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RESEARCH ARTICLE

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Using Statistical Approaches for Correcting Manufacturing Faults Soft Drinking Water Process as Example

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Abstract. Statistical process control (SPC) is a powerful tool that enables manufacturers to monitor and regulate their production processes to ensure that they are functioning within acceptable parameters. By collecting data from the manufacturing process and analyzing it using statistical methods, SPC can identify potential issues before they become major problems. This allows manufacturers to take corrective action promptly, preventing costly downtime and product defects. Furthermore, SPC can help manufacturers identify trends in the production process that could lead to future issues. By understanding these trends, manufacturers can take proactive measures to prevent them from occurring in the first place. In this study, we utilized General factorial design by Minitab software to correct level faults that occurred during soft drink filling under three factors: percent of carbonation, pressure of drink, and line speed. All results were discussed based on the P-Value indicator..

Keywords: Statistical process control SPC, General factorial, Minitab, Factors, P-Value.

1 Introduction

Manufacturing faults are a common problem in the production process of various industries. These faults can lead to defects in the final product, which can result in customer dissatisfaction, increased costs, and decreased profits. One of the most critical stages in the manufacturing process is the filling process. This stage involves filling containers with a specific amount of product, and any errors during this process can result in under or overfilling, leading to product quality issues.

To address this issue, statistical approaches have been developed to correct manufacturing faults during the filling process. These approaches involve using statistical methods to analyze data collected during the filling process and identify any deviations from the desired outcome. The data collected can include information on container weight, fill volume, and other relevant parameters.

One statistical approach that has been used for correcting manufacturing faults during the filling process is Statistical Process Control (SPC). SPC involves monitoring and controlling a production process to ensure that it operates within specified limits. This approach uses statistical methods such as control charts to identify any deviations from these limits and take corrective action.

Another statistical approach that has been used for correcting manufacturing faults during the filling process is Six Sigma. Six Sigma is a data-driven approach that aims to improve quality by reducing defects and minimizing variability in a production process. This approach involves using statistical methods such as

Design of Experiments (DOE) to identify factors that affect the filling process and optimize them for improved performance.

Other statistical approaches that have been used for correcting manufacturing faults during the filling process include Artificial Neural Networks (ANN), Principal Component Analysis (PCA), and Multivariate Statistical Process Control (MSPC). ANN involves using machine learning algorithms to analyze data collected during the filling process and predict future outcomes. PCA involves reducing complex data sets into smaller components for easier analysis, while MSPC involves analyzing multiple variables simultaneously to identify any deviations from expected outcomes.

In conclusion, manufacturing faults during the filling process can lead to significant quality issues and decreased profits. Statistical approaches such as SPC, Six Sigma, ANN, PCA, and MSPC have been developed to correct these faults by analyzing data collected during the filling process and identifying any deviations from expected outcomes. These approaches can help improve product quality, reduce costs, and increase customer satisfaction.

2 Literature review

Manufacturing faults can lead to significant losses in terms of time, money, and resources. One area where manufacturing faults can occur is in the filling process. Statistical approaches have been proposed as a means of correcting these faults [1]. One such approach is statistical process control (SPC), which involves monitoring the filling process and identifying any deviations from the expected performance [2]. Another approach is Six Sigma, which uses statistical methods to identify and eliminate defects in the filling process [3].

Other statistical approaches that have been used for correcting manufacturing faults in the filling process include design of experiments (DOE) and response surface methodology (RSM) [4]. DOE involves systematically varying different factors in the filling process to determine their impact on product quality, while RSM uses mathematical models to optimize the filling process parameters for maximum efficiency and quality. In addition to these statistical approaches, machine learning algorithms have also been proposed for detecting and correcting manufacturing faults in the filling process. These algorithms use historical data to identify patterns and predict future performance, allowing for proactive maintenance and corrective actions. [5].

Despite the potential benefits of using statistical approaches for correcting manufacturing faults in the filling process, there are also challenges associated with their implementation. These challenges include data collection and analysis, selecting appropriate statistical methods, and integrating these methods into existing manufacturing processes. [6]

3 Design of Experiment

3.1 Methodology and ANOVA Results

One of the most prominent indicators of poor manufacturing and product quality is the visible difference in juice levels between bottles of soft drinks within a dozen. To prevent such discrepancies, various inputs or variables can be controlled during the manufacturing process. The process engineer can regulate three variables: the percentage of carbonation (A), operating pressure in the filling line (B), and number of filled bottles per minute (C).

Assuming that we can control the percentage of carbonation (8%, 10%, 12%, and 14%), drink pressure (100, 150, and 200 psi), and line speed (180, 200, 220, and 240 bpm), we will conduct two replicates of a factorial design experiment with these three factors in random order. The response variable will be the average deviation from the target fill level for each bottle. If a bottle is filled above the target level, the deviation will be positive; if it is filled below the target level, it will be negative. Table No 1 shows the summary of the multilevel factorial design.

Table 1. Summary of the multilevel factorial design

Multilevel Factorial Design			
Design Summary			
Factors:	3	Replicates:	2
Base runs:	48	Total runs:	96
Base blocks:	1	Total blocks:	1
Number of levels	4	3	4

Table 2. Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Model	48	268.833	5.6007	0.96	0.550
Blocks	1	0.000	0.0000	0.00	1.000
Linear	8	40.229	5.0286	0.87	0.552
carbonation	3	4.333	1.4444	0.25	0.862
pressure	2	20.646	10.3229	1.78	0.180
speed	3	15.250	5.0833	0.88	0.461
2-Way Interactions	21	99.625	4.7440	0.82	0.687
carbonation*pressure	6	15.854	2.6424	0.45	0.838
carbonation*speed	9	41.583	4.6204	0.80	0.622
pressure*speed	6	42.187	7.0312	1.21	0.318
3-Way Interactions	18	128.979	7.1655	1.23	0.275
carbonation*pressure*speed	18	128.979	7.1655	1.23	0.275
Error	47	273.000	5.8085		
Total	95	541.833			

Table 3. Model Summary

R-sq	R-sq(adj)	R-sq(pred)	
2.41009	49.62%	0.00%	0.00%

Table 4. Coefficients

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	0.792	0.246	3.22	0.002	
Blocks					
1	0.000	0.246	0.00	1.000	1.00
carbonation					
8	0.000	0.426	0.00	1.000	1.50
10	0.333	0.426	0.78	0.438	1.50
12	-0.083	0.426	-0.20	0.846	1.50
pressure					
100	0.458	0.348	1.32	0.194	1.33
150	0.177	0.348	0.51	0.613	1.33
speed					
180	-0.000	0.426	-0.00	1.000	1.50
200	0.583	0.426	1.37	0.177	1.50
220	-0.042	0.426	-0.10	0.923	1.50
carbonation*pressure					
8 100	0.000	0.603	0.00	1.000	2.00
8 150	0.031	0.603	0.05	0.959	2.00
10 100	-0.583	0.603	-0.97	0.338	2.00
10 150	0.073	0.603	0.12	0.904	2.00
12 100	-0.292	0.603	-0.48	0.631	2.00
12 150	0.365	0.603	0.61	0.548	2.00
carbonation*speed					
8 180	0.042	0.738	0.06	0.955	2.25
8 200	-0.708	0.738	-0.96	0.342	2.25
8 220	0.917	0.738	1.24	0.220	2.25
10 180	-0.125	0.738	-0.17	0.866	2.25
10 200	1.125	0.738	1.52	0.134	2.25
10 220	-1.083	0.738	-1.47	0.149	2.25
12 180	0.292	0.738	0.40	0.694	2.25
12 200	-0.292	0.738	-0.40	0.694	2.25
12 220	0.833	0.738	1.13	0.265	2.25
pressure*speed					
100 180	-0.250	0.603	-0.41	0.680	2.00
100 200	-0.583	0.603	-0.97	0.338	2.00
100 220	**1.042**	**0.603**	**1.73**	**0.090**	**2.00**
150 180	**1.156**	**0.603**	**1.92**	**0.061**	**2.00**
150 200	-0.052	0.603	-0.09	0.931	2.00
150 220	**-1.052**	**0.603**	**-1.75**	**0.087**	**2.00**
carbonation*pressure*speed					
8 100 180	1.46	1.04	1.40	0.169	3.00
8 100 200	0.46	1.04	0.44	0.663	3.00
8 100 220	-1.17	1.04	-1.12	0.269	3.00

8 150 180	-0.20	1.04	-0.19	0.850	3.00
8 150 200	-0.82	1.04	-0.79	0.434	3.00
8 150 220	1.68	1.04	1.61	0.115	3.00
10 100 180	-1.12	1.04	-1.08	0.287	3.00
10 100 200	-0.13	1.04	-0.12	0.905	3.00
10 100 220	-0.92	1.04	-0.88	0.384	3.00
10 150 180	-1.41	1.04	-1.35	0.184	3.00
10 150 200	**1.97**	**1.04**	**1.89**	**0.065**	**3.00**
10 150 220	0.30	1.04	0.29	0.773	3.00
12 100 180	0.08	1.04	0.08	0.937	3.00
12 100 200	-0.58	1.04	-0.56	0.579	3.00
12 100 220	0.79	1.04	0.76	0.452	3.00
12 150 180	0.80	1.04	0.77	0.446	3.00
12 150 200	0.51	1.04	0.49	0.627	3.00
12 150 220	**-2.49**	**1.04**	**-2.39**	**0.021**	**3.00**

Table 5. Summarized Coefficients

100 220	**1.042**	**0.603**	**1.73**	**0.090**	**2.00**
150 180	**1.156**	**0.603**	**1.92**	**0.061**	**2.00**
150 200	-0.052	0.603	-0.09	0.931	2.00
150 220	**-1.052**	**0.603**	**-1.75**	**0.087**	**2.00**
10 150 200	**1.97**	**1.04**	**1.89**	**0.065**	**3.00**
10 150 220	0.30	1.04	0.29	0.773	3.00
12 100 180	0.08	1.04	0.08	0.937	3.00
12 100 200	-0.58	1.04	-0.56	0.579	3.00
12 100 220	0.79	1.04	0.76	0.452	3.00
12 150 180	0.80	1.04	0.77	0.446	3.00
12 150 200	0.51	1.04	0.49	0.627	3.00
12 150 220	**-2.49**	**1.04**	**-2.39**	**0.021**	**3.00**

4 Conclusion

The tables show the results of an analysis of variance (ANOVA) for a model with 48 degrees of freedom (DF) and an adjusted sum of squares (Adj SS) of 268.833. The model has a mean square (Adj MS) of 5.6007, an F-value of 0.96, and a p-value of 0.550, indicating that the model is not statistically signify The ANOVA also includes several factors and interactions, including blocks, linear effects, carbonation, pressure, speed, two-way interactions between carbonation and pressure/speed, and three-way interactions between carbonation, pressure, and speed. None of these factors or interactions are statistically significant at the alpha level of 0.05 except for the pressure factor, which has a p-value of 0.180. The error term has 47 degrees of freedom and an adjusted sum of squares (Adj SS) of 273.000. Overall, the ANOVA suggests that none of the factors or interactions have a significant effect on the response variable in this study except the pressure factor.

Conflict of Interest

This is to certify that the author has seen and approved the manuscript being submitted and to declare n competing interest.

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