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Monitoring Changes in the Blocks of One of a Bridges in Nasiriyah Using Specific Quality Control Charts

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Abstract Monitoring the quality of concrete blocks is a fundamental aspect of construction projects to ensure the safety and stability of structures. This research aims to apply a combination of traditional statistical control charts, along with a regression control chart, to monitor the quality of concrete block and diagnose the behavior of the production process, without seeking to compare the superiority of these charts. The research relied on real data consisting of (118) observations of concrete blocks tests for a bridge in Nasiriyah, obtained from the consulting office at Thi Qar University. The arithmetic mean, standard deviation, range, and moving average charts were applied, in addition to a regression chart for control purposes, by using the traditional control limits established in Shewhart charts, the results showed that the traditional control charts respond to different patterns of change in quality characteristics. The mean and moving average charts revealed changes in average compressive strength, while the standard deviation and range charts confirmed the stability of dispersion within the production process. The results of the regression control chart also showed the stability of the linear relationship between the weight of the concrete blocks and the explanatory variables related to the production and inspection process, , without the appearance of signals outside the limits of control. The research results indicate that the use of an integrated set of statistical control charts provides a more comprehensive monitoring and diagnostic framework for monitoring the quality of concrete blocks, highlighting the complementary role that the control regression chart plays alongside traditional charts.

Keywords statistical control charts, traditional control chart, regression control chart

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1. Introduction

Statistical control charts are among the most common tools for this purpose, as they provide an effective means of distinguishing normal variations from undesirable ones and supporting continuous improvement of the production process [1]. In this context, Khoo, Chew, and Teoh presented a 2015 study examining the operating-length performance of a standard deviation chart, focusing on the EWMA chart. They used simulation methods to compare its performance with traditional mean and standard deviation charts under the assumption of a normal distribution, and the results showed the superiority of the traditional charts [2].In 2019, Taha et al. proposed developing control charts based on estimating linear regression parameters using robust estimators based on a quadratic function. Simulation results showed that the proposed charts were more effective than traditional charts based on the least squares method [3]. Some studies have also extended the application of control charts to non-industrial fields. In 2022, Fawzy and Jaber used qualitative control charts to monitor the number of COVID-19 infections using Kernel PCA and K-Nearest Neighbor charts. The results showed that the data were out of control, with the KNN chart performing better in the short term [4].In recent trends, Abbasi et al. (2022) presented an Adaptive EWMA control

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scheme for monitoring non-parametric profiles in the second stage of SPC, demonstrating its superiority in terms of Average Run Length (ARL). However, the complexity of non-parametric modeling limited its applicability to simple engineering tests [5]. Ali et al. (2023) also proposed robust multivariable control charts to address the impact of outliers, and their results showed that these charts outperformed traditional Shewhart schemes, despite their higher computational cost [6]. Furthermore, Rojas-Preciado et al. (2023) developed a T2Qv scheme for monitoring multivariable qualitative data based on multiple correspondence analysis with Hotelling's T² scheme. However, its qualitative nature and the complexity of its procedures made it less suitable for quantitative structural quality applications [7]. At the level of direct engineering applications, Hameed & Jawad (2024) implemented a set of conventional control chars to monitor the quality of sulfate-resistant cement production based on a single variable, without addressing the relationships between different quality characteristics [8]. In the context of developing model-based charts, Capezza et al. (2024) proposed the functional mixture regression control chart to handle processes with multiple operating modes; however, its reliance on high-dimensional functional data limited its practical applicability [9]. Sabahno & Eriksson (2024) also presented adaptive control charts with memory and variable parameters for monitoring multiple linear regression profiles, demonstrating improved sensitivity, although computational complexity challenges remain. In the field of concrete monitoring [10], Syilviani and Sari (2025) evaluated the effectiveness of Hotelling's T² scheme for monitoring the quality of ready-mix concrete based on three properties; however, the study was limited to one scheme and a descriptive analysis [11]. Similarly, Nadi et al. (2025) studied the performance of Hotelling's T² scheme in the presence of time correlation using the VAR(p) model, demonstrating the superiority of direct application, with the requirements of advanced time modeling [12]. In another context, Amin et al. (2025) proposed control schemes based on Pearson residuals and Deviance using inverse Gaussian ridge regression to address the problem of multicollinearity; however, the assumptions of distribution limited the generality of the application [13]. Oprime et al. (2025) also addressed time-oriented process monitoring based on profile monitoring and modified site charts, without expanding on the interrelationships between quality properties. In contrast [14],Recent studies, such as AL Saadawi et al. (2025), have used machine learning models to classify the compressive strength of concrete, achieving high accuracy. However, these studies focused on prediction and classification without monitoring the production process over time. Based on the above, it is clear that most previous studies either focused on a single variable using single-chart or relied on highly complex, advanced models that are difficult to apply in routine engineering tests [15]. Furthermore, applied studies that combine traditional control charts with statistical regression charts within a simplified framework for monitoring the quality of concrete blocks remain limited. This is particularly relevant in local construction projects. Hence the current research problem and the need for an integrated applied study that utilizes traditional control charts with a statistical regression chart to clarify the different control roles of each chart without attempting to compare them in terms of "preference" approach, thus achieving a balance between statistical accuracy and ease of practical application. This research contributes by presenting a simplified applied framework that integrates traditional control charts and a regression chart to interpret quality signals in concrete block data within a practical context. Accordingly, and this research aims to clarify the functions of a set of statistical control charts-namely, the mean, standard deviation, range, moving average, and regression chart-in monitoring the quality of concrete blocks, highlighting the role of the regression chart as a model-based control tool. This is achieved through a case study of block testing for a bridge in Nasiriyah.

2. Methodology

2.1. Arithmetic Mean Chart ($\bar{X}$-Chart)

The mean chart ($\bar{X}$) is a univariate control chart used to monitor changes in the average production process over time by periodically sampling the process under study [2]. Its statistical basis rests on the assumption that the data follows a normal distribution. This chart is used to show how far each sample mean deviates from the overall mean of the process. The mean chart is represented by three parallel horizontal lines: the center line (CL), which represents the overall mean; the upper limit of control (UCL); and the lower limit of control (LCL), which define the range of statistical control. The limits of the mean chart are calculated according to the following steps [16].

1. Calculate the mean of each sample

$$\bar{x}_i = \frac{\sum_{i=1}^{n} x_i}{n} \tag{1}$$

Where, n: is the size of each sample

2. Calculate the mean of samples for all samples (the general mean), which represents the median limit of the mean chart

$$\bar{\bar{X}} = \frac{\sum_{i=1}^{m} \bar{x}_i}{m} \tag{2}$$

Where, $\bar{x}_i$ represent samples mean, m the number of selecting samples

3. Calculate the standard deviation for each sample, and from it calculate the mean standard deviation [5]

$$s_i = \sqrt{\frac{\sum_{i=1}^{n} x_i^2 - n\bar{x}^2}{n-1}} \tag{3}$$

$$\bar{s} = \frac{\sum_{i=1}^{m} s_i}{m} \tag{4}$$

4. Calculate control limits

$$\text{UCL} = \bar{\bar{X}} + 3\frac{\bar{s}}{\sqrt{n}} \tag{5}$$

$$\text{LCL} = \bar{\bar{X}} - 3\frac{\bar{s}}{\sqrt{n}} \tag{6}$$

5. Draw the control chart and identify the positions of the averages relative to the limits.

The probability ratio for the sample means falling within ($\pm 3\sigma$) standard deviations is approximately 99.73%, while the expected false signal rate is approximately 0.27%. If one or more sample means fall outside the control limits, this indicates an assignable cause that requires investigation [1][17].

2.2. *The Standard Deviation Chart (S-Chart)*

The standard deviation chart (S-Chart) is used to monitor changes in the degree of dispersion within a production process, i.e., to track the stability of variance or the change in diffusion around the mean. The mean of the standard deviations represents the midpoint of this chart. The standard deviation chart is a complementary tool to the mean chart, as it focuses on the stability of variance rather than the stability of the mean, and is calculated according to [18][19]:

$$\bar{s} = \frac{\sum_{i=1}^{m} s_i}{m} \tag{7}$$

And control limits are calculated using tabular constants as follows:

$$\text{UCL} = A_4\bar{s} \tag{8}$$

$$\text{LCL} = A_3\bar{s} \tag{9}$$

A_3, A_4 constants obtained from quality control tables

2.3. *The Range Chart (R-Chart)*

The R-chart is used to monitor changes in the dispersion of the production process by tracking the range of values within each sample. The midline of this chart represents the overall mean of the range for the samples. The R-chart complements the mean chart, focusing on the stability of the dispersion within the samples rather than the position of the mean. The limits of control are calculated using standard constants as follows [17]:

$$CL = \bar{R} \tag{10}$$

$\bar{R}$: represents the mean range of the samples
The lower and upper limits of the range chart can be calculated using control tables.

$$\text{UCL} = B_4 \bar{R} \tag{11}$$

$$\text{LCL} = B_3 \bar{R} \tag{12}$$

B_3, B_4: represent constants obtained from quality control tables and depend on the sample size.

2.4. Moving Average Control Chart (MA-Chart)

The Moving Average Chart (MA) is a univariate-variable control chart used to increase the sensitivity for detecting small, gradual deviations in the average of a process by smoothing values through the calculation of an average of several consecutive observations. This chart is distinguished by its ability to detect gradual deviations that may not be clearly visible in a traditional moving average chart [20][21][17][22]. The following steps illustrate the MA chart:
1- Calculate the arithmetic means for each sample and the general mean according to equations 1 and 2
2-Calculate the standard deviation for each sample and the general standard deviation according to equations 3 and 4
3- Calculate the mean of the standard deviation according to the following equation [21]:

$$s_{\bar{x}} = \frac{\bar{s}}{\sqrt{n}} \tag{13}$$

4. Found the values of the moving average chart (MA) for the required period.
5. Calculate the lower and upper limits of the control chart as follows [20]:

$$\text{CCL} = \bar{\bar{X}} \tag{14}$$

$$\text{UCL} = \bar{\bar{X}} + 3\frac{s_{\bar{x}}}{\sqrt{i}} \tag{15}$$

$$\text{LCL} = \bar{\bar{X}} - 3\frac{s_{\bar{x}}}{\sqrt{i}} \tag{16}$$

Points that fall outside the limits of control indicate the presence of non-random changes in the production process that require investigation into the specific causes and the necessary corrective actions.

2.5. Linear Regression Control Chart

A regression control chart is used to monitor the relationship between a main response variable and one or more explanatory variables when a meaningful linear relationship exists between these variables. This chart is a simplified form of multivariate control, as it does not monitor a univariate variable separately, but rather tracks the extent to which actual values deviate from the relationship predicted by the linear regression model. The regression model assumes that the response variable (Y) is linearly related to the explanatory variable (X), and that random errors (e_i) follow a normal distribution with a mean of zero and a constant variance, with independent observations [23].
The estimated regression line equation represents the target line of the control chart, and the control limits are parallel to the regression line, not the x-axis, which distinguishes it from traditional control charts [18][24].

2.5.1. Steps for Constructing A control Regression Chart 1- Drawing a scatter plot to verify the existence of a linear relationship and to detect outliers. In the practical application of this research, the variable (Y) represents a key quality characteristic of concrete blocks, while the variable (X) represents a geometric variable related to the production or inspection process, which justifies the use of a regression model to monitor the relationship between these characteristics within a statistical control framework.

2-Estimating the regression line equation

$$\hat{Y} = \hat{B}_0 + \hat{B}_1 x \tag{17}$$

3-Calculating control limits [19]:

$$\text{UCL} = \hat{B}_0 + \hat{B}_1 x + 2S_e \tag{18}$$

$$\text{LCL} = \hat{B}_0 + \hat{B}_1 x - 2S_e \tag{19}$$

It is possible to use $2S_e$, $3S_e$, or $6S_e$ depending on the required sensitivity in the research. Points outside the control limits indicate a deviation from the expected linear relationship, suggesting a non-random variation in the process that warrants investigation [19][24].
Since

$$S_e = \sqrt{\frac{\sum_{i=1}^{n} e_i^2}{n-2}} \tag{20}$$

Where: e_i represents the value of random errors, it is calculated according to the following equation

$$e_i = y_i - \hat{y}_i \tag{21}$$

3. Results and Discussion

The practical aspect involved applying a set of traditional statistical control charts (arithmetic mean chart, standard deviation chart, range chart, and moving average chart) along with a linear regression control chart. The aim was to diagnose the behavior of the production process and monitor the stability of the quality characteristics of concrete blocks, without seeking to compare the superiority or accuracy of these charts. The research relied on real data consisting of 118 observations of concrete block tests from a bridge in Nasiriyah, obtained from the consulting office at Thi-Qar University. Standard control limits based on the ($\pm 3\sigma$) limits commonly used in traditional Shewhart charts were employed, in accordance with standard monitoring practices.
The signals from the control charts were evaluated through graphical interpretation of the observation locations relative to the control limits, with the aim of identifying random or specific factors affecting the production process. The number of points outside the control limits is not a measure of preference, but rather an indicator of the type of change to which each chart responds.
The data were analyzed using Minitab 19, a software program specializing in statistical process control applications.

3.1. Arithmetic Mean Chart ($\bar{X}$-Chart) Results

Table (1) and Figure (1) illustrate the results of applying the arithmetic mean chart.
The measurements showed [...] quality characteristics (the dimensions of [...], average, and maximum deviation). To ensure data consistency with the assumption of a normal distribution, and maintain practical dimensions of values.
The results showed [...] observations outside the control range, representing [...]% of the total observations, which indicates the existence of assignable causes affecting the production process. This necessitates an investigative approach to identify the sources of the deviation and implement the necessary corrective actions to ensure process stability.

Table 1. The Results of The Arithmetic Mean Chart

observations are outside the limits control	Ratio	LCL	CL	UCL	SD
26	22%	1.9875	2.0129	2.0384	0.014674

The number of points outside the control limits is not a measure of superiority among different control charts, but rather reflects the nature and sensitivity of the mean chart to changes specifically affecting the process mean.

Chart($\bar{X}$) is more sensitive to deviations from the mean, while other charts, such as (S) and (R), focus on monitoring changes in dispersion within the process.

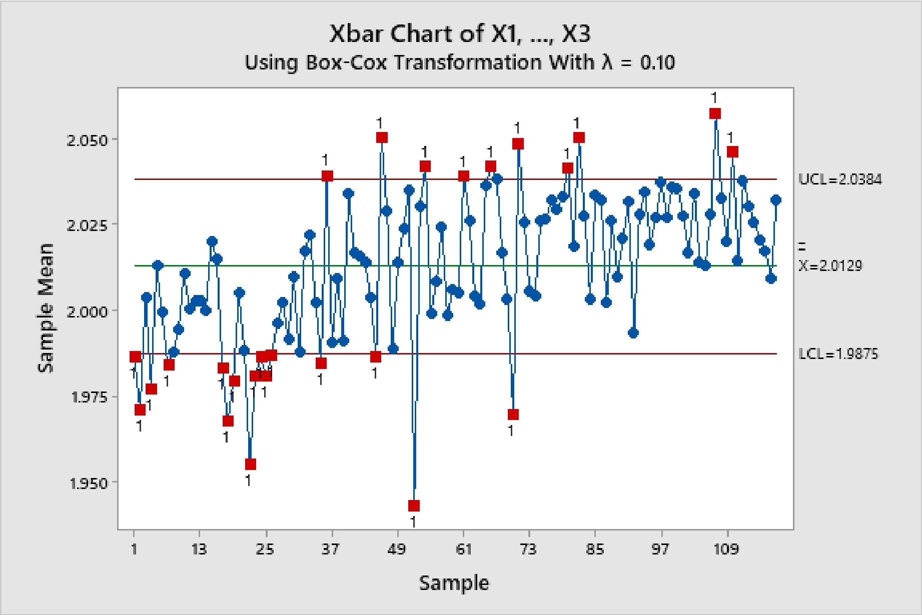

Figure 1. The Arithmetic Mean Chart ($\bar{X}$-Chart) After the Box–Cox Transformation (λ=0.10) and Within the Limits of ($\pm 3\sigma$).

3.2. *Standard Deviation Chart (S-Chart) Results*

Table (2) and Figure (2) illustrate the results of applying the standard deviation chart (S-Chart) to monitor the degree of dispersion in the quality characteristic of concrete blocks, using the traditional control limits ($\pm 3\sigma$). This chart is used to monitor the stability of variance within the production process, regardless of the behavior of the mean. These standard limits were adopted in the final presentation of the results to reduce redundancy and focus on interpreting the statistical behavior of dispersion.
The results showed no out-of-control observations at common significance levels, indicating that the dispersion of the data around the mean is highly statistically stable, and that the observed variations in the process are not due to fluctuations in variance, but rather may be related to factors affecting only the process mean. This result reflects the functional role of the standard deviation chart, as it confirms that the process is stable in terms of dispersion, even if other charts, such as the arithmetic mean chart, show indications of specific factors affecting the process mean.

Table 2. Standard Deviation Chart Results

observations are outside the limits control	Ratio	LCL	CL	UCL	SD
0	0%	0.0129	0.0140	0.0331	0.014

3.3. *Range Chart (R-Chart) Results*

Table (3) and Figure (3) illustrate the results of applying the R-Chart to monitor instantaneous changes in the quality characteristic dispersion of concrete blocks, using the conventional control limits ($\pm 3\sigma$). The R-Chart is used to monitor the stability of the change within each subsample and is more sensitive to sudden changes in dispersion compared to the standard deviation chart.

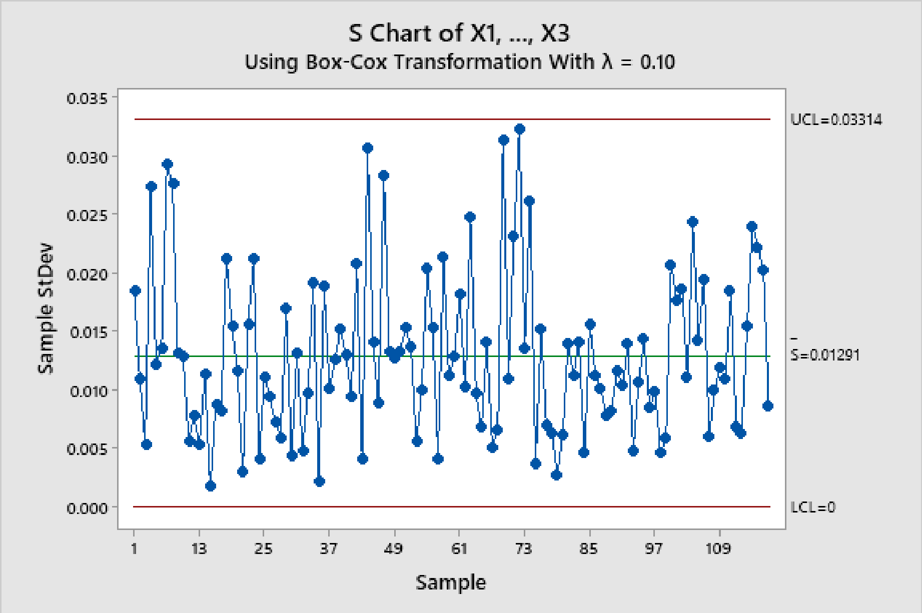

Figure 2. Standard Deviation Chart (S-Chart) for Concrete Blocks Using Control Limits ($\pm 3\sigma$).

The results showed that only one observation (0.8% of total observations) fell outside the control range, indicating a high degree of stability in the production process in terms of instantaneous changes within the samples, with a limited possibility of a specific cause affecting one of the samples. This result confirms the functional role of the range chart in detecting sudden, short-term disturbances, without implying a general flaw in the stability of the dispersion, especially given that the standard deviation chart results agree with the statistical control condition.

Table 3. Range Chart Results

observations are outside the limits control	**Ratio**	**LCL**	**CL**	**UCL**	**SD**
1	0.8%	0.0231	0.0244	0.0629	0.014

3.4. Moving Average Control Results

Table (4) and Figure (4) illustrate the results of applying the moving average chart (MA-Chart) to monitor gradual changes in the average compressive strength of concrete blocks, using the traditional control limits ($\pm 3\sigma$). This chart is distinguished by its ability to increase sensitivity for detecting small and cumulative deviations in the process average by smoothing the values using a moving average of a number of consecutive observations. The results showed that 44 observations (37%) fell outside the control range, indicating gradual deviations or slow shifts in the average process that might not be apparent on a traditional mean chart. This finding reflects the high sensitivity of moving average charts to small, continuous changes, as they respond to cumulative shifts in the average even when the dispersion remains stable, as demonstrated by standard deviation and range charts.
The high number of signals outside the control range does not necessarily indicate the superiority of this chart, but rather reflects the nature of the gradual changes affecting the average process.

Table 4. Moving Average Control Chart (MA-Chart) Results

observations are outside the limits control	**Ratio**	**LCL**	**CL**	**UCL**	**SD**
44	37%	1.998	2.0129	2.0276	0.0146

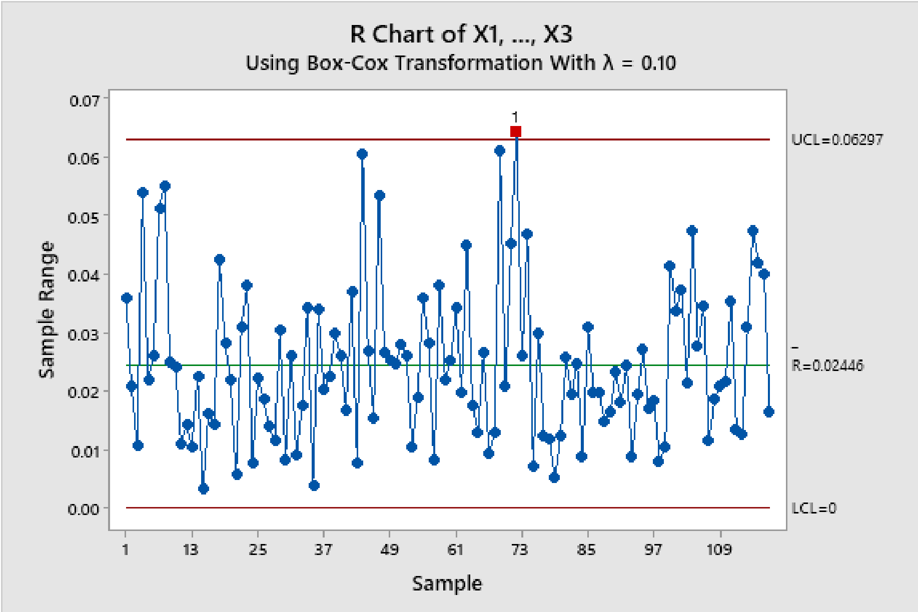

Figure 3. Range chart (R-Chart) for Concrete Blocks Using Conventional Control Limits ($\pm 3\sigma$).

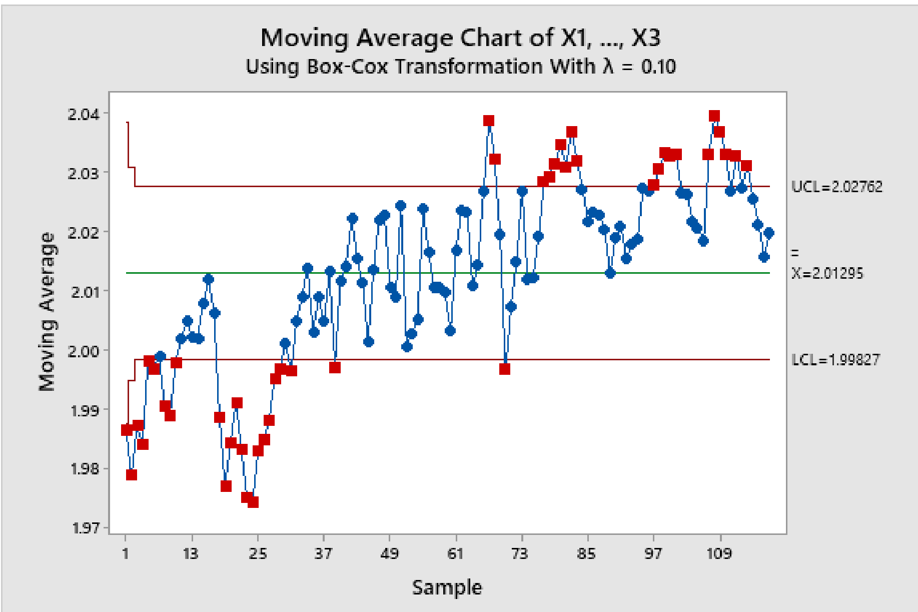

Figure 4. Moving Average Chart (MA-Chart) Using the Traditional Control Limits ($\pm\sigma 3$).

3.5. *Linear Regression Control Chart*

A regression control chart is used to monitor the statistical relationship between a key quality characteristic and explanatory variables related to the production or inspection process. It is a simplified form of multivariate control, tracking the deviation of actual values from the linear relationship predicted by the regression model, rather than monitoring each variable individually. Before constructing the regression model and its control chart, the basic statistical assumptions were verified. The data were examined using box plots to check for outliers, and the data were confirmed to meet the normality assumption. The results showed no outliers in the studied variables, and the data were suitable for applying the linear regression model. Figures 5–8 illustrate the behavior of the variables included in the model.

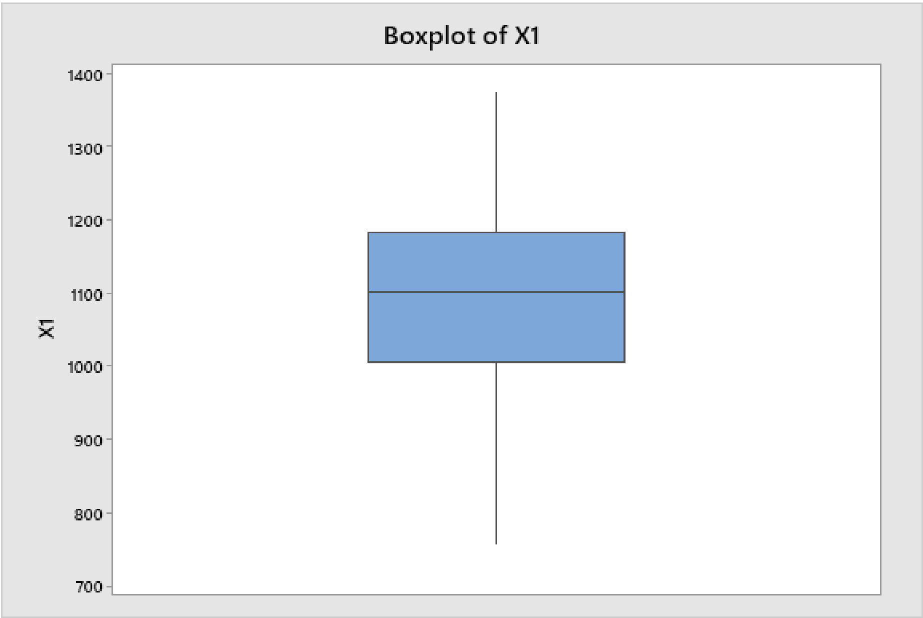

Figure 5. Testing The X_1 Variable.

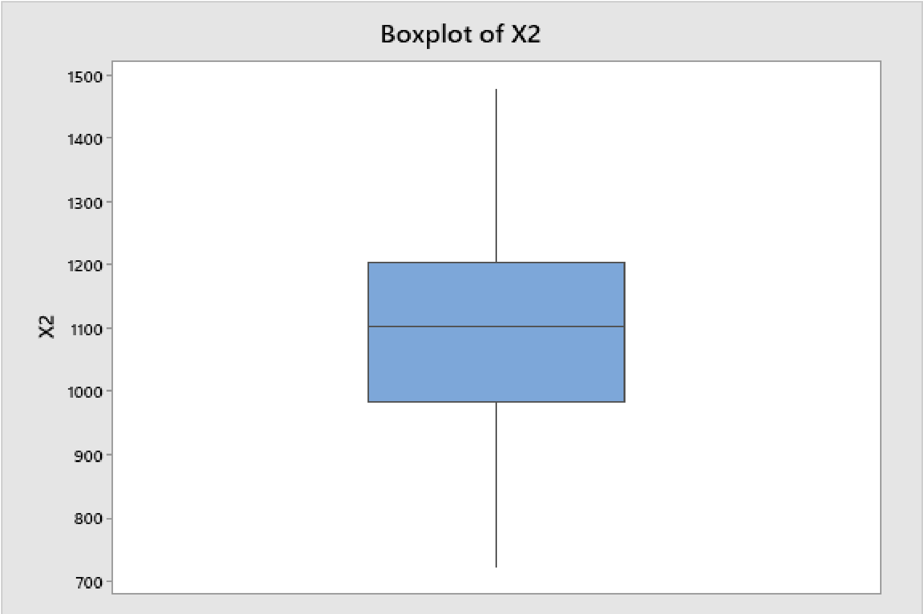

Figure 6. Testing The X_2 Variable.

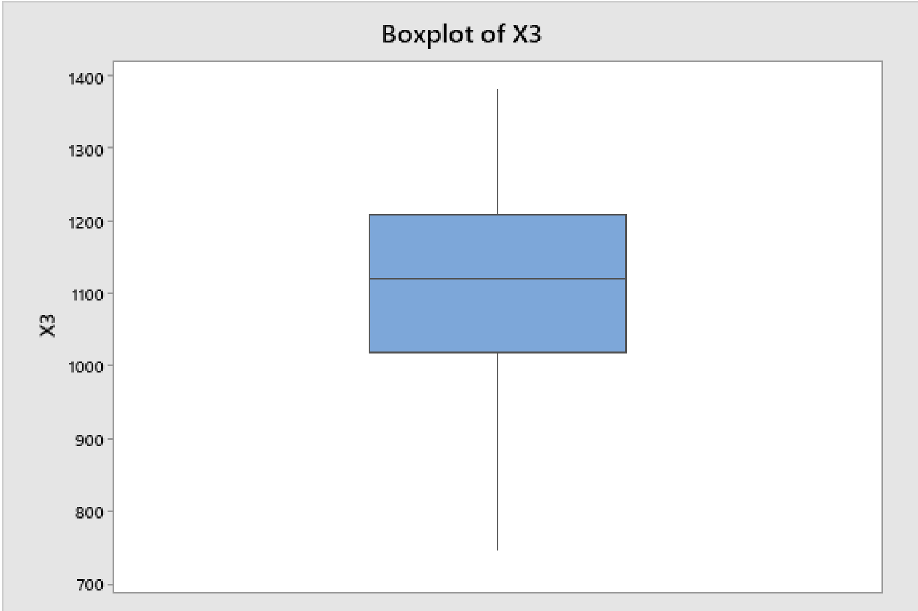

Figure 7. Testing The X_3 Variable.

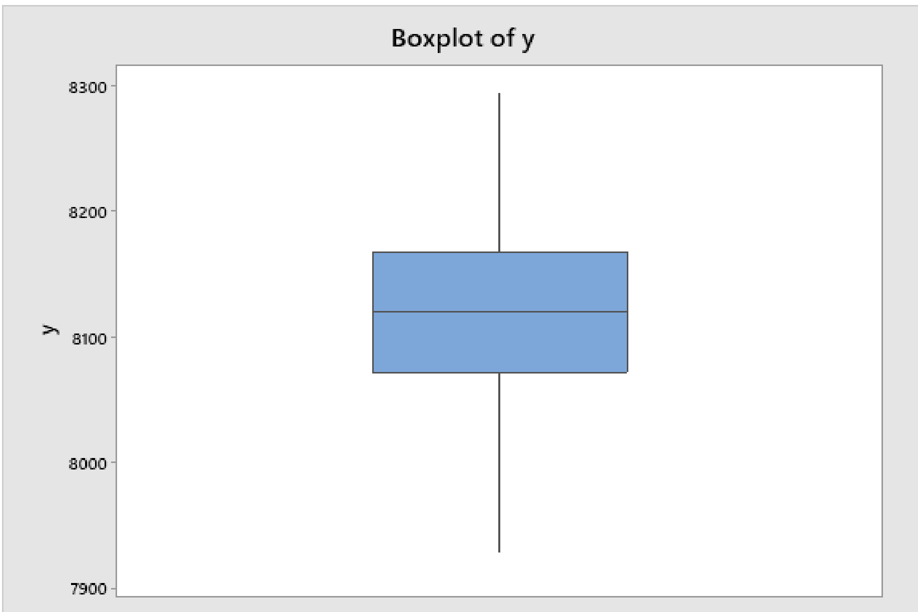

Figure 8. Testing The y Variable.

In the practical application of this research, the dependent variable Y represents the weight of a concrete block (as an overall quality characteristic), while the explanatory variables X1, X2, and X3 represent physical or engineering properties related to the production and testing process. This justifies the use of a linear regression model to monitor the relationship between these properties within a statistical control framework. After verifying the existence of a linear relationship through the scatter plots shown in Figures 9–11, the multiple linear regression model was estimated as follows:

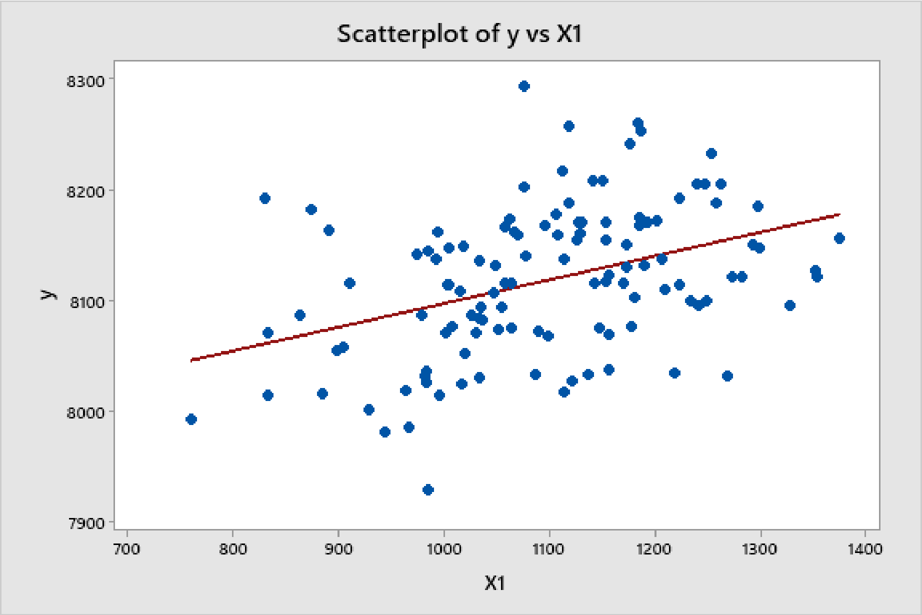

Figure 9. Scatterplot Data for Variable X_1

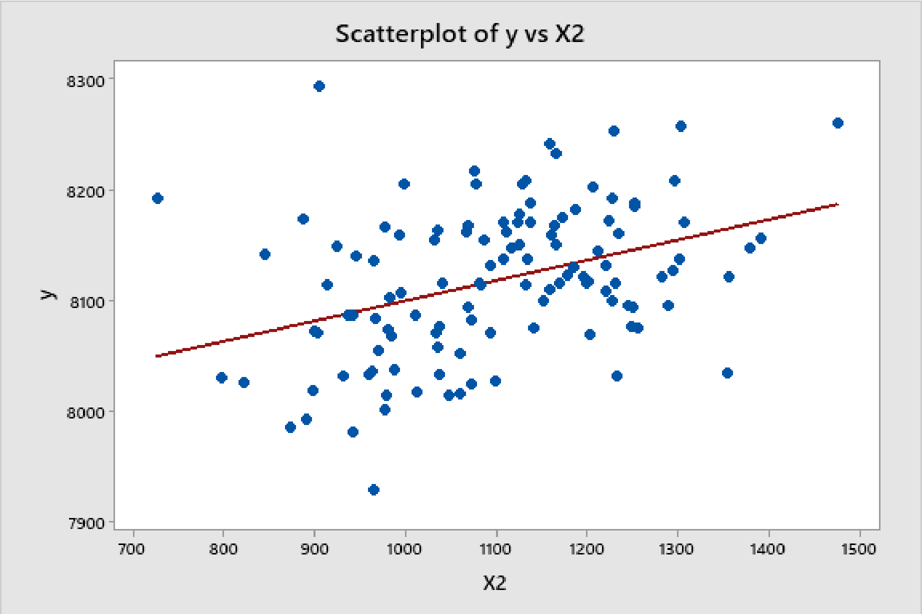

Figure 10. Scatterplot Data for Variable X_2

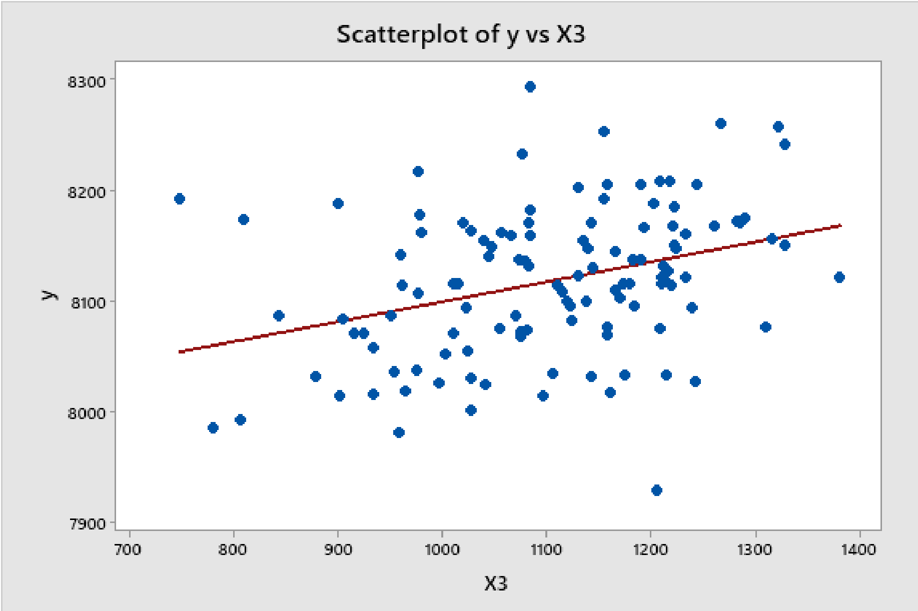

Figure 11. Scatterplot Data for Variable X_3

The liner regression model is as follows

$$y = 7839.602 + 0.134x_1 + 0.098x_2 + 0.022x_3$$

Source	DF	SS	MS	F	P
Regression	3	101108	33702.6	8.76	0.0000
Residual	114	438650	3847.81		
Total	117	539758			

Analysis of variance (ANOVA) of the model shows that the regression equation is highly statistically significant ($p < 0.001$), indicating a significant relationship between the response variable and the explanatory variables, and that the model is suitable for representing the relationship under study within the limits of the available data.
Based on the estimated regression equation, a regression plot was constructed by calculating the target line and its parallel upper and lower control limits, using the standard error of estimation (Se). Table (5) shows the estimated values of the target line and control limits for the research sample. For presentation and analysis, the results of the regression plot were visualized using MATLAB 2018b, as shown in Figure 12. The plot showed no observations falling outside the control limits, indicating that the linear relationship between the weight of the concrete blocks and the explanatory variables remained statistically stable throughout the examination period. It is important to note that the absence of out-of-control signals in the regression chart does not necessarily indicate its superiority over traditional control charts. Rather, it reflects the different monitoring role of this chart, as it monitors the stability of the relationship between several variables simultaneously, whereas traditional control charts focus on monitoring the behavior of a univariate variable (mean or dispersion) separately. Therefore, the regression chart serves as a complementary tool to traditional control charts within an integrated monitoring framework for the quality of concrete blocks.

Table 5. Upper and lower limits and target line

No	**UCL**	**LCL**	$\hat{y}$
1	8206.444	7958.321	8082.382
2	8183.937	7935.814	8059.876
3	8227.886	7979.763	8103.824
4	8210.622	7962.499	8086.561
5	8248.742	8000.62	8124.681
6	8223.656	7975.533	8099.595
7	8202.743	7954.62	8078.682
8	8195.221	7947.098	8071.16
9	8213.629	7965.506	8089.567
10	8233.734	7985.611	8109.673
11	8226.114	7977.991	8102.053
12	8224.506	7976.384	8100.445
13	8230.428	7982.305	8106.366
14	8220.396	7972.273	8096.334
15	8250.515	8002.393	8126.454
16	8244.593	7996.471	8120.532
17	8201.819	7953.697	8077.758
18	8195.933	7947.811	8071.872
19	8197.919	7949.796	8073.857
20	8230.971	7982.848	8106.909
21	8210.729	7962.606	8086.668
22	8170.391	7922.268	8046.33
23	8197.845	7949.722	8073.784
24	8208.013	7959.89	8083.951
25	8205.835	7957.712	8081.774
26	8208.582	7960.46	8084.521
27	8222.877	7974.755	8098.816
28	8223.769	7975.646	8099.708
29	8206.949	7958.826	8082.887
30	8235.148	7987.026	8111.087
31	8201.615	7953.493	8077.554
32	8245.905	7997.782	8121.844
33	8252.453	8004.331	8128.392
34	8236.975	7988.853	8112.914
35	8203.255	7955.133	8079.194
36	8270.409	8022.287	8146.348
37	8206.305	7958.182	8082.243
38	8242.213	7994.09	8118.152
39	8219.502	7971.379	8095.44
40	8270.169	8022.046	8146.108
41	8252.381	8004.258	8128.32
42	8243.901	7995.778	8119.84
43	8245.068	7996.945	8121.007
44	8228.646	7980.524	8104.585
45	8206.683	7958.561	8082.622

46	8291.582	8043.459	8167.52
47	8249.771	8001.648	8125.709
48	8216.797	7968.675	8092.736
49	8236.663	7988.541	8112.602
50	8249.037	8000.915	8124.976
51	8264.201	8016.079	8140.14
52	8162.255	7914.133	8038.194
53	8262.825	8014.703	8138.764
54	8280.001	8031.879	8155.94
55	8220.385	7972.263	8096.324
56	8243.731	7995.609	8119.67
57	8258.893	8010.771	8134.832
58	8221.341	7973.219	8097.28
59	8232.901	7984.779	8108.84
60	8237.079	7988.957	8113.018
61	8292.741	8044.619	8168.68
62	8266.435	8018.313	8142.374
63	8216.657	7968.535	8092.596
64	8227.153	7979.031	8103.092
65	8278.229	8030.107	8154.168
66	8280.431	8032.309	8156.37
67	8281.531	8033.409	8157.47
68	8250.687	8002.565	8126.626
69	8220.953	7972.831	8096.892
70	8189.439	7941.316	8065.378
71	8294.855	8046.732	8170.793
72	8258.399	8010.277	8134.338
73	8239.504	7991.382	8115.443
74	8244.679	7996.557	8120.618
75	8262.143	8014.021	8138.082
76	8262.621	8014.499	8138.56
77	8273.299	8025.177	8149.238
78	8261.067	8012.945	8137.006
79	8269.373	8021.25	8145.311
80	8287.309	8039.186	8163.247
81	8248.665	8000.543	8124.604
82	8305.247	8057.124	8181.185
83	8260.585	8012.462	8136.523
84	8229.551	7981.428	8105.489
85	8274.113	8025.991	8150.052
86	8267.708	8019.585	8143.647
87	8224.413	7976.29	8100.352
88	8255.635	8007.513	8131.574
89	8232.197	7984.075	8108.136
90	8251.012	8002.889	8126.951
91	8263.216	8015.093	8139.155
92	8223.257	7975.134	8099.195
93	8265.116	8016.993	8141.054

94	8265.758	8017.635	8141.696
95	8241.972	7993.849	8117.91
96	8257.941	8009.818	8133.88
97	8279.261	8031.138	8155.2
98	8262.124	8014.001	8138.063
99	8278.132	8030.009	8154.071
100	8284.13	8036.007	8160.068
101	8255.973	8007.85	8131.912
102	8243.682	7995.559	8119.62
103	8279.713	8031.59	8155.652
104	8236.677	7988.554	8112.615
105	8237.726	7989.603	8113.664
106	8254.764	8006.641	8130.703
107	8313.371	8065.248	8189.31
108	8276.323	8028.2	8152.262
109	8245.867	7997.744	8121.806
110	8298.601	8050.478	8174.54
111	8233.649	7985.526	8109.587
112	8272.928	8024.806	8148.867
113	8268.678	8020.555	8144.617
114	8269.515	8021.392	8145.454
115	8256.096	8007.973	8132.034
116	8240.134	7992.011	8116.072
117	8227.375	7979.252	8103.314
118	8264.224	8016.101	8140.163

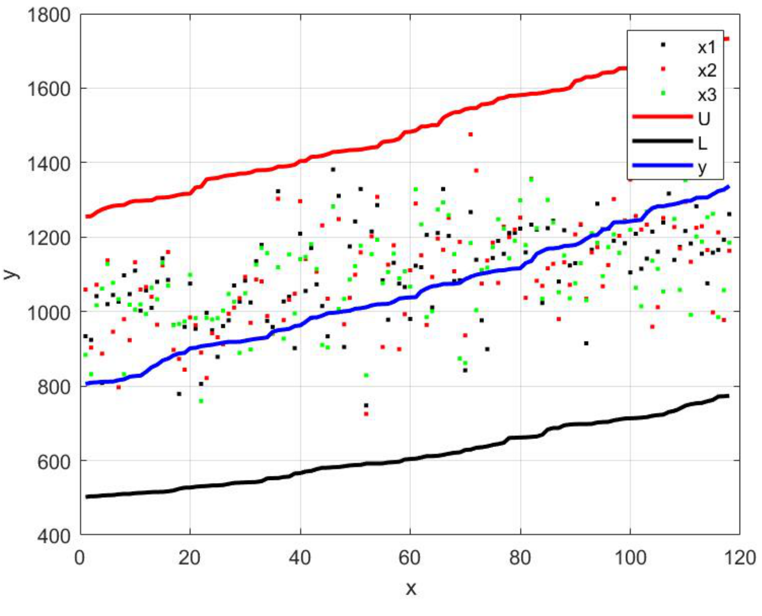

Figure 12. Linear Regression Control Chart.

3.6. Functional Sensitivity Analysis of Statistical Control Charts

This analysis aims to clarify the nature of the changes to which each statistical control chart responds. It does so by interpreting the control role of each chart based on the statistical indicator it monitors, without direct quantitative comparison or judgment of superiority. This analysis helps explain the variation in the number of signals outside the control range between different charts, as a reflection of the different nature of the changes targeted by each chart, and not as a measure of one chart's superiority over another.

Table 6. Functional Sensitivity Analysis of Statistical Control Charts

Control chart	**The type of change to which statistical control charts respond**	**Quality control feature**	**Supervisory interpretation**
$\bar{X}$-Chart	Mean deviation	Compressive strength	Reveals location changes
S-Chart	Change in dispersion	Variation of values	Monitors dissemination stability
R-Chart	Sudden changes	Range	Sensitive to outliers
MA-Chart	Gradual deviations	Mean	Enhances early detection
Regression Chart	Deviation from the relationship	Multiple properties	Monitors relationships between variables

4. Conclusions and Recommendations

The research results showed that using a comprehensive set of statistical control charts provides an effective diagnostic framework for monitoring the quality of concrete blocks, as each chart performs a different monitoring role depending on the statistical indicator it tracks. The mean and moving average charts demonstrated clear sensitivity to changes in the average compressive strength, while the standard deviation and range charts confirmed the stability of dispersion within the production process. The results of the regression plot also showed a stable linear relationship between the weight of concrete blocks and the explanatory variables related to the production and testing processes, with no out-of-control signals. This indicates the stability of the relationship between quality characteristics throughout the study period. This confirms that the regression chart is a complementary control tool to traditional control charts, not a replacement for them.

It is worth noting that the difference in the number of out-of-control signals between the charts does not reflect the superiority of one over another. Rather, it stems from the different nature of the variables to which each chart responds, as well as the influence of the statistical significance level used in defining the control limits on the sensitivity of Shewhart charts.

Accordingly, the research recommends the adoption of a set of statistical control charts within an integrated framework for monitoring the quality of concrete blocks, utilizing a regression control chart in cases where multiple variables interact. Future studies suggest expanding the application to include various construction projects and exploring the use of more advanced multivariate control charts, such as Hotelling's T^2 scheme.

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