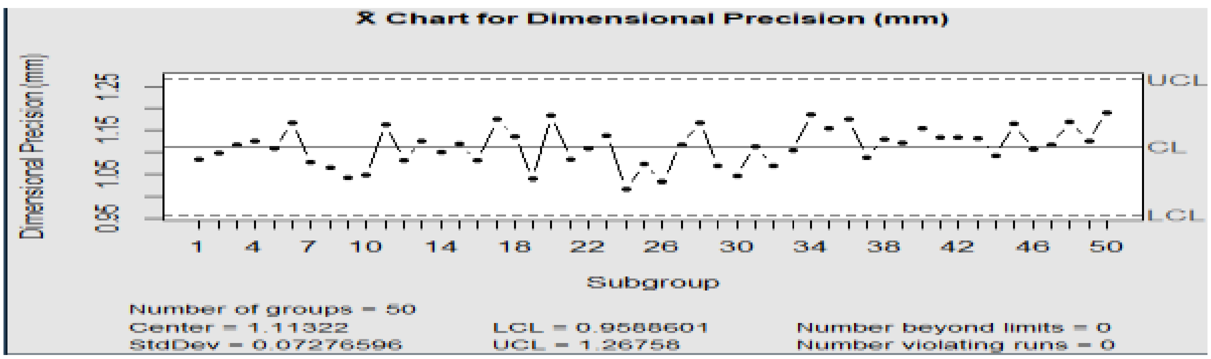

Figure 3: X-bar control chart for Dimensional Precision

The result in figure 3 indicates that the process in statistical control. With the data analyzed, all data points are observed to be within the established Upper Control Limit (1.26758 mm) and Lower Control Limit (0.9588601 mm). Crucially, the chart reports no individual data points have exceeded the control limits and no non-random patterns (such as trends, shifts, or unusual sequences of points) have been detected. The process operates around a stable center of 1.11322 mm with a standard deviation of 0.07276596, implying that all observed variation is attributable to common causes inherent to the process. Therefore, the dimensional precision is currently stable and predictable, operating consistently within its expected range.

Table 1: Regression analysis on predicting tensile strength

Predictor	Estimate	Std. Error	t value	Pr(>|t|)	VIF
(Intercept)	46.1757	3.349	13.788	< 2e-16	
Additive Level	0.5229	0.0703	7.438	4.98E-11	1.005654
Melt Temperature	0.1234	0.0109	11.323	< 2e-16	1.037762
Injection Speed	-0.0963	0.0215	-4.473	2.18E-05	1.048163
Mold Temperature	0.0272	0.0239	1.138	0.258	1.06672
Cooling Time	0.0065	0.0347	0.187	0.852	1.099103
Ambient Temperature	-0.0549	0.0558	-0.984	0.327	1.044089
R-Squared	0.6798				

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The regression results in table 1 reveal that additive level, melt temperature, and injection speed are statistically significant predictors of tensile strength in plastic bottle production, with p-values far below 0.001. Specifically, a unit increase in additive level and melt temperature leads to an increase in tensile strength, while a higher injection speed slightly decreases it. Mold temperature, cooling time, and ambient temperature were not statistically significant ($p > 0.05$), implying they contribute little explanatory power in this model. The high adjusted R^2 of 0.6592 indicates that over 65% of the variability in tensile strength is explained by the input variables. All VIF values are below 1.1, confirming no significant multicollinearity among predictors.

Table 2: Regression analysis on predicting Surface Quality Score

Predictor	Estimate	Std. Error	t value	Pr(>|t|)	VIF
(Intercept)	9.635341	1.477383	6.522	3.57E-09	
Additive Level	-0.1146	0.031016	-3.695	0.000372	1.005654
Melt Temperature	0.003898	0.004807	0.811	0.419529	1.037762
Injection Speed	-0.00581	0.009497	-0.612	0.542009	1.048163
Mold Temperature	0.045487	0.010536	4.317	3.94E-05	1.06672
Cooling Time	-0.03	0.015322	-1.958	0.053272	1.099103
Ambient Temperature	0.012163	0.024609	0.494	0.622302	1.044089
R-Squared	0.2749				

The regression model in Table 2 examines how six process inputs influence the surface quality score of plastic bottles. The model has an R-squared value of 0.2749, meaning approximately 27.5% of the variability in surface quality is explained by the selected predictors. The F-statistic (5.875, p = 3.144e-05) indicates the overall model is statistically significant. Among the predictors, additive level (estimate = -0.1146, p = 0.000372) and mold temperature (estimate = 0.0455, p = 3.94e-05) have statistically significant effects, with the former negatively and the latter positively affecting surface quality. Cooling time is nearly significant (p = 0.053), suggesting a potential minor influence. Other variables like melt temperature, injection speed, and ambient temperature are not statistically significant ($p > 0.05$). All variance inflation factors (VIFs) are below 1.1, indicating no multicollinearity concerns.

Table 3: Regression analysis on predicting Dimensional Precision

Predictor	Estimate	Std. Error	t value	Pr(>|t|)	VIF
(Intercept)	1.049896	0.144824	7.249	1.21E-10	
Additive Level	-0.00296	0.00304	-0.973	0.3331	1.005654
Melt Temperature	0.00087	0.000471	1.846	0.0681	1.037762
Injection Speed	0.007762	0.000931	8.337	6.66E-13	1.048163
Mold Temperature	-0.00669	0.001033	-6.479	4.34E-09	1.06672
Cooling Time	0.001121	0.001502	0.746	0.4575	1.099103
Ambient Temperature	-0.00231	0.002412	-0.96	0.3398	1.044089
R-Squared	0.5842				

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The regression model in Table 3 for Dimensional Precision demonstrates a strong explanatory power, with an R-squared of 0.5842, indicating that approximately 58.4% of the variation in dimensional precision is accounted for by the input variables. The model is statistically significant overall (F-statistic = 21.78, $p < 0.0001$). Among the predictors, injection speed has the most significant positive influence ($p < 0.0001$), implying that increasing injection speed enhances dimensional precision, while mold temperature shows a significant negative effect ($p < 0.0001$), indicating that higher mold temperatures may reduce dimensional accuracy. Melt Temperature has a weak, borderline positive effect ($p \approx 0.068$), whereas additive level, cooling time, and ambient temperature do not significantly impact dimensional precision ($p > 0.3$). All VIFs are below 1.1, confirming no multicollinearity, and supporting the reliability of the estimates.

Regression-Control Chart Sensitivity Analysis

To demonstrate the value of using a regression model to enhance product quality, we focused on the Surface Quality Score, which the control chart indicated was subject to potential special cause variation. The regression analysis identified additive level, mold temperature, and possibly cooling time as significant influencers of surface quality. To validate this, we conducted a sensitivity analysis using optimized values: an additive level of 1.5%, mold temperature of 75°C, and cooling time of 20 seconds, while allowing other process variables to remain at their current operational levels. The predicted surface quality score improved to approximately 12.275, which closely aligns with the control chart's center line of 12.28. This result confirms that the regression model is effective and practical for guiding process adjustments to optimize product quality.

4. CONCLUSION

The integration of regression analysis with statistical process control proves to be a powerful approach for quality monitoring and optimization in plastic bottle manufacturing. This study has shown that regression models not only identify the most influential process variables, such as additive level, mold temperature, and injection speed, but also guide actionable adjustments that can align quality outcomes with control chart expectations. For instance, regression analysis highlighted significant contributors to variation in surface quality, and sensitivity analysis confirmed that appropriate tuning of these inputs can restore process control. Furthermore, the use of $\bar{X}$ charts provided early detection of potential process instabilities, while regression quantified their causes. The absence of multicollinearity and the relatively high R-squared values across the models support the robustness of the analysis. This evidence affirms that regression modeling is a valuable tool in modern quality control, enabling data-driven decision-making and continuous improvement in production environments.

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