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Process Control for a Coal Washing Plant Using a Range Control Chart and Multidimensional Scaling Analysis

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Abstract *In this study, a coal washing plant dataset was evaluated by using the range control chart and multidimensional scaling analyses. These analyses were conducted on the density values of a heavy medium vessel circuit and a heavy medium cyclone circuit. The range control charts indicated that the variations in the density values for the heavy medium vessel circuit and the heavy medium cyclone circuit were significantly high. The density values for the heavy medium vessel circuit and the heavy medium cyclone circuit were examined by multidimensional scaling analysis. The results of multidimensional scaling analysis findings supported the results obtained from the range control charts. Finally, this study showed that the usefulness of statistical process control techniques, such as range control charts and multidimensional scaling analysis, in helping decision makers in coal washing plant management.*

Keywords coal washing plant, heavy medium cyclone circuit, heavy medium vessel circuit, multidimensional scaling analysis, range control chart, statistical process control

1. Introduction

Coal is the altered remains of prehistoric vegetation that had originally accumulated in swamps and peat bogs. The most significant uses of coal are in electricity generation, steel production, cement manufacturing and other industrial processes, and as a liquid fuel (Jorjani et al., 2008). In 2005, the worldwide electricity generation was 17,450 TWh, out of which 40% originated from coal, 20% from gas, 16% from nuclear, 16% from hydro, 7% from oil, and 2% from renewable sources (EIA, 2006; Evans et al., 2009).

Coal preparation began at a significant level from the 1960s. From 1980 onward, many plants started incorporating higher capacity washing units into their plant layout. The development of large-scale coal washing plants requires the subdivision of solid/liquid slurries at a number of stages. The subdivision of slurry into a number of unit operations in parallel (e.g., vessels, cyclones, and spirals circuits) is usually accomplished by using multi-port distributors that can have a wide range of shapes and dimensions (Rajendran et al., 2006). There is a general agreement on the need to monitor herd performance, but how to do it effectively is not known (Dohoo, 1993). Typically,

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herd measures are calculated from data collected during a fixed period and compared to the previous periods or standards (Reneau and Kinsel, 2001). Statistical analysis of herd performance data is seldom done, leaving doubts on how to interpret the data and, thus, which course of action is best (Noordhuizen et al., 1992; de Vries and Conlin, 2005).

Statistical process control (SPC) techniques refer to the use of statistically based methods to monitor, control, evaluate, analyze, and improve processes in systems (Gaafar and Keats, 1992). These techniques are very important to monitor the variations in the coal washing plant and analyze this variability on the base of the specifications.

Some studies published in the mining science that have used SPC techniques are as follows. Ipek et al. (1999) determined the process capability index of Etibank Bigadic Colemanite Plant in Turkey by using SPC techniques. Bhattacherjee and Samanta (2002) studied the use of SPC techniques in mining applications; their work, which evaluated control charts, may still provide useful qualitative information. Aykul et al. (2005) conducted a statistical process control analysis for a lignite power plant. The results of the techniques show that the variations in the characteristics of lignite are significantly high. Elevli (2006) carried out a study in which the variations in the characteristics of coal delivered to a power plant have been investigated using control charts. The results from control charts show that the variations in the characteristics of coal are significantly high.

In this study, first the SPC techniques, including R control chart and multidimensional scaling (MDS) analysis, were introduced. Next, a case study describing the SPC techniques used on a coal washing plant dataset was introduced.

2. SPC Techniques

2.1. R Control Chart

The main objective of a range (R) control chart is to detect and eliminate assignable cause process variations (Montgomery, 1996). Grant and Leavenworth (1980) proposed that the following steps should be applied for the construction of a R control chart.

- Statistical parameters related to the R control chart should be computed for each subgroup.
- The computation of statistical parameters, the ranges of subgroups (R_j) should be calculated where R_j is the difference between the largest ($X_{\max}$) and smallest ($X_{\min}$) observations in a subgroup.
- After the computation of the average of ranges ($\overline{R}$) should be calculated where $\overline{R}$ is the sum of ranges of subgroups divided by the number of subgroups in the group (m).
- The three basic parameters for the R control chart are computed as Eqs. (1)–(3):

$$UCL_R = D_4\overline{R}, \tag{1}$$

$$CL_R = \overline{R}, \tag{2}$$

$$LCL_R = D_3\overline{R}, \tag{3}$$

  where UCL_R is the upper control limit, CL_R is the central line, LCL_R is the lower control limit, and D_4 and D_3 are the constants taken from the table of the control charts.
- The R control chart can then be drawn and interpreted.

2.2. Multidimensional Scaling (MDS) Analysis

MDS analysis is an appropriate exploratory technique for treating problems with a need for exploration (Borg and Groenen, 1997). 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 the observations. In the case of MDS, the dissimilarities are quantified through Euclidean distance measurements, the distance between two observations, i and j, is given as:

$$d_{ij}^2 = \sum_{k=1}^{m}(z_{ik} - z_{jk})^2, \tag{4}$$

where d_{ij}^2 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 (Everitt, 1993; Sharma, 1996).

The output, however, is a spatial configuration of points in some preferably low-dimensional space. This is the so-called final configuration of the MDS analysis solution. The goal of the procedure is to represent the observed structure of the proximity matrix in terms of the interpoint distance in the final configuration as well as possible. While aiming to reproduce the original rank order of the proximities as close as possible, non-metric MDS analysis iteratively rearranges the points at a fixed dimension of the space until a suitable goodness of fit measure is optimized. The stress function is commonly minimized in this analysis. The number of the dimensions of a correct MDS analysis solution should be sufficient enough to reveal the hidden structure underlying the proximity data. The final step in the procedure is the interpretation of the meaningful dimensions of the MDS analysis solution (Evtimov and Ivanov, 2007).

3. Case Study

3.1. Dataset

Based on the size of the run of mine (ROM), a coal washing plant utilizes two individual circuits to clean the entire ROM coal. In the coal washing plant, the coal coarser may be −150 mm to +18 mm in a heavy medium vessel circuit and −18 mm to +0.5 mm in a heavy medium cyclone circuit. In this study, the measurements of the density from a heavy medium vessel circuit and a heavy medium cyclone circuit were taken for 24 h. The data from the heavy medium vessel circuit and the heavy medium cyclone circuit was taken automatically and was saved on a database by a computer every 10 min. A total of six data sets were obtained every hour.

In this study, SPC techniques, including control chart and MDS analyses, were used to determine whether a process was under control or not. All of the statistical calculations were performed using SPSS 16.0 and Minitab 12.0 statistical software.

3.2. Construction of R Control Charts

Using the density values collected from the heavy medium vessel circuit and the heavy medium cyclone circuit during 24 h, the statistical parameters related to the R control chart were calculated per hours as given in Table 1. Then, using the R control chart parameters, the charts were constructed. These charts were presented in Figures 1 and

Table 1
The R control chart parameters

Parameters	Heavy medium vessel circuit	Heavy medium cyclone circuit
$\overline{R}$ (g/cm^3)	0.03	0.06
UCL_R (g/cm^3)	0.06	0.11
CL_R (g/cm^3)	0.03	0.06
LCL_R (g/cm^3)	0.00	0.00
D_3	0.00	0.00
D_4	2.00	2.00

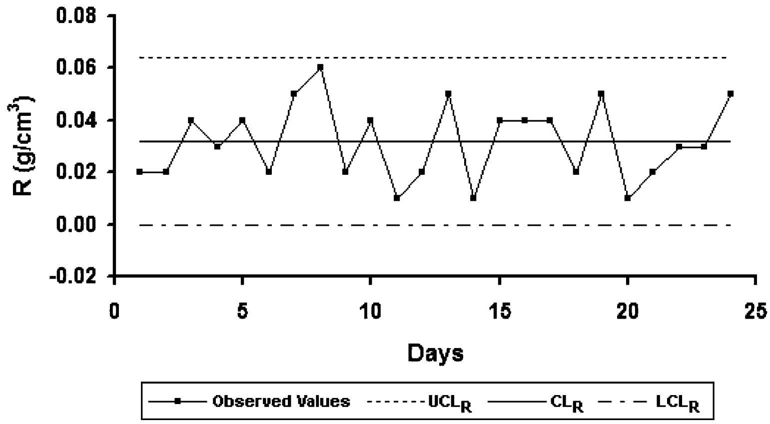

Figure 1. The R control chart for heavy medium vessel circuit.

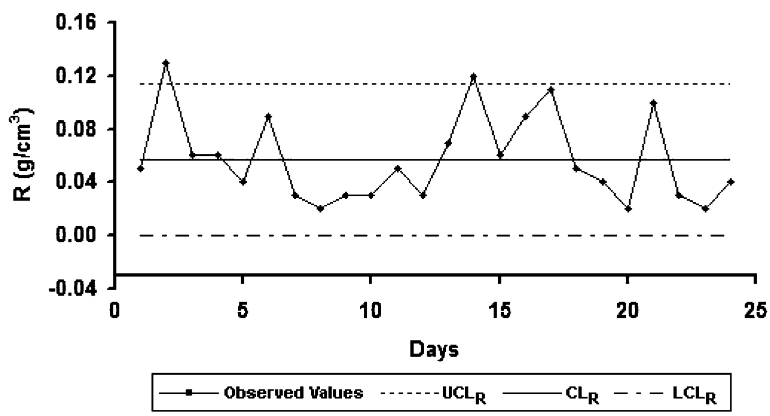

Figure 2. The R control chart for heavy medium cyclone circuit.

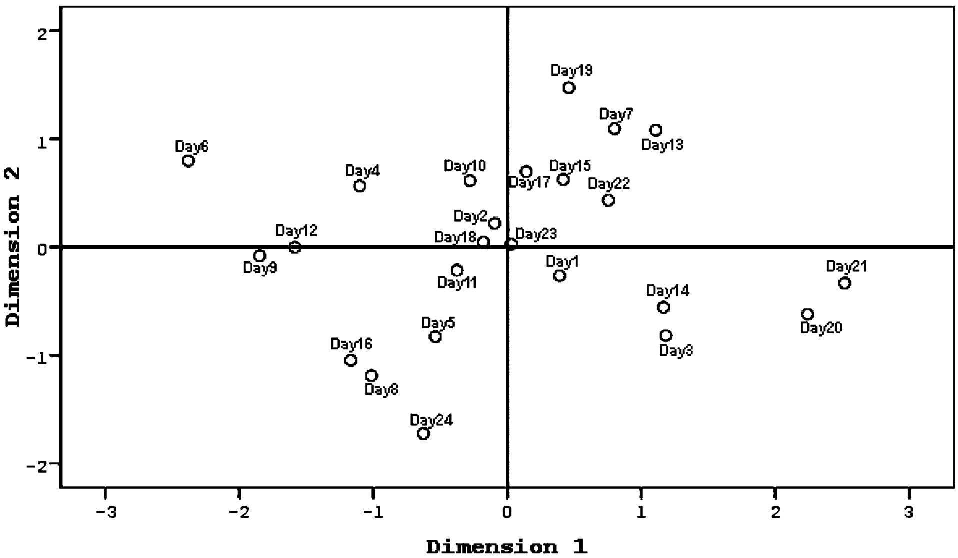

Figure 3. MDS graph for heavy medium vessel circuit.

2, for the heavy medium vessel circuit and for the heavy medium cyclone circuit, respectively. Figure 1 indicated that all the ranges of density values lie in the control area. However, since some range values were very close to control limits, an irregular pattern was observed. Figure 2 demonstrated that the process was out of statistical control since there were two points outside the control limits and the distribution of the days around the central line was irregular. Thus, Figures 1 and 2 showed that the processes were not under control.

3.3. Results of MDS

The density values for the heavy medium vessel circuit and the heavy medium cyclone circuit were interpreted by using MDS analysis in this study to determinate the similarities or differences between hours. Standardized residual sum of squares, used to assess how well a particular configuration reproduces the observed distance matrix, was found to be 0.005 even for MDS analysis. Standardized residual sum of squares values close to zero show that the "fit" is almost perfect; and, therefore, the results of the MDS analysis were reasonable and reliable (Iscen et al., 2008). These coordinate values were used to generate the plots given in Figures 3 and 4. The figures demonstrated that the processes were not under control.

4. Conclusions

SPC techniques including R control charts and MDS analysis can successfully be used to acquire the relevant information from a coal washing plant dataset. In this study, density values for a heavy medium vessel circuit and a heavy medium cyclone circuit, which were recorded for 24 h, were evaluated using R control charts and MDS analysis. R control charts showed that the density values for the heavy medium vessel circuit and the heavy medium cyclone circuit were not under control. The results of MDS analysis

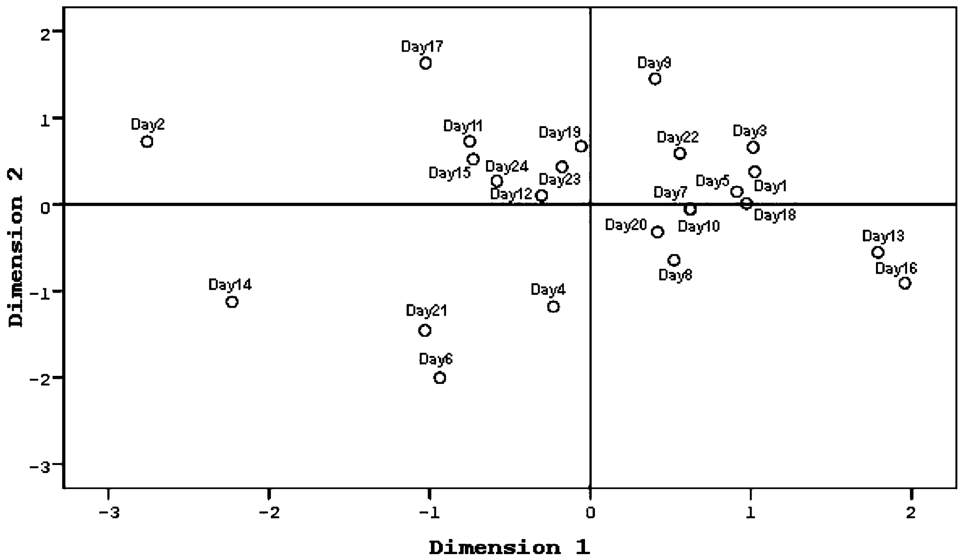

Figure 4. MDS graph for heavy medium cyclone circuit.

confirmed the results of *R* control charts. Examining the MDS analysis graph, the density values for the heavy medium vessel circuit and the heavy medium cyclone circuit were not shown to be under control.

Finally, this study shows the usefulness of *R* control charts and MDS analysis in the determination of density values in order to get better information for a more effective management of a coal washing plant.

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