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Statistical Process Control for Çayeli Copper Companies using X-R Control Charts and Multidimensional Scaling Analysis

X-R Kontrol Kartları ve Çok Boyutlu Ölçekleme Analizi Kullanılarak Çayeli Bakır İşletmelerinin İstatistiksel Proses Kontrolü

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Abstract

The feeding materials, concentrates and tailings of zinc and copper ores were examined by multidimensional scaling analysis. The calculated LCL_X, UCL_X and UCL_R values for copper (feeding material, concentrate, and tailing) according to X-R analysis are 1.94, 16.92, 0.16; 2.96, 22.90, 0.41 and 0.89, 5.19, 0.21 respectively. Likewise, these values for zinc are 0.31, 43.46, 0.23; 3.00, 50.33, 0.66 and 2.34, 5.97, 0.37 respectively. The calculated Cp copper and zinc values are 2.08, 1.42, 1.39 and 1.82, 1.54, 1.25 respectively. The feeding material, concentrate, and tailing parameters of the copper and zinc products are greater than 1.0. Likewise, this study shows that the calculated Cpk values for copper and zinc (2.15, 1.20, 1.72 and 3.82, 1.05, 1.53 respectively) are larger than 1. Stress value was calculated at the first step of the analysis and established at 0.00258 and 0.00674 for copper and zinc, respectively, which indicates a fair fit for both. Nevertheless, the coefficient of determination (RSQ) was calculated as 0.9998 and 0.9986 for copper and zinc, respectively. These values indicated a high correlation between factors. Finally, this study showed that the usefulness of statistical process control techniques, such as mean and range control charts, process capability indexes and multidimensional scaling analysis, in helping decision makers in Çayeli Copper Companies.

Keywords: *Copper, Control charts, Multidimensional scaling analysis, Process capability indexes, Zinc.*

Öz

Çinko ve bakır cevherlerinin besleme malı, konsantre ve atıkları çok boyutlu ölçekleme analizi ile incelenmiştir. X-R analizine göre bakır (besleme malı, konsantre ve artık) için hesaplanan LCL_X, UCL_X and UCL_R değerleri sırasıyla 1.94, 16.92, 0.16; 2.96, 22.90, 0.41 ve 0.89, 5.19, 0.21'dir. Benzer şekilde, çinko için bu değerler sırasıyla 0.31, 43.46, 0.23; 3.00, 50.33, 0.66 ve 2.34, 5.97, 0.37'dir. Hesaplanan Cp bakır ve çinko değerleri sırasıyla 2,08, 1,42, 1,39 ve 1,82, 1,54 ve 1,25'tir. Bakır ve çinkonun besleme malı, konsantre ve atık parametreleri 1,0'den büyüktür. Benzer şekilde, bu çalışma bakır ve çinko için hesaplanan Cpk değerlerinin (2,15, 1,20 ve 1,72 ; 3,82, 1,05 ve 1,53) 1,0'den büyük olduğunu göstermektedir. Stress değerleri, analizin ilk aşamasında hesaplanmış ve bakır ve çinko için sırasıyla 0,00258 ve 0,00674'te belirlenmiştir. Bununla birlikte RSQ, sırasıyla bakır ve çinko için 0,9998 ve 0,9986 olarak hesaplanmıştır. Bu değerler faktörler arasında yüksek bir korelasyon olduğunu göstermiştir. Son olarak, bu çalışma Çayeli Bakır İşletmelerinde karar vericilere yardımcı olmak için ortalama ve aralık kontrol çizelgeleri, süreç doğruluk indeksleri ve çok boyutlu ölçekleme analizi gibi istatistiksel işlem kontrol tekniklerinin kullanışlılığını göstermiştir.

Anahtar Kelimeler: *Bakır, Kontrol kartları, Çok boyutlu ölçekleme analizi, Süreç doğruluk indeksleri, Çinko.*

1. Introduction

The basic theory of statistical process control (SPC) was developed in the US around the late 1920s by Dr. Shewhart and was promoted worldwide by Dr. Deming. Both observed that repeated measurements from a process exhibit variation. Shewhart originally worked with manufacturing processes, but he and Deming quickly realized that their observations could be applied to any sort of process [1]. By detecting and correcting variations of a process, the quality could be improved, and waste could be reduced, decreasing the likelihood that problems will be passed on to the customer. With its emphasis on early detection and prevention of problems, SPC has a distinct advantage over other quality methods, such as inspection, that apply resources in detecting and correcting problems after they have occurred. When a process is considered out of control, an alarm is raised, and engineers can look for assignable causes of variation and try to eliminate them. Instead, a proactive and preventive approach would improve the system by adjusting it to eliminate non-conforming items, thus decreasing negative performance. The SPC approach incorporates identification of key product characteristics and process variations which are critical to customers [2-5].

The purpose of SPC implementation is to improve product quality, improve productivity, reduce waste, reduce defects, and improve customer value [6,7]. Statistical techniques used in SPC enable optimization of the amount of information needed for decision making, through understating of business baselines, insights for process improvements, communication of value and results of processes, and active as well as visible involvement. SPC also provides real-time analysis to establish controllable baselines; learn, set, and dynamically improve process capabilities; and focus business on areas that need improvement [5,8].

Multidimensional scaling (MDS) is a technique used to visualize similarities in separate parts of a dataset. MDS assigns a point to each item in a multidimensional space and arranges them to reproduce the observed similarities. Often, similarities are considered dissimilarities, or distances, between objects. For two or three dimensions, the resulting locations may be displayed in a "map" that can be visually analyzed [9]. MDS had its origin in behavioral sciences for its help in understanding judgments of individuals (such as preference or relatedness) concerning elements in a set of objects. Nowadays, MDS is used for a large variety of real data, such as biological taxonomy, finance, marketing, sociology, physics, geophysics, mining, communication networks, biology, biomedicine, and others [10].

Çayeli Copper Companies was founded in 1983. It is located on the Black Sea coast of Turkey approximately 7 km inland from the coastal town of Çayeli and adjacent to the town of Madenli. For over 20 years, the company has produced copper and zinc concentrates from our underground mine. The demand for the commodities that we produce is largely driven by consumers of electrical and electronic products. First Quantum Minerals bought out Çayeli Copper in 2013. Çayeli Copper, which produces copper and zinc ore, has the capacity to produce 1.23 million tons of ore annually. The company supplies about one-third of Turkey's copper mine demand. By 2015, it was in second place in the mining sector with 115.7 million dollars in export. The flowsheet of Çayeli Copper Company is given in Figure 1.

In this study, statistical quality control and MDS analysis were applied to copper and zinc samples obtained from Çayeli Copper Companies. During the test period, fluctuations in feeding material, concentrate, and tailing samples were examined with the help of a mean-range control chart. Subsequently, MDS was applied to reveal the similarities and differences between errors in operation, and these errors were grouped according to their similarities. All of these data have been tried to put forward the appropriate solution proposal.

2. Material and Methods

2.1. Calculation of trial control limits

The X control chart monitors the process means, and the R chart monitors the within group variation at a given time point. The range of a sample is simply the difference between the largest and smallest observations. Let $\bar{X}_1, \bar{X}_2, \bar{X}_3, ..., \bar{X}_m$ ($R_1, R_2, R_3, ..., R_m$) be the means (ranges) of m subgroups with size n; the grand average and average range are given in Eqs. 1 and 2. The three-sigma control limits for the $\bar{X}$ chart are shown in Eq. 3.

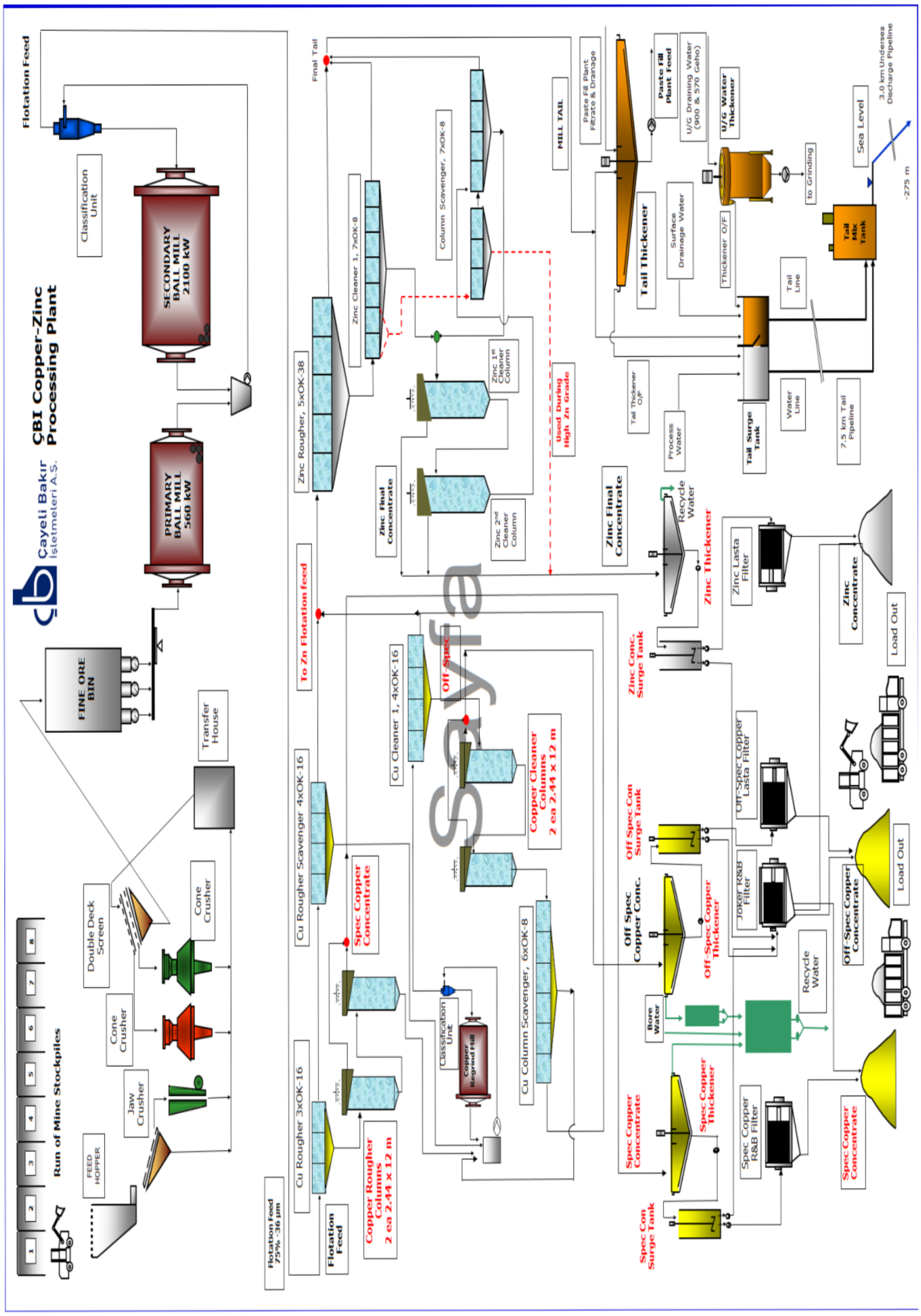

Figure 1. The flowsheet of Çayeli Copper Company

$$\overline{\overline{X}} = \frac{\overline{X_1} + \overline{X_2} + \overline{X_3} + . \dots + \overline{X_m}}{m} \quad (1)$$

$$\overline{R} = \frac{R_1 + R_2 + R_3 + \cdots + R_m}{m} \quad (2)$$

$$UCL_X = \overline{\overline{X}} + \frac{3}{d_2\sqrt{n}}\overline{R} = \overline{\overline{X}} + A_2\overline{R} \quad ; \quad CL_X = \overline{\overline{X}} \ ;$$

$$LCL_X = \overline{\overline{X}} - \frac{3}{d_2\sqrt{n}}\overline{R} = \overline{\overline{X}} - A_2\overline{R} \quad (3)$$

The constant A_2 is tabulated for various sample sizes. To compute the control limits of the R chart. The three-sigma control limits for the R chart follow Eq. 4 and the constants are given in Eq. 5.

$$UCL_R = \overline{R} + 3d_3\frac{\overline{R}}{d_2} = \overline{R}D_4 \quad ; \quad CL_R = \overline{R} \ ;$$

$$LCL_R = \overline{R} - 3d_3\frac{\overline{R}}{d_2} = \overline{R}D_3 \quad (4)$$

$$A_2 = \frac{3}{d_2\sqrt{n}} \ ; D_3 = 1 - \frac{3d_3}{d_2} \ ; \ D_4 = 1 + \frac{3d_3}{d_2} \quad (5)$$

where d_2, D_3, and D_4 depend on the subgroup size n and are calculated when the distribution is normal [11-14].

2.2. Calculation of capability indices

The capability of a process is defined as the ratio of the distance from the process center to the nearest specification limit divided by a measure of the process variability. Capability analysis helps in determining the ability for manufacturing parts within the tolerance limits and engineering values. Machine tool capability (C_p) and process capability (C_{pk}) are used to determine the efficiency. C_p is used to determine the system's location within tolerance limits. C_{pk} is used to determine the average of capability so that the system will work better within specification limits. C_p and C_{pk} are defined by the following Eq. 6:

$$C_p = \frac{USL - LSL}{6\sigma} \quad ; \quad \sigma = \frac{\bar{R}}{d_2} \quad ;$$

$$C_{pk} = min\left(\frac{USL - \bar{\bar{X}}}{3\sigma} \ or \ \frac{\bar{\bar{X}} - LSL}{3\sigma}\right) \quad (6)$$

where USL and LSL are the upper and lower specification limits, respectively, and $\bar{\bar{X}}$ and σ are the process mean and standard deviation, respectively, for individual measurements of the characteristic of interest. These values are usually estimated from the data collected from the process [15-17].

2.3. Calculation of multidimensional scaling analysis

MDS analysis is an appropriate exploratory technique for treating problems with a need for exploration. The input of the procedure is the proximity matrix of the objects under investigation. It contains the values of a quantitative measure of the pair-wise dissimilarities between observations. Euclidean distance is used in this study, as shown in Eq. 7,

$$d_{ij} = \sqrt{\sum_{k=1}^{m} \left(z_{ik} - z_{jk}\right)^2} \quad (7)$$

where d_{ij} donates the Euclidean distance, z_{ik} and z_{jk} are the values of variable k for observations i and j, respectively, and m is the number of variables. Stress dimension (Eq. 8) has a common use in MDS analysis. It is used as a criterion for correlation and for determining whether the dimension number is appropriate that was used in graphical organizing gathered at the end of the analysis. The stress dimension is expressed as,

$$Stress = S = \sqrt{\frac{\sum_{ij}\left(\delta_{ij} - d_{ij}\right)^2}{\sum_{ij} {d_{ij}}^2}} \quad (8)$$

where δij is the value of the proximities between items *i* and *j*, and *dij* is the spatial distance between them. Stress ratio is used as a criterion for determining the suitability of the MDS analysis. A low stress value shows a good correlation of the analysis; a high stress value shows a poor correlation. Kruskal provided a guide indicating correlation of analysis to interpret stress value in 1964 (Table 1) [18-21].

Table 1. Kruskal's rule of thumb

Stress-value	Goodness of Fit
0.10 – 0.20	Poor
0.05 – <0.10	Fair
0.025 – <0.05	Good
0 – <0.025	Excellent

Another diagnostic tool for assessing the appropriateness of the MDS model is the squared correlation index (R^2), which indicates the proportion of variance of the input data accounted for by the MDS procedure ($R^2 \geq 0.60$ is considered an acceptable fit).

3. Results and Discussion

3.1. Analysis of mean-range control charts

At the present time, SPC methods are based upon the product quality data and have been the standard approach in process monitoring. The copper and zinc samples were obtained from this plant and analyzed. To analyze the feeding material, concentrate, and tailing of the copper and zinc samples with control charts, data were gathered over 90 days. The data were arranged as *m*= 90 (number of sample) and *n*= 2 (subgroup). Using X and R charts, the control limits for the parameters were calculated using A_2= 1.880, D_3= 0, and D_4= 3.267 [22,23]. The following calculations for the X-R control charts were made and the details are given below.

For Copper Feeding Material;

$$\bar{\bar{X}} = \frac{227.94}{93} = 2.45 \quad ; \quad \bar{R} = \frac{25.30}{93} = 0.27$$

$$LCL_x = 2.45 - [1.880 \times 0.27] = 1.94$$

$$CL_x = \bar{\bar{X}} = 2.45 \quad ; \quad CL_R = \bar{R} = 0.27$$

$$UCL_x = 2.45 + [1.880 \times 0.27] = 2.96$$

$$UCL_R = 3.267 \times 0.27 = 0.89$$

For Copper Concentrate;

$$\bar{\bar{X}} = \frac{1851.33}{93} = 19.91 \quad ; \quad \bar{R} = \frac{147.85}{93} = 1.59$$

$$LCL_x = 27.77 - [1.880 \times 1.59] = 16.92$$

$$CL_x = \bar{\bar{X}} = 19.91 \quad ; \quad CL_R = \bar{R} = 1.59$$

$$UCL_x = 27.77 + [1.880 \times 1.59] = 22.90$$

$$UCL_R = 3.267 \times 1.59 = 5.19$$

For Copper Tailing;

$$\bar{\bar{X}} = \frac{26.62}{93} = 0.29 \quad ; \quad \bar{R} = \frac{6.07}{93} = 0.07$$

$$LCL_x = 0.29 - [1.880 \times 0.07] = 0.16$$

$$CL_x = \bar{\bar{X}} = 0.29 \quad ; \quad CL_R = \bar{R} = 0.07$$

$$UCL_x = 0.29 + [1.880 \times 0.07] = 0.41$$

$$UCL_R = 3.267 \times 0.07 = 0.21$$

For Zinc Feeding Material;

$$\bar{\bar{X}} = \frac{153.56}{93} = 1.65 \quad ; \quad \bar{R} = \frac{66.50}{93} = 0.72$$

$$LCL_x = 1.65 - [1.880 \times 0.72] = 0.31$$

$$CL_x = \bar{\bar{X}} = 1.65 \quad ; \quad CL_R = \bar{R} = 0.72$$

$$UCL_x = 1.65 + [1.880 \times 0.72] = 3.00$$

$$UCL_R = 3.267 \times 0.72 = 2.34$$

For Zinc Concentrate;

$$\bar{\bar{X}} = \frac{4361.51}{93} = 46.90 \quad ; \quad \bar{R} = \frac{169.94}{93} = 1.83$$

$$LCL_x = 46.90 - [1.880 \times 1.83] = 43.46$$

$$CL_x = \bar{\bar{X}} = 46.90 \quad ; \quad CL_R = \bar{R} = 1.83$$

$$UCL_x = 46.90 + [1.880 \times 1.83] = 50.33$$

$$UCL_R = 3.267 \times 1.83 = 5.97$$

For Zinc Tailing;

$$\bar{\bar{X}} = \frac{41.08}{93} = 0.44 \quad ; \quad \bar{R} = \frac{10.60}{93} = 0.11$$

$$LCL_x = 0.44 - [1.880 \times 0.11] = 0.23$$

$$CL_x = \bar{\bar{X}} = 0.44 \quad ; \quad CL_R = \bar{R} = 0.11$$

$$UCL_x = 0.44 + [1.880 \times 0.11] = 0.66$$

$$UCL_R = 3.267 \times 0.11 = 0.37$$

Using the data obtained from the statistical calculations in Çayeli Copper Companies, mean and range graphics charts were prepared, and normal distribution curves were plotted for the plant. Fig. 2 indicates that the copper feeding material levels of the ores at this plant were above the upper control line for 7 days and below the lower control line for 5 days. Generally, it was not observed that there was a serious problem at this factory during the period of testing. However, copper feeding material values must be constantly monitored. When examining the X-R control charts in Fig. 3, it is clear that, although the average values of the zinc feeding material are not near the central line, the majority of the zinc feeding material values were within the control limits during the period of testing, except for 8 days. When the X-R control charts created with copper and zinc concentrates in the plant were examined, it was observed that the copper and zinc concentrates are above the central line and there are large fluctuations. The reason for this might be that the feeding copper and zinc concentrate properties at the plant were not homogenous. In the mean-range control graphics shown in Fig. 4, there are many fluctuations in the values of copper and zinc wastes, but they do not greatly exceed the upper and lower control limits. However, these fluctuations must be constantly monitored, and interventions are needed to address problems. Finally, the system should be monitored in SPC. If the system encounters problems, the production must be stopped immediately and examined, and necessary arrangements must be made. It was determined that a small change in the properties of copper and zinc changes the ores considerably.

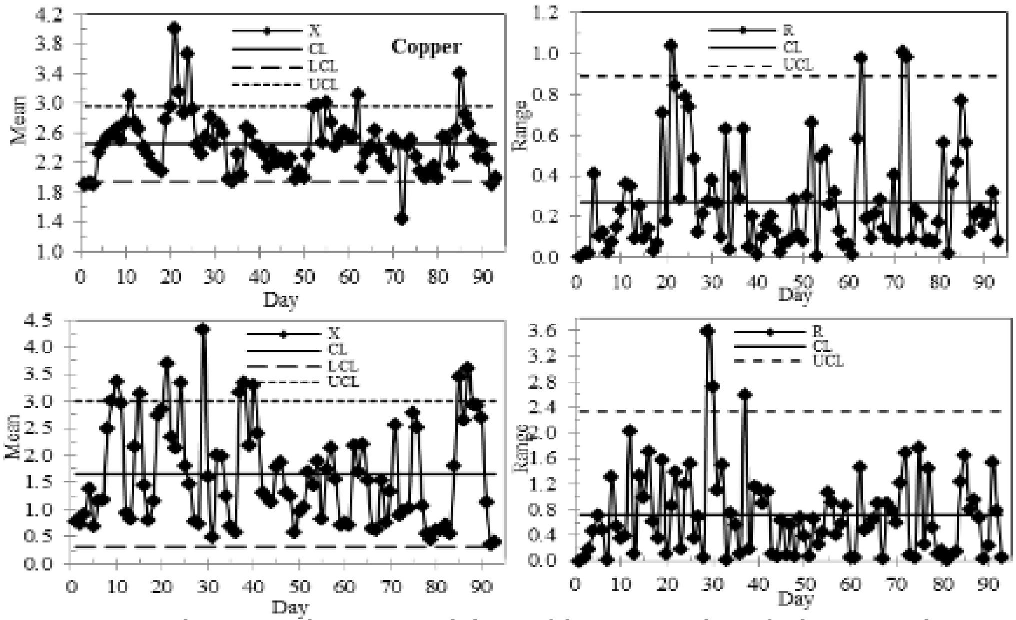

Figure 2. The mean and range control charts of the copper and zinc feeding materials.

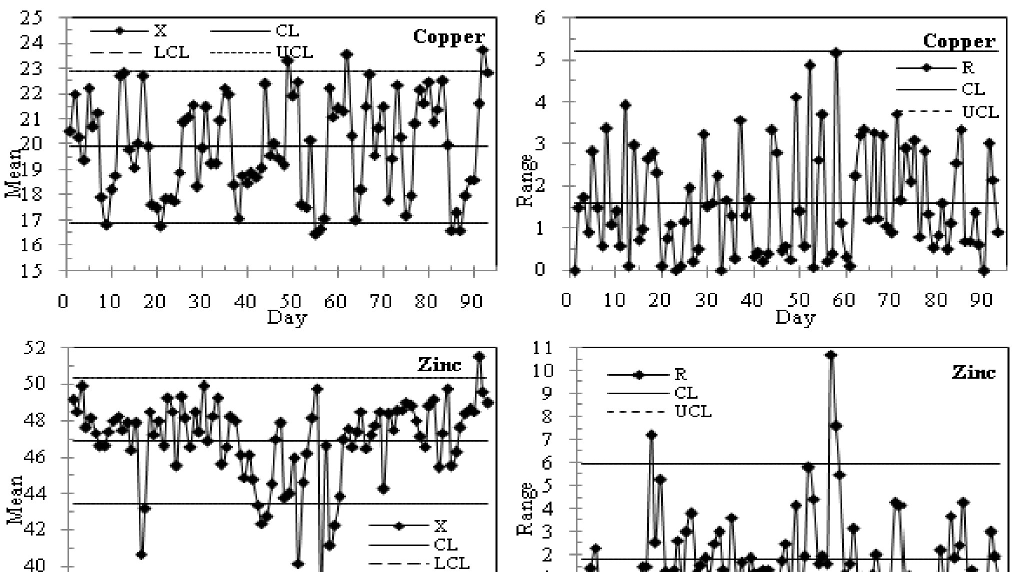

Figure 3. The mean and range control charts of the copper and zinc concentrates.

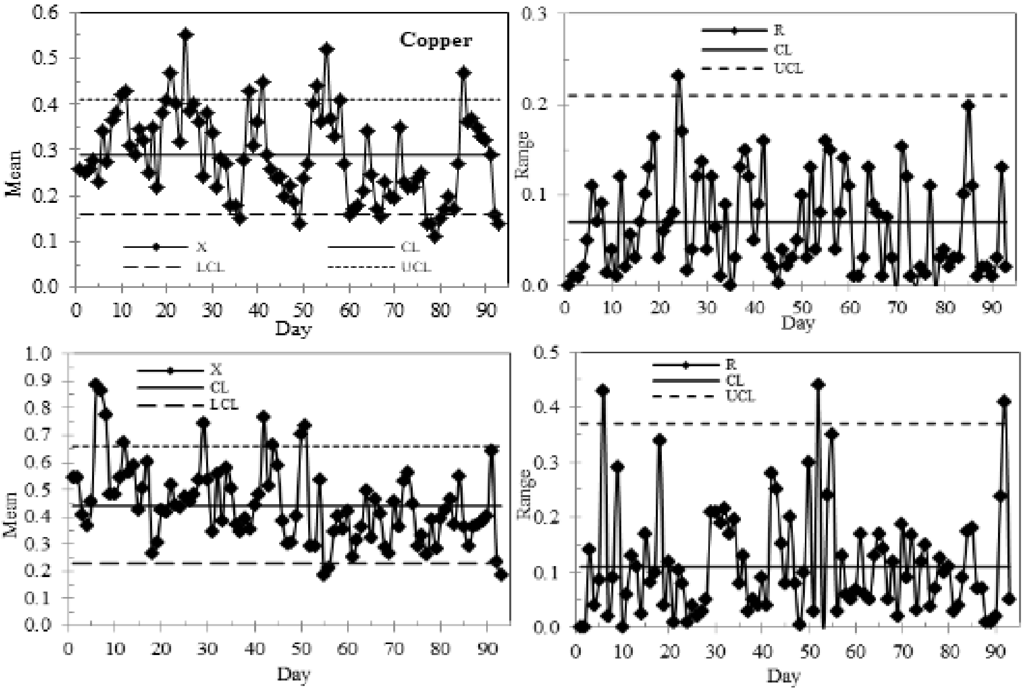

Figure 4. The mean and range control charts of the copper and zinc tailings.

3.2. Estimation of process capability

The process capability study is a longer-term study. In addition to variation arising from the machine, all other external factors that influence the production process over a longer operating time must be taken into account [24]. Process capability indexes are a statistical overview of process performance and are useful in the analysis of process capability or incapability. The USL and LSL as expected values for the calculation indexes were obtained from the management of the plant. The process capability index can give three different conclusions. A value of the process capability index (C_p and C_{pk}) less than 1 indicates that the process is considered unfit to produce items according to the specification limits. In other words, the process yields a significant proportion of non-conforming items, and this implies that corrective actions are needed. If C_{pk} is equal to 1 and $1 \leq C_p < 1.33$, then this indicates that the process variability is very similar to the specification limits. In this situation, it is said that the process is minimally capable, since a small variation on any parameter of the process can considerably increase the proportion of non-conforming items. Finally, it is said that the process is capable of producing items within specification limits if C_{pk} is larger than 1 and if C_p is larger than 1.33. In this situation, it is clear that the width of the specification limits is larger than the width of the process variability. As mentioned previously, it is important to recall that the capability analysis must be carried out when the process is believed to be in control. For obvious reasons, it does not make sense to perform a capability analysis when the process is not stable [25]. It is obvious that the values of all C_p and C_{pk} are above the limits and that the process is adequate and meets specifications. There is no need for any arrangement and improvement in the plant.

For Copper and Zinc Feeding Material;

$$\sigma = \frac{0.27}{1.128} = 0.24 \quad ; \quad \sigma = \frac{0.72}{1.128} = 0.64$$

$$C_p = \frac{4-1}{6 \times 0.24} = 2.08 \quad ; \quad C_p = \frac{9-2}{6 \times 0.64} = 1.82$$

$$C_{pk} = \frac{4-2.45}{3 \times 0.24} = 2.15 \quad ; \quad C_{pk} = \frac{9-1.65}{3 \times 0.64} = 3.82$$

For Copper and Zinc Concentrate;

$$\sigma = \frac{1.59}{1.128} = 1.41 \quad ; \quad \sigma = \frac{1.83}{1.128} = 1.62$$

$$C_p = \frac{25-13}{6\times 1.41} = 1.42 \quad ; \quad C_p = \frac{52-38}{6\times 1.62} = 1.54$$

$$C_{pk} = \frac{25-19.91}{3\times 1.41} = 1.20 \; ; \; C_{pk} = \frac{52-46.9}{3\times 1.62} = 1.05$$

For Copper and Zinc Tailing;

$$\sigma = \frac{0.07}{1.128} = 0.06 \quad ; \quad \sigma = \frac{0.11}{1.128} = 0.10$$

$$C_p = \frac{0.6-0.1}{6\times 0.06} = 1.39 \; ; \; C_p = \frac{0.9-0.15}{6\times 0.1} = 1.25$$

$$C_{pk} = \frac{0.6-0.29}{3\times 0.06} = 1.72 \; ; \; C_{pk} = \frac{0.9-0.44}{3\times 0.1} = 1.53$$

3.3. Evaluation of multidimensional scaling analysis

MDS analysis elucidates factors that affect consumer preferences. In this scope, feeding material, concentrate, and tailing for copper and zinc have been presented in a two-dimensional graph. Stress value was calculated at the first step of the analysis, and the value 0.00258 indicates a fair fit for copper. Nevertheless, another statistic, the coefficient of determination, denoted R^2 or RSQ was calculated as 0.9998 and indicated a higher correlation between factors. The stress value and RSQ are 0.00674 and 0.9986, respectively, for zinc. There is a strong correlation between data distance and configuration distance. Stimulus coordinates are the numerical coordinate locations relating stimuli to dimensions. Feeding material, concentrate, and tailing are determined to have important effects on the copper and zinc products (Fig. 5). The figure demonstrated that the process was under control. Showing the data in a two-dimensional geometrical form showed a correlation with linear form, and observational distances and differences (disparities) exhibit a linear correlation. A scatterplot with a linear fit (Sheppard diagram) displays disparities on the Y axis and disparities on the X axis (Fig. 6). Distances are the original distances for any two points in the input matrix. Disparities are the reproduced distances and measure the distance of two points in the MDS space created in two dimensions [20,21,26].

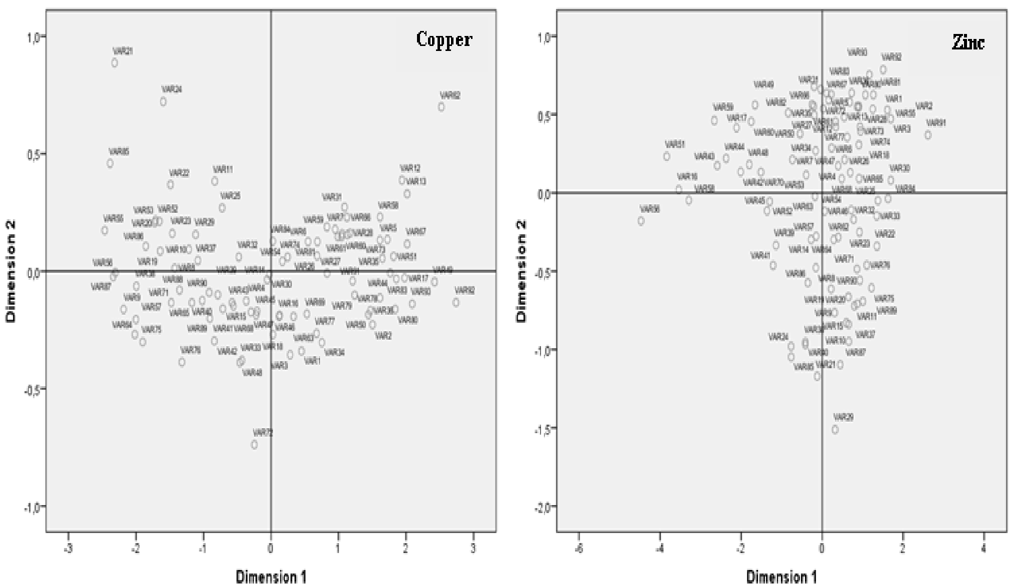

Figure 5. MDS maps based on the copper and zinc correlation indexes.

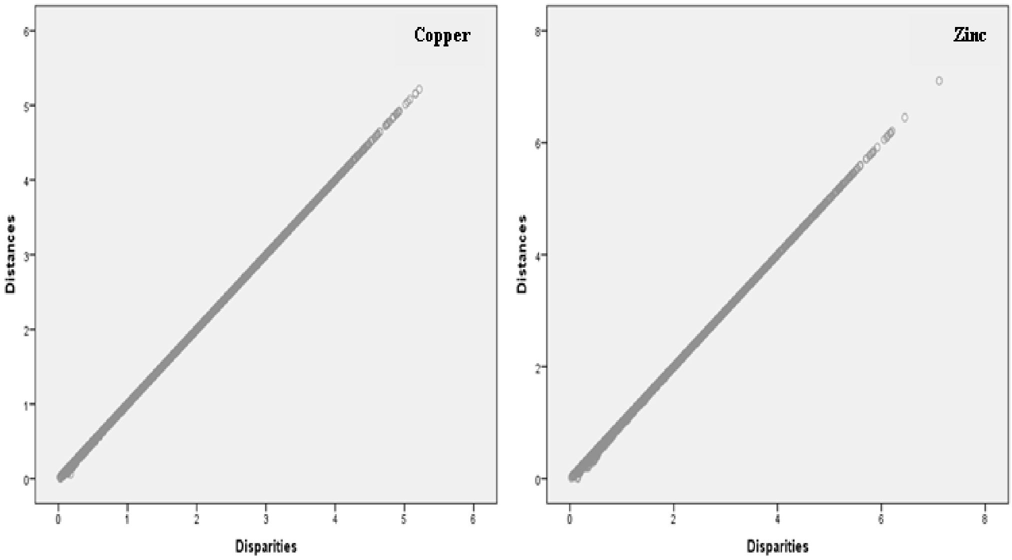

Figure 6. Sheppard diagrams for the MDS map based on the copper and zinc correlation indexes.

4. Conclusions

Several important conclusions can be drawn from the present study.

Statistical process control techniques, including X-R control charts, process capability index, and multidimensional scaling (MDS) analysis, can successfully be used to acquire the relevant information from the Çayeli Copper Companies dataset.

X-R control charts created with feeding materials, concentrates, and tailings for copper and zinc are examined and show that the values of these parameters are above and below the central line within specified limits a majority of the time. This indicates that SPC is an effective means for controlling and improving the process quality.

If process adequacy ratios are below 1, it means that the process is inadequate. However, the calculated C_p copper values (2.08 for feeding, 1.42 for concentrate, and 1.39 for tailing) and C_p zinc values (1.82 for feeding, 1.54 for concentrate, and 1.25 for tailing) for the important feeding material, concentrate, and tailing parameters of the copper and zinc products are greater than 1.0.

Likewise, if C_{pk} values are below 1, this would also mean that the process has a relatively low quality. However, this study shows that the calculated C_{pk} values for copper and zinc (2.15 for feeding, 1.20 for concentrate, and 1.72 for tailing, and 3.82 for feeding, 1.05 for concentrate, and 1.53 for tailing, respectively) are larger than 1. Therefore, it can be said that the process is adequate.

Stress value was calculated at the first step of the analysis and established at 0.00258 and 0.00674 for copper and zinc, respectively, which indicates a fair fit for both. Nevertheless, the coefficient of determination (RSQ) was calculated as 0.9998 and 0.9986 for copper and zinc, respectively. These values indicated a high correlation between factors. There is a strong correlation between data distance and configuration distance. The results of the MDS analysis confirmed the results of the mean and range control charts and process capability indexes. Examining the MDS analysis graph, the feeding materials, concentrates, and tailings for copper and zinc were shown to be under control.

Finally, this study shows the ability of X-R control charts, process capability indexes, and MDS analysis for analyzing copper and zinc values to improve monitoring and control of the process quality for more effective management of Çayeli Copper Companies.

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