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STATISTICAL PROCESS CONTROL CHARTS APPLIED TO OPTIMAL QUALITY IMPROVEMENT FOR STEELMAKING PROCESSES

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ABSTRACT

The complex nature for steelmaking processes makes the classical Statistical Process Control (SPC) methodologies are optimal when used to monitor and control steam boiler generation used to supply the required steam for vacuum degassing processes. These processes include a large number of variables that need to be monitored and controlled, while classical SPC requires a control chart for each variable. Thus the effect of one variable can be confounded with effects of other correlated variables. Such a situation can lead to false alarm signals. Univariate control charts are also difficult to manage and analyze because of the large numbers of control charts of each variable. An alternative approach is to construct a single multivariate control T^2 chart that minimizes the occurrence of false process alarms as well as monitors the relationships between the variables, and identifies real process changes not detectable using univariate charts. It is necessary to simultaneously monitor and control these variables to achieve optimal vacuum degassing process performance to remove harmful gases from the molten steel before casting. This represents the main concern of the presented paper. This paper also studies the application of univariate and multivariate control charts in the field of steel industry. The performance analysis for each one is studied using the Average Run Length (ARL). A comparison of the univariate out-of-control signals based on the multivariate out-of-control signals is also made to illustrate the efficiency of the Hotelling's T^2 statistics.

إن طبيعة عمليات تصنيع الصلب المعقدة تجعل المراقبة الإحصائية التقليدية للعملية الإنتاجية غير مثالية عند استخدامها فى مراقبة وضبط مرجل توليد البخار اللازم لعملية تفريغ الغازات. وهذه العمليات تحتوى على عدد كبير من المتغيرات الواجب مراقبتها وضبطها ، ا لمراقبة الإحصائية التقليدية للعملية تتطلب لوحة ضبط لكل عملية. وهكذا فإن تأثير متغير واحد يمكن أن يكون مرتبكا مع المتغيرات المرتبطة الأخرى. وكل حالة يمكن أن تؤدى إلى إشارات إنذار غير حقيقية. أيضا فإن لوحات الضبط الأحادية يصعب تدبرها وتحليلها بسبب العدد الكبير من اللوحات لكل متغير. وعليه تستخدم طريقة بديلة بإنشاء لوحة ضبط واحدة ذات متغيرات متعددة يمكنها تقليل حدوث الإنذارات غير الحقيقية فى العملية الإنتاجية بالإضافة إلى مراقبة العلاقة بين المتغيرات بعضها بعضا، و معرفة التغيرات الحقيقية فيها والتى لاتكتشف من خلال لوحة الضبط الأحادية . ومن الضرورى مراقبة وضبط هذه المتغيرات فى آن واحد لتحقيق الأداء المثالى لعملية تفريغ الغازات للتخلص من الغازات الضارة فى الصلب المصهور قبل صبه. وهذا يمثل الاهتمام الرئيسى لهذا البحث. وهو يدرس أيضا تطبيق كل من لوحات الضبط الأحادية والمتعددة المتغيرات فى مجال صناعة الصلب. وقد تم دراسة تحليل الأداء لكل نوع با ستخدام طول الركض المتوسط. ولبيان كفاية لوحات الضبط المتعددة، وعقدت مقارنة إشارات عدم الضبط للوحات الأحادية وفقا للوحات المتعددة.

Keywords: Statistical Process Control (SPC), Univariate Control Charts, Multivariate Control Techniques, Hotelling's T^2 statistics, Average Run Length (ARL).

1. INTRODUCTION

In large and complex manufacturing systems, statistical methods are used to monitor whether or not the processes remain in control. Control charts are widely used as process monitoring tools, primarily to detect changes in the process mean or in its standard deviation which can indicate a deterioration in quality. Quality control problems arise when processes or products with two or more related quality variables are to be monitored or controlled. When these variables are correlated, a more appropriate approach would be required to monitor them simultaneously. On-line statistical process control is the primary tool traditionally used to improve process performance and to reduce variation of key parameters. Recently, many businesses use Univariate Statistical Process Control (USPC) (Montgomery [11]) in both their manufacturing and service operations. Automated data collection, low-cost computation, products and processes designed to facilitate measurement, demands for higher quality, lower cost, and increased reliability have accelerated the use of USPC.

However, in many situations the widespread use of USPC has caused a backlash as processes are frequently adjusted or shutdown when nothing is really wrong because the probability of false positives (Type I error) is calculated based on USPC. It also takes little or no account of the multiple tests that are being performed or the correlation structure that may exist in the data. It is very likely that these variables will be correlated due to the large number of variables collected at a given time. Consequently, multivariate statistical methods which provide simultaneous scrutiny of several variables are needed for monitoring and diagnosis purposes in modern manufacturing systems. A more appropriate method of detecting and isolating process faults is to utilize Multivariate Statistical Process Control (MSPC) approaches (Wise and Gallagher [20]; MacGregor and Kourti, [10]).

A great deal of work on multivariate statistical control procedures was performed in the 1930's and in the 1940's by Hotelling [5], who has developed the T^2 procedure and its extensions to control charts. The field took a backstage until the 1960's, when, with advances in computer technology, interest in multivariate statistical quality control was revived. Many of the concepts of multivariate quality control techniques are due to Hotelling [5]. Excellent discussions of these techniques are presented by Alt [1] and Jackson [6]. A number of related papers were published in the ensuing years. Jackson [7] mentioned in his paper that the multivariate techniques should possess three important properties: (1) they produce a single answer to the question: is the process in-control?, (2) has the specified type I error been maintained?, and (3) these techniques must take into account the relationship between the variables.

This paper deals with both conventional methods and new approaches that can be used to monitor the manufacturing processes for the purpose of fault detection and diagnosis. The main concern of the paper is to improve steel quality using statistical process control techniques to improve the performance of steam boiler generation, which forms an important part of a steel manufacturing process. Also, the performance of univariate control charts such as Shewhart, EWMA, and CUSUM is compared with a multivariate control chart through the Average Run Length (ARL). To implement this study, Qualstat and Microsoft Excel softwares are used.

2. UNIVARIATE CONTROL CHARTS

Statistical Process Control techniques are employed to monitor production processes over time to detect changes. The basic fundamentals of statistical process control and control charting were proposed by Walter Shewhart [17] in the 1920's and 1930's. The basic Shewhart $\overline{X}$- charting for monitoring both the mean and the variance of a process, however sensitivity of $\overline{X}$ - chart to shifts in the variance is often considered inadequate. So, it is common to use $\overline{X}$ - chart coupled with either R chart or S chart, both of $\overline{X}$ - R chart or $\overline{X}$ - S chart are used to monitor changes in the mean and the variance of the process. Other methods have been proposed to improve sensitivity to small and moderate – sized shifts in the mean. In particular, run rules have been used to signal for unusual patterns on the chart, such as having eight samples means in a row either all above or all below the centerline. Page [14] was the first one who has suggested the use of a separate set of control limits, called warning lines, that lie inside the ordinary control limits. It was proposed that if two consecutive points fell outside the warning lines it would be sufficient cause for a signal. This additional signal criterion is called a run rule. Run rules improve the sensitivity, but also increase the number of false alarms (Champ and Woodall [2]).

The statistic EWMA is calculated using:

$$z_i = \lambda x_i + (1-\lambda) z_{i-1} \tag{1}$$

The control limits of EWMA control chart are:

$$UCL = \mu + L\sigma\sqrt{\frac{\lambda}{2-\lambda}}\sqrt{\left[1-(1-\lambda)^{2i}\right]} \tag{2}$$

$$LCL = \mu - L\sigma\sqrt{\frac{\lambda}{2-\lambda}}\sqrt{\left[1-(1-\lambda)^{2i}\right]} \tag{3}$$

The tabular CUSUM method is used to represent CUSUM control chart for monitoring the process mean. The tabular CUSUM works by accumulating derivations from the target (μ_0) that are above the target with one statistic S_h and accumulating derivations from the target (μ_0) that are below target with another statistic S_l. The statistics S_h and S_l are called one-sided upper and lower CUSUM, respectively. They are computed (Montgomery [13]) as follows:

$$S_h^i = \max\left[0, x_i - (\mu_0 + k) + S_h^{(i-1)}\right] \quad (4)$$

$$S_l^i = \max\left[0, (\mu_0 - k) - x_i + S_l^{(i-1)}\right] \quad (5)$$

where the starting values are $S_h^0 = S_l^0 = 0$.

In Equations (4) and (6), k is called reference value (or the allowance, or the slack value), and it is often chosen about halfway between the target μ_0 and the out-of-control value of the mean μ_1 that we are interested in detecting quickly.

If the shift is expressed in standard deviation units as $\mu_1 = \mu_0 + \delta\sigma$ or ($\delta = |\mu_1 - \mu_0|/\sigma$), then K is one-half the magnitude of the shift or

$$K = \frac{\delta}{2}\sigma = \frac{|\mu_1 - \mu_0|}{2} \quad (6)$$

where S_h and S_l accumulate deviations from the target value μ_0 that are greater than K, with both quantities reset to zero upon becoming negative. If either S_h or S_l exceed the decision interval H, the process is considered to be out-of-control. The reasonable value for H is five times the process standard deviation σ.

The performance of SPC charts is typically measured in terms of the run length. The run length is the number of subgroups from a starting subgroup up to the subgroup which triggers a signal. The run length follows the geometric distribution when observations are independently and identically distributed and control limits are assumed to be known (Quesenberry [15]). This performance metric is termed the Average Run Length ARL_δ, where δ is the mean shift in standard deviations. So the most sensitive charting technique will have a short ARL_δ. A false alarm signal is specified by an ARL_0. In addition, it is important to minimize false alarm signals, even when the process is properly centered.

Lucas and Saccucci [9] have shown that CUSUM and EWMA control charts provide faster detection of small step changes than a Shewhart chart without an increase in the false-alarm rate. However, previous searches have shown that exponentially weighted moving average (EWMA) and cumulative-sum (CUSUM) charts are better in determining process mean shifts than the Shewhart chart.

In conjunction with the Shewhart chart for monitoring the process mean, it is useful to monitor the three sigma variability for each subgroup of measurements. The three sigma chart provides valuable information on the process stability. All of these techniques are univariate control charts and thus only monitor a single parameter or output at a time. Therefore they cannot detect changes in the relationship between multiple parameters.

3. MULTIVARIATE CONTROL CHARTS

Quality is generally determined by several quality characteristics which may be correlated. Multivariate control charts take this correlation into account in monitoring the mean vector or variance-covariance matrix. The first development of a multivariate control chart was performed by Hotelling [5]. Hotelling's chart uses Hotelling's T^2 statistic to monitor several quality characteristics simultaneously with a specified value of α.

Tracy, Young, and Mason [18] presented an exact method for constructing a multivariate control chart for use when individual observations are collected in the start-up stage of the process. Hawkins [4] stated that large values of T^2 can also be caused by changes in the covariance matrix and not just by changes in the mean vector. He proposed that it is important to base the constructed control limits on accurate estimates of the parameters. During the start-up stage, when using subgroups consisting of individual observations (i.e., subgroups of size 1) with measurement variables, the beta distribution should be utilized to obtain control limits for the T^2 statistic. Use of the exact distribution is better than employing approximate F and chi-square distribute ions, especially when the number of subgroups is small. If the size of the historical sample is large, it is common to assume that estimates ($\overline{X}$ and S) are equal to the true population parameters μ and Σ. However, as noted by Tracy, Young, and Mason [18], that assumption is not necessary in multivariate charting.

Alt [1] proposed that when the population covariance matrix is known, Hotelling's statistic is equivalent to the χ^2 statistic

$$\chi^2 = (X - \mu_0)' \Sigma^{-1} (X - \mu_0) \quad (7)$$

Also, when $\mu = \mu_0$, there is probability α that this statistic exceeds a critical point of $\chi^2_{p,\alpha}$, (p is the number of variables) so that the overall error rate can be maintained exactly at the level α by triggering a warning only when

$$\chi^2 > \chi^2_{p,\alpha} \tag{8}$$

Lowry and Montgomery [8] discussed the out-of-control signals in multivariate control charts and proposed that the performance of multivariate control charts in detecting process disturbances tends to deteriorate as the number of monitored quality characteristics increases. Hawkins [3], as well as Wade and Woodall [19], uses regression adjustments for individual variables to improve the diagnostic power of multivariate T^2 charts.

The process being monitored with the Historical Data Set (HDS) is being available and the parameters of the underlying multivariate normal distribution are unknown and must be estimated. The T^2 value associated with X is given by

$$T^2 = (X - \overline{X})' S^{-1} (X - \overline{X}) \tag{9}$$

where $\overline{X}$ and S are the common estimators of the mean vector and covariance matrix obtained from an in-control historical data set.

In case of phase II setting for individual, the T^2 statistic in (9) follows F distribution and the UCL is computed as

$$\text{UCL} = \left(\frac{p(n+1)(n-1)}{n(n-p)} \right) F_{(\alpha,p,n-p)} \tag{10}$$

where n is the size of the HDS, p is the number of variables, and $F_{\alpha;p,n-p)}$ is the α th quantile of $F_{(p;p,n-p)}$.

In the same time, the data of monitoring Phase II is used to construct T^2 control chart as subgroup m using the equations for the value of T^2 and UCL in equations (11) and (12), respectively.

$$T_j^2 = (\overline{X}i - \overline{\overline{X}})' S^{-1} (\overline{X}i - \overline{\overline{X}}) \tag{11}$$

$$\text{UCL} = \left(\frac{p(m+n)(n-1)}{mn(n-p)} \right) F_{(\alpha,p,n-p)} \tag{12}$$

4. STEELMAKING PROCESSES

The process of producing special steel contains four main processes. The first process is melting in Electric Arc Furnace (EAF), where scrap and ferro alloys (raw materials) are added to melt by generating the arc in (EAF), and adjusting the required chemical composition by adding ferro alloys. The second process is the secondary Ladle Refining Process (LRF) to adjust the required chemical composition of special steel and to get high cleanliness degree through desulphurization. In fact, the secondary refining process is considered as the last chance for the steelmaker to improve the quality of producing special steel before casting.

The third process is Vacuum Degassing (VD) to remove harmful gases such as Nitrogen (N_2) and Hydrogen (H_2) from molten steel by stirring it under the vacuum condition. The vacuum process condition is achieved using steam generated by a boiler with a capacity of 4 ton/hr of steam. This steam is used as a power to operate a number of pumps to generate vacuum conditions inside the container of VD process. The vacuum pressure reaches to less than 1 mbar to suck the harmful gases out of the molten steel in about 15 min. The last process is to cast the molten steel in ingot casting or billet casting using Continuous Casting Machine (CCM).

5. AN APPLICATION STUDY

The present application study is carried out in an Egyptian steel industry (ARCO Steel, Sadat City, Minoufiya) on the boiler of steam generation process shown in Fig. 1. This process begins by feeding natural gases as a fuel mixed with air in the combustion chamber for boiling the water (input to boiler from deaerator which eliminates oxygen from the water) to convert it to steam with high pressure. The high-pressure steam is passed into two passes, namely; steam accumulator and super heater to increase the temperature of steam. The steam is passing to steam header to the vacuum degassing process. To increase the boiler efficiency and performance, it has some equipment such as (Rashed [16]):

- Deaerator is used to remove oxygen from the feed water to the boiler. It has a line of steam to increase the temperature of feed water to boiler through pressure regulator.
- Economizer is used as a heat exchanger to transfer the temperature of fume gases from the boiler to the feed water from the deaerator to increase the boiler efficiency.

The overall process is controlled by monitoring seven quality variables of boiler, namely; water level (Wl %), water input temperature from economizer (T_{bwi}), fume gases temperature (T_{gb}), boiler pressure (P_b), accumulator pressure (P_a), steam header pressure (P_h), and steam header temperature (T_h).

In fact, there is a difficulty to reach a vacuum pressure less than 1 mbar that is required to remove the harmful gases. This represents a large problem. Practically, this takes a long time (more than 20 min).

To overcome this problem, initial data about the seven quality variables are collected to construct

Phase I of control charts. 125 measurements were first collected then were grouped into 25 subgroups.

Table 1 Averages and ranges of subgroups for the boiler process for Phase II.

Sub group	Chart	Wl %	T_{bwi}	T_{gb}	P_b	P_a	P_h	T_h
1	Xbar	61.8	117.0	259.4	22.0	18.6	14.0	198.8
	R	3.0	11.0	3.0	3.4	5.6	0.0	1.0
2	Xbar	61.2	120.4	260.8	20.4	16.5	13.9	198.0
	R	4.0	11.0	2.0	4.1	4.4	0.7	2.0
3	Xbar	60.6	112.8	256.2	19.4	14.8	13.2	196.2
	R	4.0	21.0	16.0	1.7	4.6	2.6	7.0
4	Xbar	61.6	118.8	258.6	21.0	17.3	14.0	198.0
	R	5.0	5.0	5.0	4.1	4.7	0.1	0.0
5	Xbar	61.2	121.4	258.6	20.96	17.1	13.8	197.4
	R	5.0	13.0	10.0	4.2	5.0	1.0	3.0
6	Xbar	60.2	116.2	259.6	21.3	17.3	13.9	198.4
	R	2.0	11.0	6.0	3.9	4.9	0.2	2.0
7	Xbar	61.2	124.8	259.6	20.2	16.1	13.9	198.8
	R	5.0	12.0	7.0	4.7	5.8	1.0	6.0
8	Xbar	61.8	114.4	258.4	21.68	17.9	13.96	199.6
	R	3	12	13	4.3	2.4	0.1	3
9	Xbar	61.8	110	252	23.38	20.28	14.18	199.04
	R	4	11	18	2.6	4.1	0.9	3
10	Xbar	62.3	106.6	249.8	21.84	19.5	13.96	199
	R	6.5	6	7	5.4	4.9	0.4	5
11	Xbar	62.6	104.6	252.4	21.46	17.6	13.82	197.8
	R	4	6	7	4	5	1.1	3
12	Xbar	63.2	107.4	252.4	20.7	17.8	13.94	198.2
	R	2	5	9	6.4	4.6	0.3	1
13	Xbar	63.4	105.6	253.2	22.04	18.18	13.96	198.4
	R	4	4	3	2.6	3.6	0.1	1
14	Xbar	61.8	111.4	253.8	21.12	16.08	13.74	197
	R	6	6	7	5	7	1.2	5
15	Xbar	61.6	109.6	255	22.34	18.36	13.96	197.8
	R	5	6	8	4	6.1	0.1	1
16	Xbar	61.4	112.6	256.8	21.46	15.8	13.66	197.6
	R	4	9	3	2.3	3.6	1.4	4
17	Xbar	60.2	115	258.6	19.64	15.52	13.96	198
	R	5	7	6	1.3	2.2	0.3	0
18	Xbar	61.6	114.8	254	19.2	14.12	12.86	195.4
	R	5	10	8	4.7	4.1	2.9	8
19	Xbar	59.4	113.8	259	18.48	13.66	12.68	193
	R	3	9	2	3.4	4.7	2.2	9
20	Xbar	60.4	113.8	258	22.62	17.9	13.92	198.2
	R	1	16	6	1.8	2.7	0.1	1
21	Xbar	61	115	258	21.46	16.98	13.96	198.4
	R	5	9	5	3.3	3.4	0.2	2

Table 1 Contiued.

Sub group	Chart	Wl %	T_{bwi}	T_{gb}	P_b	P_a	P_h	T_h
22	Xbar	61	113.8	254.2	21.52	17.34	13.88	197.6
	R	3	5	10	3.5	4.5	0.5	2
23	Xbar	59.8	119.4	258	21.84	17.26	13.92	198
	R	3	4	2	2.3	3.9	0.1	0
24	Xbar	59.4	111.8	255	20.46	18.26	13.44	196.2
	R	2	7	8	4.1	4	2.6	9
25	Xbar	60.6	121.6	258.2	23.06	18.62	13.92	198
	R	2	10	3	3	3.7	0.1	0
26	Xbar	60.4	112.6	254.4	19.22	14.48	12.7	193.6
	R	5	7	7	4.7	6.9	3.2	12
27	Xbar	62.6	116.4	251.8	23.3	19.16	13.94	198.2
	R	3	8	15	1.9	0.8	0.1	1
28	Xbar	60.8	115.8	251.8	21.56	17.9	13.88	198
	R	4	7	10	3.8	4.5	0.2	0
29	Xbar	60.8	115.8	253.2	18.82	15.24	12.76	195.4
	R	6	12	9	8.8	6.8	2.4	7
30	Xbar	60.6	113.6	257	22.08	17.86	13.9	198
	R	4	12	4	3.3	2.2	0	2
31	Xbar	60.6	113.6	254.2	21.58	16.98	13.74	198
	R	4	14	9	3.3	5.2	0.7	2

Table 2 Significant linear correlations greater than 0.35

#	Variables		*R**	#	Variables		*R**
1	P_h	T_h	0.9162	6	P_b	T_h	0.6110
2	P_h	P_a	0.8553	7	T_{bwi}	T_{gb}	0.4590
3	P_a	P_b	0.6324	8	Wl	T_h	0.4254
4	P_b	P_h	0.6294	9	Wl	P_a	0.4091
5	P_a	T_h	0.6227	10	Wl	P_h	0.3695

* Coefficient of correlation

Also, in Phase II (monitoring phase), 155 measurements were collected into 31 subgroups as shown in Table 1.

The significant linear correlations (greater than 0.35) are summarized in Table 2.

6. RESULTS AND DISCUSSIONS

Initially, the collected data must be filtered to obtain a preliminary data set from which the Historical Data Set can be constructed. A preliminary data set should be thoroughly examined using procedures and graphical tools. A graph of the individual variables over specified period of time is presented in Figs. 2-a to 2-g for the seven quality variables, which indicate some patterns. Fig. 2-a indicates that the water level Wl % is initially stable, while in Fig. 2-b the boiler water input T_{bwi} is increased with time. The figures of other variables are indicating that they are slightly stable with time.

6.1. Shewhart Control Charts

Figures 3 to 9 show the seven Shewhart control charts for the subgroup of the boiler variables. In Fig. 3, X bar and R control charts of Wl % are constructed. It is clear that there is indication that X bar and R charts are in-control, whereas the variable T_{bwi} is unstable as shown in Figs. 4 and 5. The T_{bwi} and T_{gb} control charts have three zones A, B, and C. In zone A, the process is started with out-of-control case. The investigation of this zone indicates that at subgroup No. 3 (Fig. 4) the servo-motor, which is responsible of controlling the flow of natural gases used as a fuel in boiler, is improperly. The servo-motor is temporarily repaired until ordering new one at subgroup No. 9. At this subgroup in Fig. 5, T_{gb} is decreased due to increasing both of boiler load and water level (Wl %). At the same time, the pressure regulator is manually opened, consequently the steam flow is increased to deaerator at zone A. This leads to an increase in boiler water input temperature T_{bwi}. In zone B, there is no indication for out-of-control signals until subgroup No. 15. Also, in zone C the trend of the boiler water temperature T_{bwi} is gradually increased the UCL.

After investigation, it has been found that as the result of increasing the steam consumption in VD process, due
to the leakage in the seal of the container of VD process, the boiler operator opens the pressure regulator manually to increase the quantity of steam flow to the deaerator to improve the boiler efficiency.

As shown in Fig. 6 for boiler pressure P_b, out-of-control signals in subgroups No.18, 19, 26 and 29 are detected due to increasing the steam consumption in VD process and consequently P_b is decreased. On the other hand, accumulator pressure P_a, steam header pressure P_h, and steam header temperature T_h in Figs. 7, 8 and 9, respectively, out-of-control signals are noted in subgroups 3, 18, 19, 26, and 29. A failure is found in servo-motor at subgroup No. 3 and consequently the air to fuel ratio is uncontrolled.

Some corrective actions were taken as a result of detecting the out-of-control signals during the monitoring phase (Phase II) including:

- Install new servo-motor for controlling the Air/Fuel ratio,
- Initiate detailed work instruction for boiler process,
- Prevent leakage in VD container,
- Install water level measure with signal at specified level of the accumulator, and
- Repair the pressure regulator.

After carrying out these corrective actions, 24 subgroups were collected for each variable and hence X bar and R charts could be constructed. In this case, no indication of out-of-control signals is found, the performance of VD process becomes stable, and a 1 mbar or less could be reached through the required time.

6.2. EWMA Control Charts

Practically, weighting parameter having $\lambda = 0.1$, the width of the control limits L = 2.7, and z_0 equals to the grand mean $\bar{\bar{X}}$ of the variable, were chosen and consequently EWMA is constructed for the 31 subgroups with each of size five.

The EWMA control chart of the water level Wl % shown in Fig. 10, indicates out-of-control signals at subgroups Nos. 13, 14, 15, and 16. On the other hand, EWMA of the boiler water input temperature T_{bwi} indicates that T_{bwi} is unstable as shown in Fig. 11. The subgroups Nos. 5, 6, 7, 8 and 9 are out of UCL. There is also a gradual decrease at subgroup No. 7 until subgroup No. 15. This leads to subgroups Nos. 13, 14, 15, 16 and 17 are out LCL. On the contrary, the EWMA of gas boiler temperature T_{gb} in Fig. 12 indicates a gradual increase in the mean. The EWMA of boiler pressure P_b, accumulator pressure P_a and steam header temperature T_h are in control conditions as shown in Figs. 13, 14, and 16, respectively. Finally, EWMA of steam header pressure P_h has out-of-control signal at subgroup No.1 as shown in Fig. 15.

6.3. CUSUM Control Charts

S_h and S_l of each variable were calculated for the 31 subgroups with each of size five. There is no indication of out-of-control signals for steam header pressure P_h. On the contrary, there are out-of-control signals of the variables water level Wl %, boiler water input temperature T_{bwi}, gas temperature T_{gb}, boiler pressure P_b, accumulator pressure P_a, and steam header temperature T_h.

6.4. Multivariate T^2 Control Charts

Calculations of Hotelling T^2 statistic require an estimate of the mean and covariance matrices after obtaining the historical data set for all the seven variables. 125 measurements are chosen as a Phase I. The procedure was to construct the Hotelling T^2 statistic as 155 measurements as individuals T^2 and 31 subgroups with five measurements for each as subgroup T^2 for Phase II (monitoring phase).

Figures 17 and 18 show T^2 charts for individuals and subgroups respectively. In fact, T^2 chart for individuals has out-of-control signals at measurements numbers 14, 15, 21, 70, 76, 86, 87, 90, 92, 93, 94, 117, 129, 130, 133, 139, 141, 143, and 144. On the other hand, the subgroup numbers 1, 8, 11, 13 and 15 are out-of-control at T^2 chart for subgroups.

7. PERFORMANCE COMPARISON

In case of Shewhart control chart with three sigma limits, the probability that the measurement exceeds its control limits is $1/ARL_0$ (1/370 or 0.0027). The probability that the process is within the 3 sigma limits is simply ($1 - 1/ARL_0$) or 0.9973. In general, for a process consisting of p statistically independent parameters being monitored, the probability that all p parameters can be plotted in 3 sigma control limits when they are in control (Montgomery [12]), i.e.

$$P\{all\ p\ means\ plot\ in\ control\} = (0.9973)^p \qquad (13)$$

In the case of seven variables ($p = 7$), the detection probability is reduced from 0.9973 to 0.9813. This means that ARL_0 of seven variables have been reduced from 370 (single uncorrelated univariate chart) to 54. It is important to note that equation (13) assumes that seven variables are statistically independent. It is more typical that the variables are partially dependent which could produce an even smaller $ARL_0 = 54$.

For monitoring and control of the steam generation process, it is helpful to compare these separate techniques for determining out-of-control signals. At the beginning, the total number of out-of-control signals generated by the seven univariate control charts in phase II were counted. Secondly, counting the out-of-control signals is indicated using a single multivariate control chart based on Hotelling T^2 statistic with individuals and subgroups.

7.1. Performance Comparison of Univariate Control Charts

Table 3 gives the out-of-control signals of univariate control charts that were detected from the 31 subgroups of the studied different variables. Also, it shows the number of out-of-control signals of each variable for Shewhart, EWMA, and CUSUM control charts. As shown in Fig. 19, out-of-control signals detected by Shewhart control chart are higher than both EWMA and CUSUM in all variables. This does not mean that Shewhart has better performance than EWMA and CUSUM. In fact, Shewhart control chart has high false alarms signals than EWMA and CUSUM. Consequently, it is believed that Shewhart control chart generates the highest incidence of false alarm signals and do not provide a clear indication of the known or assignable process shifts. The out-of-control signals of both EWMA and CUSUM control charts are slightly the same.

The performance comparison of EWMA and Shewhart is clear in Fig. 20. The ARL of two EWMA's have been presented for comparison.

Keeping in mind that the smaller the out-of-control ARL for a control chart the better it is, Fig. 20 shows that EWMA is more effective for small shifts, but less or equally effective as the Shewhart control chart for bigger shifts. That is the EWMA importance as far as monitoring is concerned. When small shifts detection is desired EWMA is the best choice.

Table 3 Detected out-of-control signals from 31 subgroups.

Control Chart		Shewhart	EWMA	CUSUM
Wl	#	0	4	2
%	%	0	12.9	6.5
T_{bwi}	#	23	10	9
	%	74.2	32.3	29
T_{gb}	#	10	7	10
	%	32.3	22.6	32.3
P_b	#	4	2	1
	%	12.9	6.5	3.2
P_a	#	5	0	2
	%	16.1	0	6.5
P_h	#	10	0	0
	%	32.3	0	0
T_h	#	7	4	1
	%	22.6	12.9	3.2

7.2. Performance Comparison of Multivariate Control Charts

7.2.1. Comparison of T^2 with Individuals and Subgroups

It is helpful to compare the two separate techniques (T^2 with Individuals and Subgroups) for determining out-of-control signals. In Fig. 20, number of out-of-control signals with subgroups equals 26 signals, while at T^2 with Individuals equals 10 signals. Subgroups number 3, 5, 14, 16, 18, 19, 24, 26, 27, and 29 are totally signaled in both cases, but the other 16 subgroups are not signaled at T^2 with individuals. It is clear that the T^2 with subgroups has higher performance than individuals.

7.2.2. Comparison of T^2 Subgroup and Shewhart Control Charts

The number of out-of-control signals of Shewhart control chart for each variable are summed for each subgroup. Figure 22 Shows that the number of out-of-control signals detected by Shewhart and T^2 control charts are 61 and 26, respectively. It is noticed that five subgroups are signaled by the Shewhart control chart and not detected by T^2 chart, and only one subgroup (No.15) is not signaled by two different charts.

8. CONCLUSIONS

In this paper, the process of steam generation boiler, in steelmaking, was monitored using conventional univariate control charts (Shewhart, EWMA, and CUSUM) and a single multivariate control chart. Seven variables of boiler water level Wl %, boiler water input temperature T_{bwi}, fume gases temperature T_{gb}, accumulator pressure P_a, steam header pressure P_h, and steam header temperature T_h were monitored. Based on these seven