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A new chart-independent method for fast identification of control level of industrial processes using continuous data

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Abstract

A new method is developed for a fast identification of the stability situation of industrial processes. The proposed method includes two factor ratios of the control constants for the upper and lower control limits to process these constants. An indication ratio is then defined as the ratio of the maximum data range value to the difference between the maximum and average values for individual data points. It is shown that if the indication ratio comes into values between the corresponding control factor ratios, the process will be under control, and otherwise, if the indication ratio decreases to smaller than the lower control factor ratio or gets more than the upper control factor ratio, the process will be expected to be out-of-control. Validation of the method was successfully resulted using two series of quality control datasets obtained from Zarand Iron Ore Complex (Zarand, Iran) and Miduk Copper Complex (Shahr Babak, Iran). The results obtained show that the process responses predicted by the proposed method are in agreement with those indicated by the conventional chart-based method. The developed method eliminates the need for drawing the process control charts used to assess the process control level. The superiority of the proposed method over the chart-based method becomes apparent especially when a large number of control charts are necessary to be drawn and interpreted for engineering decision-making purposes.

Keywords: *Process Monitoring, Control Chart, Factor Ratio, Industrial Process, Continuous Data.*

1. Introduction

Process safety and product quality are two important issues for modern industrial processes. As one of the key technologies in the process system engineering and control area, the process monitoring methods can be used to improve product quality and enhance process safety. If a process fault can be anticipated at an early stage and corrected in time, product loss can be greatly reduced. Timely identification of faults can also be used to initiate the removal of out-of-spec products, thereby, preserving high standards of product quality. In addition, the decisions and expert advice obtained from process-monitoring procedures can be used for process improvement [1].

Statistical process control (SPC) is one of the most effective continuous quality improvement strategies and quality control methods, by exerting statistical methods for monitoring process performance and product quality. The application of SPC involves three main phases of activity: 1) understanding the process and the specification limits, 2) eliminating the assignable (special) sources of variation so that the process is stable, and 3) monitoring the on-going production process assisted by the use of control charts to detect significant changes of mean or variation [2, 3].

In the SPC analysis, quality data in the form of product or process measurements are obtained in real-time during process monitoring. This data is then plotted on a graph, called control chart, with pre-determined control limits by the capability of the process, whereas process specifications are determined by the client's needs. Therefore, control charts operate on the specifications of control limits normally given by the data of the process.

An industrial process can be in the *in-control* or *out-of-control* state. When a process is stable and under control, it displays a common cause variation, a variation that is inherent to the process. A process is in-control when, based on the past experience, it can be predicted how the process will vary (within the limits) in the future. If the process is unstable, it displays a special cause variation, a non-random variation in external factors. The main objective of a quality control chart is to detect quickly the occurrence of the factors that lead to the out-of-control process and correct the process. In addition, control charts attempt to distinguish between two types of process variation: 1) common-cause variation that is intrinsic to the process and is always present, and 2) special-cause variation, which stems from external sources and indicates that the process is out of statistical control [4, 5].

In a traditional design of control charts, a sample of certain size is collected at equal and constant sampling or time intervals. Then quality-related statistics are plotted on the control chart. As soon as a point falls above the upper control limit (UCL) or below the lower control limit (LCL), the process is assumed to be out-of-control, otherwise, it is considered as an in-control process [5].

A multiplicity of methods has been proposed for designing control charts including Shewhart, statistical criteria, economic criteria or joint economic and statistical criteria. Each method has some advantages and disadvantages such as complexity in implementation, statistical configurations, and cost-effectiveness. The type of control chart that an engineer uses depends on the type of data. It is shown, for example, that the Shewhart charts are quite good at detecting large changes in the process mean or variance. Other types of control charts have been developed such as the EWMA chart, CUSUM chart, and real-time contrasts chart, which detect smaller changes more efficiently by making use of information from the observations collected prior to the most recent data point [3, 6].

Regardless of the type of control charts and their advantages, the existing control chart design models suffer from the lack of flexibility and adaptability in real-world problem-solving when a large number of data should be analyzed. This is an impractical and mostly irrecoverable time-consuming approach, requiring a large number of control charts being interpreted to identify the control situation of a real process. In the recent years, many new SPC methodologies have been developed for improving the traditional SPC methods and for handling new SPC applications, which focus on development of the time- and cost-efficient design of control charts. In the efficient design of a control chart, different components associated with the process are considered, and an optimal control chart minimizes the long-run expected average cost per unit time. Several economic designs have recently been published, considering two main components of sampling interval and time by exerting mathematical or statistical methods (e.g. [3, 5, 7-21]).

However, the main problem, i.e. the need for plotting the process control charts to be interpreted, has not been resolved. The main objective of this study was to introduce a new method to identify the control situation of industrial processes with no need to draw process control charts. The method was also verified using two series of practical data obtained from different mineral processing plants through a comparative study against conventional process control approaches.

2. Description of New Method

The most conventional statistical process control tools are the Shewhart control charts, which monitor operational processes using continuous data and utilizing the Gaussian distribution assumption to design the upper and lower control limits. The interval of process response variations between these limits indicates the normal operating and in-control region for the process. If the process response shifts to outside these limits, the process is taken as an abnormal out-of-control state, and a process fault or disturbance occurs. The Shewhart control charts can be divided into two groups, as shown in Figure 1:

- Variable charts: These control charts apply variable sampling intervals, where the lengths of the sampling intervals are varied according to the process quality. A long sampling interval is considered when the process quality indicates a possible in-control situation, while a short sampling interval is considered, otherwise. The variable charts are used for identification of the control level of continuous processes [22-25].
- Attribute charts: These charts are constructed on the basis of the data that can be grouped and counted as present or not. Attribute charts are also called count charts,

and attribute data is also known as discrete data. These types of control charts are complicated when interpreting, and are thus used for detecting possible defectives in the samples taken from a process not for identification of control situation of the process [22].

Data Type	Defect Definition	Subgroup Size	Chart Type
Attribute Data (Known as Discrete Data)	Defect Data (Number of defects, not number of defective units)	Constant Subgroup Size	*c*-Chart Number of Defects
		Variable Subgroup Size	*u*-Chart Defects per Unit
	Defective Unit Data	Constant Subgroup Size, Usually ≥ 50	*np*-Chart Number of Defective Units
		Variable Subgroup Size, Usually ≥ 50	*p*-Chart Fraction of Defective Units
Variable Data (Known as Continuous Data)		Subgroup Size = 1	X and MR Moving Range
		Subgroup Size < 10	Xbar and R
		Subgroup Size ≥ 10	Xbar and s Standard Deviation

Figure 1. Types of variable and attribute Shewhart control charts [1, 2].

The Shewhart variable charts are easy to understand, and are, therefore, widely used in industrial applications. Three types of variable charts are available, which are known as the individuals and moving range (I-MR), Xbar and range (Xbar-R), and Xbar and standard deviation (Xbar-s) charts. The I-MR chart is one of the most commonly used control charts for continuous data; it is applicable when one data point is collected at each point in time. The Xbar-R chart is used when measurements can rationally be collected in sub-groups of 2 to 10 observations. Each sub-group is a snapshot of the process at a given point in time. The Xbar-s chart is used when the distribution for the process characteristic is stable and the sampling volume is high.

The variable control charts are actually two charts used in tandem. Together, they monitor the process average as well as the process variation. The data chart either individuals (Xbar) chart is used to detect trends and shifts in the data and thus in the process. The data chart must have the data time-ordered, i.e. the data must be entered in the sequence in which it was generated. Process chart shows short-term variability in a process – an assessment of the stability and control situation of process variation [26, 27].

Each control chart has three main elements of a time series graph, a central line (CL), as a visual reference for detecting shifts or trend, and two control limits, so called upper and lower ones (UCL and LCL), which are computed from available data and placed equidistant from the central line. These elements can be determined using a formula developed on the basis of statistical calculations. Table 1 lists the equations used for determination of the central line and control limits of the Shewhart variable charts.

Table 1. Formula for calculation of central line and control limits of Shewhart variable charts [2].

Chart Type	Sub-Chart	Center Line (CL)	Control Limits	
			Upper (UCL)	**Lower (LCL)**
I-MR	Individuals	$CL_I = \bar{X}$	$UCL_I = \bar{X} + E_2\bar{R}$	$LCL_I = \bar{X} - E_2\bar{R}$
	Moving range	$CL_R = \bar{R}$	$UCL_R = D_4\bar{R}$	$LCL_R = D_3\bar{R}$
Xbar-R	X bar	$CL_{\bar{X}} = \bar{\bar{X}}$	$UCL_{\bar{X}} = \bar{\bar{X}} + A_2\bar{R}$	$LCL_{\bar{X}} = \bar{\bar{X}} - A_2\bar{R}$
	Range	$CL_R = \bar{R}$	$UCL_R = D_4\bar{R}$	$LCL_R = D_3\bar{R}$
Xbar-s	X bar	$CL_{\bar{X}} = \bar{\bar{X}}$	$UCL_{\bar{X}} = \bar{\bar{X}} + A_3\bar{R}$	$LCL_{\bar{X}} = \bar{\bar{X}} - A_3\bar{R}$
	Standard deviation	$CL_s = \bar{s}$	$UCL_s = B_4\bar{s}$	$LCL_s = B_3\bar{s}$

The key point for the use of control charts is that the process charts should be checked before the data chart is interpreted. If the process is under control, then the data chart can be checked for any possible defects; otherwise, if the process is out-of-control, the special causes must be eliminated, and the process should be returned to the threshold and/or favourable state. Once the effect of any out-of-control points is removed from the process chart, the data chart would be checked. As already mentioned, the interpretation of control charts becomes more complicated when a large number of data should be controlled as situations that are very common in many industries. Preparation of annual balance reports by quality control office in mineral processing plants is a good example; in such reports, a huge number of data with different sources such as grade and recovery of product streams, separation efficiency values, and moisture content should be included and interpreted. Therefore, numerous process charts should first be drawn and checked for any possible instability, and then the data charts assessed for case defects in sampling point and/or time. The following discussion deals with a series of mathematical calculations to develop a new method for fast identification of control situation of industrial processes with no need for drawing process control charts.

When using the I-MR chart, for example, the data and process take an in-control situation only if each single data point and multiple range point fall inside the upper and lower control limits, that is:

$$\overline{X} - E_2\overline{R} < X_{\mathrm{i}} < \overline{X} + E_2\overline{R} \tag{1}$$

and

$$D_3\overline{R} < R_{\mathrm{i}} < D_4\overline{R} \tag{2}$$

For a set of data, the I-MR chart can be sorted by magnitude, such that:

$$X_{\min} < X_{\mathrm{i}} < X_{\max}$$

$$R_{\min} < R_{\mathrm{i}} < R_{\max}$$

Thus it can be stated that:

$$\overline{X} - \mathrm{E}_2\overline{R} \langle X_{\max} \langle \overline{X} + E_2\overline{R} \tag{3}$$

$$D_3\overline{R} \langle R_{\max} \langle D_4\overline{R} \tag{4}$$

From the upper limit of Eq. (3):

$$X_{\max} \langle \overline{X} + E_2\overline{R} \rightarrow X_{\max} - \overline{X} \langle E_2\overline{R}$$

Thus:

$$\frac{X_{\max} - \overline{X}}{E_2} \langle \overline{R} \tag{5}$$

The following relation is derived from the lower limit of Eq. (4):

$$D_3\overline{R} \langle R_{\max} \rightarrow \overline{R} \langle \frac{R_{\max}}{D_3} \tag{6}$$

Combination of Eqs. (5) and (6) gives:

$$\frac{X_{\max} - \overline{X}}{E_2} \langle \overline{R} \langle \frac{R_{\max}}{D_3} \rightarrow \frac{X_{\max} - \overline{X}}{E_2} \langle \frac{R_{\max}}{D_3}$$

As a result:

$$\frac{D_3}{E_2} \langle \frac{R_{\max}}{X_{\max} - \overline{X}} \tag{7}$$

Using a similar approach for the upper limit of Eq. (3) and lower limit of Eq. (4), the following calculations can be done for the reverse limits of Eqs. (3) and (4):

$$\overline{X} - \mathrm{E}_2\overline{R} \langle X_{\max} \rightarrow -E_2\overline{R} \langle X_{\max} - \overline{X}$$

$$-\overline{R} \langle \frac{X_{\max} - \overline{X}}{\mathrm{E}_2} \tag{8}$$

It should be noted that the range values can get negative or positive signs but an absolute value is used in calculations [1, 2]. Therefore, Eq. (8) can be restated as follows:

$$\left|-\overline{R}\right| \sim \overline{R} \langle \frac{X_{\max} - \overline{X}}{\mathrm{E}_2} \tag{9}$$

and:

$$R_{\max} \langle D_4\overline{R}$$

$$\frac{R_{\max}}{D_4} \langle \overline{R} \tag{10}$$

A combined equation is obtained from Eqs. (9) and (10) as follows:

$$\frac{R_{\max}}{D_4} \langle \overline{R} \langle \frac{X_{\max} - \overline{X}}{\mathrm{E}_2} \rightarrow \frac{R_{\max}}{D_4} \langle \frac{X_{\max} - \overline{X}}{\mathrm{E}_2}$$

Thus:

$$\frac{R_{\max}}{X_{\max} - \overline{X}} \langle \frac{D_4}{\mathrm{E}_2} \tag{11}$$

Comparison of Eqs. (7) and (11) leads to the following final relation:

$$\frac{D_3}{E_2} \langle \frac{R_{\max}}{X_{\max} - \overline{X}} \langle \frac{D_4}{\mathrm{E}_2} \tag{12}$$

Eq. (12) can be accepted as a fast indicator for the control situation of a continuous process. It shows that if the ratio of the maximum value for the range to the upper domain of individual data gets values between their corresponding control factor ratios, the process is in-control, and otherwise, if the indication ratio becomes smaller than the lower control factor ratio or more than the upper control factor ratio, the process would be expected to be out-of-control.

Constants E_2, D_3, and D_4 are available via standard tables. These values depend upon the sub-group size selected during sampling and monitoring program. The control factors for different Shewhart control charts are listed in Table 2.

Table 2. Factors used for calculation of upper and lower limits of control charts [1, 2].

Sub-group size	E_2	D_3	D_4	A_2	A_3	B_3	B_4
1	2.660	0	3.267	1.880	2.659	0	3.267
2	2.660	0	3.267	1.880	2.659	0	3.267
3	1.772	0	2.574	1.023	1.954	0	2.568
4	1.457	0	2.282	0.729	1.628	0	2.266
5	1.290	0	2.114	0.557	1.427	0	2.089
6	1.184	0	2.004	0.483	1.287	0.030	1.970
7	1.109	0.076	1.924	0.419	1.182	0.118	1.882
8	1.054	0.136	1.864	0.373	1.099	0.185	1.815
9	1.010	0.184	1.816	0.337	1.032	0.239	1.761
10	0.975	0.223	1.777	0.308	0.975	0.284	1.716
15	-	0.347	1.653	0.223	0.789	0.428	1.572
25	-	0.459	1.541	0.153	0.606	0.565	1.435

A similar approach, as employed to the I-MR control chart, can be considered for the Xbar-R and Xbar-s charts. Calculations for the Xbar-R chart include:

$$\overline{\overline{X}} - A_2\overline{R} \langle X_{\max} \langle \overline{\overline{X}} + A_2\overline{R} \tag{13}$$

$$D_3\overline{R} \langle R_{\max} \langle D_4\overline{R} \tag{14}$$

From the upper limit of Eq. (13):

$$X_{\max} \langle \overline{\overline{X}} + A_2\overline{R} \rightarrow X_{\max} - \overline{\overline{X}} \langle A_2\overline{R}$$

Thus:

$$\frac{X_{\max} - \overline{\overline{X}}}{A_2} \langle \overline{R} \tag{15}$$

From the lower limit of Eq. (14):

$$D_3\overline{R} \langle R_{\max} \rightarrow \overline{R} \langle \frac{R_{\max}}{D_3} \tag{16}$$

and the final combined equation is obtained as follows:

$$\frac{X_{\max} - \overline{\overline{X}}}{A_2} \langle \overline{R} \langle \frac{R_{\max}}{D_3} \rightarrow \frac{X_{\max} - \overline{\overline{X}}}{A_2} \langle \frac{R_{\max}}{D_3}$$

$$\frac{D_3}{A_2} \langle \frac{R_{\max}}{X_{\max} - \overline{\overline{X}}} \tag{17}$$

The following calculations can be done for the lower limit of Eq. (13) and the upper limit of Eq. (14):

$$\overline{\overline{X}} - A_2\overline{R} \langle X_{\max} \rightarrow -A_2\overline{R} \langle X_{\max} - \overline{\overline{X}}$$

$$\left|-\overline{R}\right| \sim \overline{R} \langle \frac{X_{\max} - \overline{\overline{X}}}{A_2} \tag{18}$$

and:

$$R_{\max} \langle D_4\overline{R}$$

$$\frac{R_{\max}}{D_4} \langle \overline{R} \tag{19}$$

Thus:

$$\frac{R_{\max}}{D_4} \langle \overline{R} \langle \frac{X_{\max} - \overline{\overline{X}}}{A_2} \rightarrow \frac{R_{\max}}{D_4} \langle \frac{X_{\max} - \overline{\overline{X}}}{A_2}$$

$$\frac{R_{\max}}{X_{\max} - \overline{\overline{X}}} \langle \frac{D_4}{A_2} \tag{20}$$

Referring to Eqs. (17) and (20), the identification relation is obtained as follows:

$$\frac{D_3}{A_2} \langle \frac{R_{\max}}{X_{\max} - \overline{\overline{X}}} \langle \frac{D_4}{A_2} \tag{21}$$

and the final fast response equation for the Xbar-s control chart is obtained using a similar calculation approach, used for the I-MR and Xbar-R charts:

$$\frac{B_3}{A_3} \langle \frac{s_{\max}}{X_{\max} - \overline{\overline{X}}} \langle \frac{B_4}{A_3} \tag{22}$$

The calculated factor ratios for the Shewhart control charts are given in Table 3.

Table 3. Factor ratios proposed for fast identification of control level of industrial processes.

Chart type	I-MR		Xbar-R		Xbar-s	
Process stability condition	$\frac{D_3}{E_2}\langle\frac{R_{max}}{X_{max}-\overline{\overline{X}}}\langle\frac{D_4}{E_2}$		$\frac{D_3}{A_2}\langle\frac{R_{max}}{X_{max}-\overline{\overline{X}}}\langle\frac{D_4}{A_2}$		$\frac{B_3}{A_3}\langle\frac{s_{max}}{X_{max}-\overline{\overline{X}}}\langle\frac{B_4}{A_3}$	
Sub-group size	Lower limit	Upper limit	Lower limit	Upper limit	Lower limit	Upper limit
1	0	1.2282	0	1.7378	0	1.2287
2	0	1.2282	0	1.7378	0	1.2287
3	0	1.4526	0	2.5161	0	1.3142
4	0	1.5662	0	3.1303	0	1.3919
5	0	1.6388	0	3.7953	0	1.4639
6	0	1.6926	0	4.1491	0.0233	1.5307
7	0.0685	1.7349	0.1814	4.5919	0.0998	1.5922
8	0.1290	1.7685	0.3646	4.9973	0.1683	1.6515
9	0.1822	1.7980	0.5460	5.3887	0.2316	1.7064
10	0.2287	1.8226	0.7240	5.7695	0.2913	1.76
15	-	-	1.5560	7.4126	0.5425	1.9924
25	-	-	3	10.0719	0.9323	2.3680

3. Verification of Proposed Method

In order to verify the applicability of the proposed method in industrial environments, two series of real data sets were obtained from different mineral processing plants. The control response of each process was first predicted using the developed model (based on the I-MR approach), and the results obtained were compared with those indicated by drawing the process control charts.

3.1. Case study 1: Ball charge at Zarand Iron Ore Complex

The first verification case study was the unit ball charge in grinding circuit at Zarand Iron Ore Complex. The grinding circuit includes two similar ball mills in series that prepare feed to magnetic separators. The details of ball charge data sheet during 2015 are presented in Table 4. The total ball charge per each ton of feed has been accepted and interpreted as process response by the processing division engineers. Since only one value was reported in each month, the I-MR control chart was applied. In addition, the sub-group size was equal to unity. Thus the lower and upper factor ratios from Table 3 are 0 and 1.2282, respectively. If the I-MR indication ratio was between 0 and 1.2282, the process would be under control, and the ball charge program is acceptable; otherwise, the process would be out-of-control, and the reasons should be identified. The average values for the individual data points ($\overline{X}$) and their range ($\overline{R}$) were 1110.5845 and 883.3655, respectively (Table 5). X_{max} and R_{max} were 3210.45 and 2936.62 g/t, respectively. From Table 2, the values for the control factors are E_2 = 2.66, D_3 = 0, and D_4 = 3.267. Thus:

$$0 \not< \frac{R_{max}}{X_{max}-\overline{\overline{X}}} = \frac{2936.62}{3210.45-1110.58} = 1.3985 \not< 1.2282$$

Therefore, the process is expected to be out-of-control. For verification of the prediction, the process chart was drawn using the range values given in Table 5. From Table 1, the graphical control lines can be determined as follow:

$$CL_R = \overline{R} = 883.3655$$

$$UCL_R = D_4\overline{R} = 3.267 \times 883.3655 = 2885.9550$$

$$LCL_R = D_3\overline{R} = 0$$

The process chart for the ball charge data is shown in Figure 2. As seen, an instability trend is observed in September, indicating that the process is out-of-control, which is in agreement with the predicted result.

Table 4. Ball charge data sheet at Zarand Iron Ore Complex during 2015.

Month	Mill 1 power (MW)	Mill 2 power (MW)	Ball Charge Mill 1 (t)	Ball Charge Mill 2 (t)	Total Ball Charge (t)	Total Throughput (t)	Unit Ball Charge 1 (g/t)	Unit Ball Charge 2 (g/t)	Total Unit Ball Charge (g/t)
Jan.	3.9	3.8	100.62	87.36	187.98	113636	885.46	768.77	1654.23
Feb.	3.8	3.76	34.12	91	125.12	106478	320.49	854.64	1175.12
Mar.	3.6	3.7	32.37	57.33	89.70	54333	595.77	1055.16	1650.93
Apr.	3.98	4.03	47.25	32.04	79.29	123206	383.50	260.05	643.56
May	3.85	4	60.37	84.63	145	161401	374.04	524.35	898.38
Jun.	3.6	3.5	28.87	27.3	56.17	88029	328.02	310.12	638.14
Jul.	3.56	3.42	64.75	84.63	149.38	234441	276.19	360.99	637.17
Aug.	3.24	3	39.37	0	39.37	96043	409.97	0	409.97
Sep.	3.03	3.09	59.03	88.23	147.26	45869	1286.93	1923.52	3210.45
Oct.	3.5	3.5	34.61	32.22	66.83	244056	141.81	132.02	273.83
Nov.	3.8	3.8	32.22	78.98	111.20	90567	355.76	872.06	1227.82
Dec.	3.9	3.6	65.78	42.11	107.89	118900	553.24	354.16	907.40

Table 5. Range values calculated from individual data for unit ball charges.

Response	Month	Jan.	Feb.	Mar.	Apr.	May	Jun.	Jul.	Aug.	Sep.	Oct.	Nov.	Dec.	Ave.
Total Unit Ball Charge (g/t)	Individuals	1654.23	1175.13	1650.93	643.56	898.38	638.14	637.18	409.97	3210.45	273.83	1227.82	907.40	1110.58
	Range	-	479.10	475.80	1007.37	254.83	260.24	0.97	227.20	2800.47	2936.62	953.99	320.42	883.37

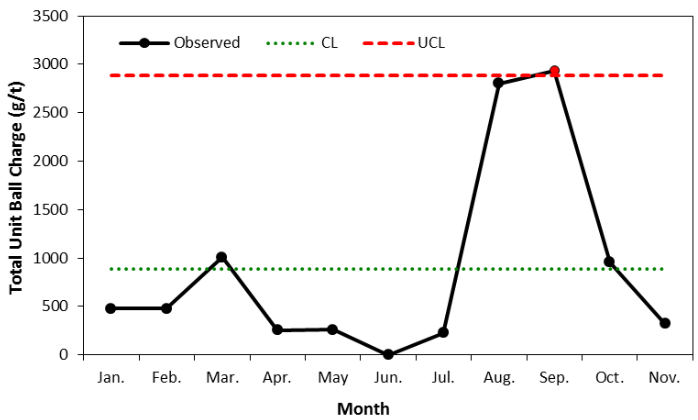

Figure 2. Process chart for total unit ball charge at Zarand Iron Ore Complex.

3.2. Case study 2: Metallurgical performance at Miduk Copper Complex

Table 6 shows the metallurgical balance data sheet for Miduk Copper Complex in August 2015. As seen, the data sheet reports six quality factors including daily tonnages and grades of feed and product streams, grade of tailings, and final concentrate recovery. Each dataset is an average value of three measurements during three working shifts per day. In order to evaluate the validation of the proposed method, the identification ratio was first used to assess the control level of each factor. Since each dataset was an average of three measurements, the sub-group size was three. Therefore, the factor ratios were 0 and 1.4526 for the lower and upper limits, respectively. The single, average, and maximum values for individuals and range were calculated for the metallurgical factors and shown in Table 6. Using the I-MR identification equation (Table 3), the control level of each factor can be predicted as follows:

- Feed tonnage is under control because

$$0 < \frac{2253.68}{21540.93 - 19394.88} = 1.0501 < 1.4526$$

- Feed grade is under control because $0 < \dfrac{0.14}{0.81 - 0.68} = 1.1224 < 1.4526$
- Concentrate tonnage is under control because $0 < \dfrac{78.59}{499.57 - 402.86} = 0.8127 < 1.4526$
- Concentrate grade is under control because $0 < \dfrac{2.32}{32.64 - 3034} = 1.0112 < 1.4526$
- Tailings grade is out-of-control because $0 \not< \dfrac{0.06}{0.1 - 0.07} = 1.7654 \not< 1.4526$
- Recovery is out-of-control because $0 \not< \dfrac{34.12}{113.96 - 92.20} = 1.5681 \not< 1.4526$

Process control charts were also drawn for the metallurgical factors using the conventional equations given in Table 1. Figure 3 shows the process charts plotted using the center line and control limits calculated for all factors (Table 7). As seen, the control charts clearly confirm the conditions predicted by the developed method. The superiority of the proposed method over the conventional chart-based method is highlighted when an engineer decides to run a comprehensive control monitoring program for the entire 2015. There, the engineer must first check 72 process control charts (12 months × 6 factors) to indicate the process level situation before evaluation of 72 data control charts. Using the developed method, the need for plotting process control charts is eliminated, and the engineer would need only to check the data charts.

Table 6. Control parameters and metallurgical performance data sheet for Miduk Copper Complex.

Date	Feed				Concentrate				Tailings		Recovery (%)	
	Tonnage (t/d)		Grade (%)		Tonnage (t/d)		Grade (%)		Grade (%)			
	X_i	R_i	X_i	R_i	X_i	R_i	X_i	R_i	X_i	R_i	X_i	R_i
Aug-01-15	19642.23	-	0.58	-	421.34	-	28.72	-	0.06	-	106.81	-
Aug-02-15	19836.25	194.02	0.68	0.108	467.85	46.509	27.10	1.618	0.04	0.013	93.78	13.030
Aug-03-15	19546.18	290.07	0.70	0.019	473.59	5.742	27.29	0.193	0.06	0.017	94.43	0.644
Aug-04-15	19834.33	288.15	0.60	0.098	432.36	41.233	26.75	0.541	0.05	0.010	96.86	2.438
Aug-05-15	19594.20	240.12	0.70	0.094	438.17	5.810	29.07	2.325	0.09	0.040	93.39	3.473
Aug-06-15	20266.55	672.35	0.76	0.065	470.16	31.994	30.69	1.614	0.06	0.030	93.58	0.189
Aug-07-15	19388.46	878.09	0.73	0.030	404.90	65.265	32.52	1.835	0.06	0	92.91	0.666
Aug-08-15	19243.77	144.69	0.73	0.005	405.94	1.047	32.26	0.263	0.05	0.013	93.70	0.786
Aug-09-15	19272.71	28.94	0.64	0.082	372.75	33.194	30.78	1.479	0.08	0.033	92.39	1.309
Aug-10-15	19089.43	183.27	0.68	0.036	383.81	11.066	31.52	0.739	0.05	0.032	93.12	0.730
Aug-11-15	18491.38	598.05	0.62	0.056	341.11	42.702	31.30	0.216	0.05	0	92.53	0.591
Aug-12-15	19292.00	800.61	0.61	0.014	376.61	35.498	29.26	2.045	0.04	0.007	93.57	1.045
Aug-13-15	19388.46	96.46	0.61	0.003	370.34	6.269	29.77	0.508	0.10	0.060	93.54	0.030
Aug-14-15	18894.24	494.22	0.63	0.023	382.91	12.567	28.54	1.224	0.08	0.020	91.75	1.798
Aug-15-15	18547.38	346.86	0.67	0.039	326.32	56.589	28.70	0.159	0.10	0.020	75.37	16.379
Aug-16-15	19788.25	1240.87	0.77	0.099	325.97	0.350	30.69	1.991	0.07	0.025	65.77	9.601
Aug-17-15	19109.43	678.82	0.63	0.139	389.37	63.398	30.87	0.173	0.05	0.025	99.88	34.118
Aug-18-15	18481.38	628.05	0.68	0.050	442.34	52.971	32.38	1.513	0.05	0.004	113.96	14.077
Aug-19-15	20185.33	1703.94	0.80	0.121	462.77	20.429	32.64	0.261	0.06	0.006	93.45	20.513
Aug-20-15	20088.98	96.35	0.81	0.007	475.91	13.139	31.91	0.734	0.07	0.010	93.55	0.103
Aug-21-15	19423.80	665.17	0.68	0.130	397.31	78.593	30.57	1.340	0.10	0.030	92.27	1.287
Aug-22-15	19807.48	383.68	0.62	0.058	342.82	54.495	32.20	1.639	0.06	0.037	90.08	2.190
Aug-23-15	20191.16	383.68	0.74	0.124	410.65	67.836	31.94	0.265	0.06	0	87.40	2.674
Aug-24-15	19615.64	575.52	0.70	0.044	386.04	24.615	30.56	1.382	0.10	0.036	86.04	1.365
Aug-25-15	18867.46	748.17	0.66	0.036	389.19	3.148	29.77	0.788	0.05	0.050	92.61	6.578

Table 6. Continued.

Aug-26-15	19500.54	633.07	0.63	0.032	387.62	1.566	29.94	0.169	0.04	0.013	94.29	1.676
Aug-27-15	18233.96	1266.58	0.71	0.079	372.27	15.357	30.02	0.083	0.05	0.011	86.30	7.988
Aug-28-15	16770.12	1463.84	0.71	0.002	347.09	25.175	31.36	1.339	0.08	0.033	91.13	4.831
Aug-29-15	19023.80	2253.68	0.61	0.098	359.45	12.359	30.00	1.365	0.07	0.014	92.26	1.124
Aug-30-15	20285.33	1261.52	0.74	0.128	432.11	72.661	31.56	1.567	0.10	0.034	90.56	1.694
Aug-31-15	21540.93	1255.60	0.76	0.019	499.57	67.459	29.88	1.685	0.07	0.030	91.02	0.454
Average	**19394.88**	**683.15**	**0.68**	**0.060**	**402.86**	**32.300**	**30.34**	**1.040**	**0.07**	**0.020**	**92.20**	**5.110**
Max.	**21540.93**	**2253.68**	**0.81**	**0.140**	**499.57**	**78.590**	**32.64**	**2.320**	**0.10**	**0.060**	**113.96**	**34.120**

Table 7. Center line and control limits calculated for metallurgical factors of Miduk Copper Complex.

Factor	Center Line (CL_R)	Control Limits	
		Upper (UCL_R)	Lower (LCL_R)
Feed tonnage	683.15	1758.4272	0
Feed grade	0.06	0.1575	0
Concentrate tonnage	32.30	83.1432	0
Concentrate grade	1.04	2.664307802	0
Tailings grade	0.02	0.0562	0
Concentrate recovery	5.11	13.1601	0

Figure 3. Process charts for metallurgical factors at Miduk Copper Complex.

4. Conclusions

A common method to assess the stability and control conditions of industrial processes is the use of control charts. However, when a large number of data is needed to be analyzed, drawing the corresponding control charts is significantly time-consuming. Although these charts can be drawn using some professional softwares, special difficulties usually arise during interpretation of and decision-making about the correlation between the data and the process charts. The developed method accelerates the interpretation process of the data charts by eliminating the need for drawing the process charts. The proposed method was verified through a comparative study of the mineral processing plants in Zarand Iron Complex and Meiduk Copper Complex.

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روشی جدید به منظور تعیین سریع شرایط کنترلی فرآیندهای صنعتی با استفاده از داده‌های پیوسته بدون نیاز به رسم نمودارهای کنترلی

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چکیده:

در این مقاله، روشی جدید به منظور تعیین سریع شرایط پایداری فرآیندهای صنعتی ارائه شده است که شامل دو نسبت فاکتور مشتق شده از ثوابت کنترلی برای حدود کنترلی بالا و پایین هر فرآیند است. سپس، یک نسبت تعیین (شاخص) به صورت نسبت بیشترین مقدار دامنه داده‌ها به تفاضل مقادیر حداکثری و میانگین داده‌های خام تعریف شد. بر اساس پارامترهای تعریف شده، چنانچه نسبت تعیین برای یک سری داده پیوسته صنعتی بین مقادیر کمینه و بیشینه نسبت‌های فاکتور متناظر قرار گیرد، فرآیند تحت کنترل است و در غیر این صورت، فرآیند خارج از کنترل خواهد بود. اعتبارسنجی روش پیشنهادی به طور موفقیت‌آمیز با استفاده از دو دسته داده به دست آمده از مجتمع سنگ آهن زرند (زرند، ایران) و مجتمع مس میدوک (شهر بابک، ایران) انجام شد. نتایج مطالعات اعتبارسنجی نشان داد که پیش‌بینی انجام شده با روش جدید با روش متداول رسم و تحلیل نمودارهای کنترل فرآیند، سازگار است. از مزایای کلیدی روش جدید، عدم نیاز به رسم نمودارهای کنترلی برای ارزیابی شرایط کنترلی فرآیند است. این مزیت زمانی آشکارتر می‌شود که برای تحلیل شرایط یک فرآیند نیاز به رسم و تحلیل تعداد قابل توجهی از نمودارهای کنترلی باشد؛ شرایطی که در اغلب کارخانه‌های بزرگ مشاهده می‌شود.

کلمات کلیدی: پایش فرآیند، نمودار کنترلی، نسبت فاکتور، فرآیندهای صنعتی، داده‌های پیوسته.