(REFEREED RESEARCH)

AN APPLICATION ON FANCY SHIRTING FABRIC PRODUCTION THROUGH DISTRIBUTION-FREE QUALITY CONTROL CHARTS

KADIN GÖMLEĞİ DOKUMA KUMAŞ ÜRETİMİNDE DAĞILIMDAN BAĞIMSIZ KALİTE KONTROL KARTLARININ UYGULANMASI

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ABSTRACT

This paper presents a case study of distribution-free quality control charts on fancy shirting fabric production. The distribution-free quality control chart used in this paper is proposed by (1). False alarm rate (FAR) and average run length (ARL) values for different design parameters are calculated. The process data obtained from the production mill in textile sector is analyzed with this distribution-free control chart and it is concluded that the process is statistically in control.

Keywords: Statistical Quality Control, Distribution-Free Quality Control Charts, False Alarm Rate, Average Run Length, Fancy Shirting Fabric, Textile Sector.

ÖZET

Bu çalışmada dağılımdan bağımsız kalite kontrol kartlarının bayan gömleği için dokuma üretiminde uygulaması verilmiştir. Çalışmada kullanılan dağılımdan bağımsız kalite kontrol kartı, (1) tarafından önerilmiştir. Farklı tasarım parametreleri için yanlış alarm oranı (FAR) ve ortalama çalışma uzunluğu (ARL) değerleri hesaplanmıştır. Bayan gömlekleri için dokuma üretimi yapan bir fabrikaya ait veriler bu kalite kontrol kartı ile analiz edilmiş ve sürecin istatistiksel olarak kontrol altında olup olmadığı incelenmiştir.

Anahtar Kelimeler: İstatistiksel Kalite Kontrolü, Dağılımdan Bağımsız Kalite Kontrol Kartları, Hatalı Alarm Oranı (FAR), Ortalama Çalışma Uzunluğu (ARL), Bayan Gömleği Dokuması, Tekstil Sektörü.

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1. INTRODUCTION

Statistical quality control can be defined as the application of statistical methods for monitoring and controlling a process to ensure that it operates at its full potential for producing conforming products to specifications. These methods are indispensable for making qualified production in many sectors today, including textile production factories.

In statistical quality control, causes of variation in the processes can be detected by using quality control charts. Quality control charts are plots of sample statistics over time to distinguish between general and special causes of variation. Just like many statistical methods, the control limits of traditional Shewhart control charts are based on the assumption that the continuous quality characteristic is distributed normally. But frequently, this normality assumption is not satisfied in real life data and this affects the statistical properties of standard quality control charts.

When this is the situation, that is when normality assumption is not satisfied, distribution-free or non-parametric quality control charts offer a good alternative method. Distribution-free control charts find wide applications in statistical quality control and there are several papers published in literature. Using distribution-free quality control charts provide many advantages to the researchers. The first of these advantages is that, they do not need to assume a particular probability distribution. Secondly, they do not require known process variance. Besides, they have the robustness feature of standard nonparametric procedures and therefore, they are less likely to be affected by outliers, or the shape of the distribution. Also, in-control run length distribution is the same for all continuous distributions. They are more robust and more efficient in detecting changes when the underlying distribution is non-normal. The effects of non-normality on sample mean have been studied in the literature, such as (2) and (3). Also, more details can be found in (4), (5), (6), (7) and (8).

Among various distribution-free quality control chart types, the median based ones are quite advantageous. One of the most important reasons of this is that, median is less sensitive than other location measures (such as the mean) to outliers, measurement or recording errors, etc. in the data set.

On every field of science, practicability of newly proposed methods on real life data is of great importance. The objective of our study is to examine how this distribution-free quality control chart behaves with a real life problem, to investigate FAR and ARL values of this chart for different design parameters and to guide the people studying on textile sector. The false alarm rate shows the frequency of a chart to give a false signal when the process is actually under control. The average run length is the mean number of samples taken until an alarm is signaled by the chart which determines the performance of the chart. For the details see (9) and (10).

This study consists of 6 sections. In Section 2, literature review on distribution-free median charts is given. The method proposed by (1) which is studied in this paper is given in Section 3 together with some information on average run length in Section 4. This method is applied with data obtained from a production mill in textile sector and this application is given in Section 5. Finally, Section 6 gives the results of this study.

2. LITERATURE REVIEW ON DISTRIBUTION-FREE MEDIAN CHART

Generally, Shewhart $\overline{X}$ control chart has been used for detecting shifts in the processes. As stated earlier, this chart gives reliable results for normally distributed data. If the quality characteristic monitored is not distributed normally, using control charts based on mean may cause inappropriate charts that will either fail to detect real changes in the process or create false alarms even though the process has not changed, as in (11). For such situations, various distribution free control charts have been proposed. One of these is median chart which is advantageous as the median is less sensitive to outliers than the mean.

In the literature, many median control charts have been proposed, some of which are (12), (13), and (14) and (15). A new median control chart with the sign test statistic is proposed (16). Also, efficiency of the control charts is compared. It is concluded that, for symmetric distributions, the median control chart with bootstrap control limits shows a higher performance than other nonparametric control charts. (17) compared the efficiency of three different nonparametric control charts based on the sign test, based on the Hodges–Lehmann estimator and based on the Mann–Whitney statistic. As a result of the study, it is concluded that Hodges–Lehmann method is more efficient for symmetric-mesokurtic and symmetric-leptokurtic distributions. Mann-Whitney method is more efficient for symmetric-platykurtic distributions, and sign test is more efficient for asymmetric distributions.

(13) proposed median based control charts which keep the traditional format and have reasonable power. In the proposed chart, the process is assumed to be "in control" and there is a reference sample of size N. Test samples of size n are taken from this reference sample. These test samples are used to determine whether the process is still in control or not, by searching a change in the location of the underlying distribution. Control limits and action limits are determined from the reference sample by using sample medians of test samples instead of sample means. In order to detect a change in location, the median m of the test sample is compared with control limits or action limits. As the distribution of the reference sample is unknown, control or action limits are chosen as $(j)^{th}$ and $(N-j+1)^{th}$ order statistics of the reference sample. Consequently, their results have some power loss for normal distribution but are more reliable for non-normal distributions.

(18) suggested further generalizations to the chart proposed by (13). In the proposed charts, the decision is based only on a specific quantile such as the median. But, it is possible that this single observation may be between the control limits while the main part of the test sample is outside of the control limits. This can be stated as a disadvantage of the median control chart and its extensions proposed by (18). The proposed precedence charts offer an alternative to the usual $\overline{X}$ chart in practice.

For overcoming the disadvantages of the median chart, (1) proposed a distribution-free control chart which considers both the location of a single order statistic of the test sample and the number of observations that lie between the control limits in the test sample. The empirical study in the paper revealed that the new chart is preferable from a robustness point of view in comparison to a Shewhart control chart and also the nonparametric chart of (18).

3. THE METHOD

It is assumed that there is a reference sample of size m, $X_1, X_2, ..., X_m$ and a test sample of size n, $Y_1, Y_2, ..., Y_n$ is taken from it. The reference sample is assumed to have an in-control distribution $F(x)$ and the purpose of this method is to detect whether there is a change in $F(x)$ towards an out-of-control distribution $G(x)$ or not.

If the reference sample of size m, $X_1, X_2, ..., X_m$ are sequenced in ascending order of magnitude and then obtained $X_{1:m} \le X_{2:m} \le \cdots \le X_{m:m}$ denote ordered random variables. Here, $X_{i:m}$ is the i^{th} order statistic, $i = 1, 2, ..., m$. If the random variable X_i is assumed to be independent and identically distributed, $X_{i:m}$ will be dependent because of the inequality relations among them.

Two specific order statistics are chosen from this reference sample which are used as control limits where $1 \le a < b \le m$.

$$LCL = X_{a:m} \ , \ UCL = X_{b:m} \tag{1}$$

j^{th} order statistic $Y_{j:n}$ of the test sample, which is the median, is chosen. Besides, L is defined as the number of observations in the test sample that are between the control limits determined from the reference sample. r is the lower limit for L. The decision rule for being in-control is given by (1) as:

$$LCL \le Y_{j:n} \le UCL \;\; and \;\; L \ge r \tag{2}$$

where

$$L = L(Y_1, Y_2, ..., Y_n; X_{a:m}, X_{b:m}) = \left|\{i \in \{1,2,...,n\} : X_{a:m} \le Y_i \le X_{b:m}\}\right|. \tag{3}$$

m, n, a, b, j and r are the design parameters of this control chart which can be determined according to a specified false alarm rate; see (13), (18) and (1).

(1) improved the design parameters m, n, a, b, j and r by (13) and (18) which can be determined according to a specified false alarm rate given in equation (4)

$$FAR = 1 - P_c\left(LCL \le Y_{j:n} \le UCL \;\; and \;\; L \ge r\right) \tag{4}$$

where c shows that the process is in-control. FAR is defined as the probability of getting an out-of-control signal while the process is actually in-control. It can be calculated as in equation (5) under the null hypothesis $H_0 : F = G$,

$$\begin{aligned} FAR &= 1 - p(m,n,a,b,j,r;F,G) = 1 - p(m,n,a,b,j,r;F,F) \\ &= 1 - P\left(X_{a:m} \le Y_{j:n} \le X_{b:m} \; and \; L(Y_1, Y_2, ..., Y_n; X_{a:m}, X_{b:m}) \ge r\right) \end{aligned} \tag{5}$$

where p is the probability that the chart does not give a signal. It is clear that $1-p$ shows the probability that the chart gives an out-of-control signal. (1) gives the calculation of false alarm rate as follows

$$FAR = 1 - \sum_{c=0}^{n-1} \sum_{d=\max(r-c-1,0)}^{n-c-1} \int_0^1 \int_0^t q_{c,d}(s,t) f(s,t)\, ds\, dt \tag{6}$$

where

$$q(s,t;r) = \sum_{r-1 \le c+d \le n-1} q_{c,d}(s,t), \;\; 0 \le s < t \le 1, \tag{7}$$

$$q_{c,d}(s,t) = \binom{n}{j-c-1,\, c+d+1,\, n-j-d} s^{j-c-1} (t-s)^{c+d+1} (1-t)^{n-j-d}$$

$$f(s,t) = \frac{m!}{(a-1)!(b-a-1)!(m-b)!} s^{a-1} (t-s)^{b-a-1} (1-t)^{m-b}, \;\; 0 < s < t < 1 \tag{8}$$

4. AVERAGE RUN LENGTH

For determining the performance of a control chart, another important measure used is the average run length (ARL). Run length distribution is the distribution of the waiting time random variable which is the number of samples until the first out-of-control signal is given by the chart. Higher values of ARL show the process performs well and lower values show that the process has gone out of control.

(1) gives the calculation of average run length rate as given by

$$ARL_{in} = \int_0^1 \int_0^t \frac{1}{1 - q(s,t;r)} f(s,t)\, ds\, dt \tag{9}$$

where $q(s,t;r)$ and $f(s,t)$ are given in equations (7) and (8), respectively.

Table 1 gives FAR and ARL_{in} values for various design parameters m, n, a, b, j and r. It should be noted that $b = m - a + 1$ and $j = (n+1)/2$. Also, $1 \le a \le m$ is selected so that the probability to get an out-of control signal while the process is in-control (FAR) does not exceed a prespecified FAR level *f*;

$$1 - FAR = P\left(LCL < M < UCL \middle| H_0\right) \ge 1 - f \, . \tag{10}$$

Table 1. FAR and ARL_{in} values for various m, n, a, b, j, r and specific f

f	m	n	a	b	j	r	FAR	ARL_{in}
0.01	50	9	2	49	5	6	0.00770	∞
		17	4	47	9	10	0.00827	∞
		27	6	45	14	14	0.00832	20622600
	100	9	13	88	5	1	0.00888	216.491
		17	19	82	9	5	0.00896	349.753
		27	24	77	14	4	0.00895	481.484
	200	9	27	174	5	3	0.00993	138.403
		17	40	161	9	5	0.00962	173.057
		27	51	150	14	4	0.00988	182.410
	500	9	42	459	5	5	0.00983	123.113
		17	38	463	9	11	0.00997	141.451
		27	96	405	14	11	0.00993	154.189
0.005	50	9	4	47	5	2	0.00233	8942.900
		17	7	44	9	1	0.00249	29430.200
		27	9	42	14	1	0.00250	432549
	100	9	11	90	5	1	0.00462	506.986
		17	17	84	9	5	0.00431	949.598
		27	21	80	14	8	0.00467	2120.590
	200	9	23	178	5	2	0.00443	331.895
		17	37	164	9	4	0.00456	380.499
		27	35	166	14	11	0.00463	895.750
	500	9	61	440	5	1	0.00491	232.757
		17	94	407	9	5	0.00493	254.518
		27	122	379	14	5	0.00495	261.181
0.0027	50	9	4	47	5	1	0.00232	8944.190
		17	7	44	9	1	0.00249	29430.200
		27	9	42	14	1	0.00250	432549
	100	9	3	98	5	6	0.00234	∞
		17	5	96	9	11	0.00208	30787.500
		27	17	84	14	10	0.00208	19686.600
	200	9	20	181	5	2	0.00245	654.537
		17	34	167	9	3	0.00252	756.805
		27	43	158	14	7	0.00249	1101.460
	500	9	53	448	5	1	0.00264	447.542
		17	89	412	9	2	0.00265	472.534
		27	108	393	14	8	0.00268	577.214

5. CASE STUDY

The aim of this study is to use the distribution-free quality control charts in real life data. As mentioned before, traditional Shewhart quality control charts have the assumption of normality. But in real life, data are not always distributed normally. Therefore, it is better to use distribution-free quality control charts instead of traditional quality control charts when the normality assumption is not satisfied. For this purpose, the data obtained from a production mill in textile sector are used. The mill which is located in Bursa has more than 200 employees. This mill produces fancy shirting fabric for women woven outerwear. The data are the quantities of produced woven fabric by the weaving loom at once. For example, 210 meters shows the produced quantity by the loom at once, without any stop.

For the case study, 3 different data sets are obtained which are shown in Tables 2, 3 and 4, respectively. The first one consists of 50 data. The second one consists of 100 data. The third one consists of 200 data. In order to show why traditional control charts cannot be used for these data, Anderson-Darling (AD) normality test are realized for each data set under the null hypothesis H_0: The data is distributed normally. The results are given in Figures 1, 2 and 3 respectively. Figure 1 shows that p value is less than significance level α=0.05. Thus, the null hypothesis H_0 is rejected and this means that the first data set is not distributed normally at α=0.05. Figure 2 shows that p value is less than α=0.05. H_0 is rejected. The second data set is not distributed normally at α=0.05. Finally, Figure 3 shows that p value is less than α=0.05. H_0 is rejected. The third data set is not distributed normally at α=0.05.

Table 2. The first data set which is the first reference sample of $m = 50$

42.4	53.0	38.0	24.0	42.0	37.1	97.0	30.0	70.0	43.0
26.5	42.4	31.8	84.8	63.6	31.8	99.0	80.0	89.0	67.0
53.0	84.8	37.1	35.0	53.0	32.0	42.0	33.0	88.0	26.5
63.6	42.4	63.6	23.0	31.8	48.0	95.4	52.0	28.0	65.0
42.4	86.8	38.0	47.7	40.0	76.0	76.0	69.0	25.0	77.0

Table 3. The second data set which is the second reference sample of $m = 100$

210.0	169.6	212.0	110.0	164.0	190.0	159.0	102.0	200.0	92.2
212.0	169.6	222.6	158.0	262.0	126.0	159.0	105.0	240.0	212.0
212.0	106.0	318.0	159.0	132.0	212.0	150.0	215.0	116.0	132.0
254.0	125.0	122.0	140.0	164.0	212.0	158.0	138.0	146.0	177.0
106.0	191.0	160.0	118.0	260.0	119.0	195.0	127.2	148.0	101.0
212.0	256.0	211.0	142.0	160.0	92.0	118.0	159.0	169.6	159.0
84.8	84.8	143.0	97.0	227.0	111.0	197.0	106.0	339.2	129.0
86.8	129.0	303.0	124.0	212.0	123.0	233.2	106.0	205.0	212.0
260.0	102.0	172.0	99.0	159.0	149.0	106.0	103.0	147.0	264.0
333.6	174.0	161.0	106.0	149.0	400.0	169.6	194.0	100.0	200.0

Table 4. The third data set which is the third reference sample of $m = 200$

210.0	260.0	102.0	172.0	42.0	70.0	111.0	195.0	51.0	339.2
212.0	333.6	174.0	161.0	95.4	89.0	32.0	118.0	53.0	55.0
42.4	169.6	63.6	40.0	76.0	212.0	42.4	53.0	53.0	80.0
26.5	169.6	212.0	37.1	30.0	159.0	123.0	68.0	38.0	205.0
53.0	38.0	63.6	31.8	106.0	53.0	47.7	197.0	37.1	147.0
53.0	31.8	222.6	32.0	164.0	53.0	149.0	233.2	38.0	100.0
212.0	37.1	63.6	31.8	262.0	53.0	400.0	106.0	37.1	92.2
254.0	106.0	63.6	32.0	80.0	149.0	580.8	26.5	37.1	212.0
53.0	125.0	636.0	110.0	132.0	88.0	480.0	26.5	38.0	63.0
53.0	191.0	424.0	48.0	53.0	190.0	480.0	26.5	37.1	53.0
106.0	63.6	318.0	158.0	53.0	126.0	159.0	169.6	106.0	132.0
212.0	256.0	31.8	159.0	53.0	37.1	480.0	70.0	103.0	177.0
63.6	38.0	53.0	140.0	33.0	212.0	159.0	102.0	194.0	101.0
63.6	24.0	53.0	118.0	33.0	64.0	42.0	105.0	424.0	67.0
42.4	84.8	122.0	142.0	164.0	64.0	42.4	215.0	200.0	159.0
53.0	35.0	160.0	76.0	260.0	42.4	150.0	138.0	240.0	53.0
42.4	23.0	211.0	97.0	160.0	212.0	27.0	127.2	116.0	53.0
84.8	129.0	143.0	124.0	52.0	26.5	53.0	159.0	146.0	52.0
42.4	47.7	31.8	99.0	227.0	119.0	53.0	106.0	148.0	54.0
86.8	42.0	303.0	53.0	69.0	92.0	158.0	75.0	169.6	129.0

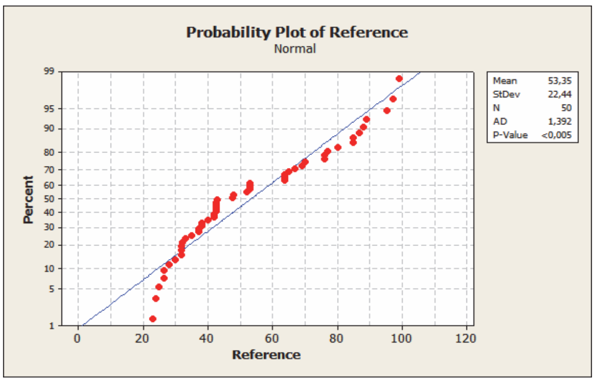

Figure 1. The result of AD normality test for the first data set ($m = 50$)

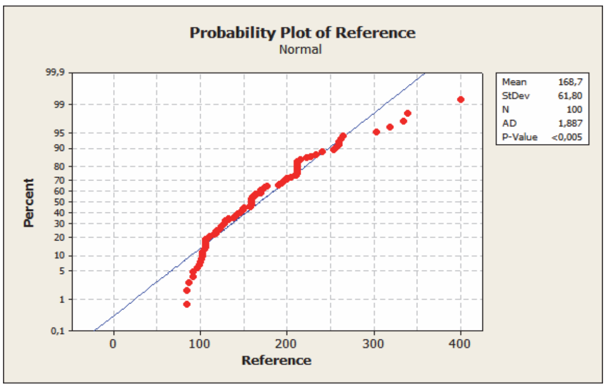

Figure 2. The result of AD normality test for the second data set ($m = 100$)

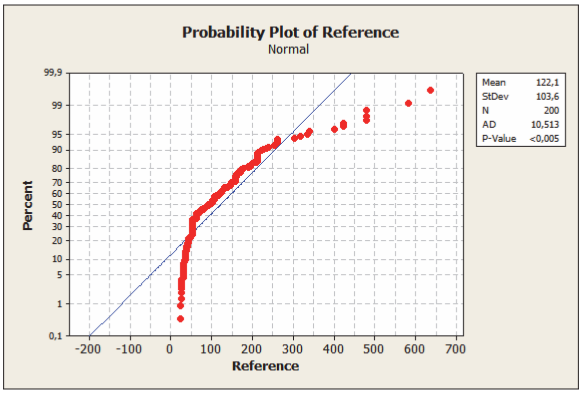

Figure 3. The result of AD normality test for the third data set ($m = 200$)

As all three data sets are not normally distributed, it is convenient to use distribution-free control charts. For the design parameters given in Table 1, random samples of sizes 9, 17 and 27 are taken from each data set. Here, three data sets of sizes 50, 100 and 200 are reference samples and random samples of sizes 9, 17 and 27 are test samples. Using these reference samples and test samples, control limits ($X_{a:m}$ and $X_{b:m}$), median values ($Y_{j:n}$) and L values are determined as shown in Tables 5, 6 and 7, respectively. The *f* values of 0.01, 0.005, and 0.0027 are based on (1). According to these values, two conditions of the control chart given are checked and it is decided whether the process is in control or not.

Table 5. Values of design parameters for the first data set $(m = 50)$

f	n	$X_{a:m}$	$X_{b:m}$	$Y_{j:n}$	L	**Condition 1** $(LCL \le Y_{j:n} \le UCL)$	**Condition 2** $(L \ge r)$	**State of the process**
0.01	9	24	97	63.6	8	$X_{2:50} \le Y_{5:9} \le X_{49:50}$	$8 \ge 6$	In Control
	17	26.5	89	47.7	15	$X_{4:50} \le Y_{9:17} \le X_{47:50}$	$15 \ge 10$	In Control
	27	28	86.8	48	22	$X_{6:50} \le Y_{14:27} \le X_{45:50}$	$22 \ge 14$	In Control
0.005	9	26.5	89	47.7	7	$X_{4:50} \le Y_{5:9} \le X_{47:50}$	$7 \ge 2$	In Control
	17	30	84.8	42.4	14	$X_{7:50} \le Y_{9:17} \le X_{44:50}$	$14 \ge 1$	In Control
	27	31.8	80	38	15	$X_{9:50} \le Y_{14:27} \le X_{42:50}$	$15 \ge 1$	In Control
0.0027	9	26.5	89	53	7	$X_{4:50} \le Y_{5:9} \le X_{47:50}$	$7 \ge 1$	In Control
	17	30	84.8	42.4	11	$X_{7:50} \le Y_{9:17} \le X_{44:50}$	$11 \ge 1$	In Control
	27	31.8	80	35	15	$X_{9:50} \le Y_{14:27} \le X_{42:50}$	$15 \ge 1$	In Control

Table 6. Values of design parameters for the second data set ($m = 100$)

f	n	$X_{a:m}$	$X_{b:m}$	$Y_{j:n}$	L	**Condition 1** $(LCL \le Y_{j:n} \le UCL)$	**Condition 2** $(L \ge r)$	**State of the process**
0.01	9	105	233.2	164	8	$X_{13:100} \le Y_{5:9} \le X_{88:100}$	$8 \ge 1$	In Control
	17	106	212	129	15	$X_{19:100} \le Y_{9:17} \le X_{82:100}$	$15 \ge 5$	In Control
	27	118	212	169.6	16	$X_{24:100} \le Y_{14:27} \le X_{77:100}$	$16 \ge 4$	In Control
0.005	9	102	254	212	5	$X_{11:100} \le Y_{5:9} \le X_{90:100}$	$5 \ge 1$	In Control
	17	106	212	158	11	$X_{17:100} \le Y_{9:17} \le X_{84:100}$	$11 \ge 5$	In Control
	27	111	212	146	19	$X_{21:100} \le Y_{14:27} \le X_{80:100}$	$19 \ge 8$	In Control
0.0027	9	86.8	333.6	200	9	$X_{3:100} \le Y_{5:9} \le X_{98:100}$	$9 \ge 6$	In Control
	17	92.2	303	138	17	$X_{5:100} \le Y_{9:17} \le X_{96:100}$	$17 \ge 11$	In Control
	27	106	212	159	21	$X_{17:100} \le Y_{14:27} \le X_{84:100}$	$21 \ge 10$	In Control

Table 7. Values of design parameters for the third data set ($m = 200$)

f	n	$X_{a:m}$	$X_{b:m}$	$Y_{j:n}$	L	**Condition 1** $(LCL \le Y_{j:n} \le UCL)$	**Condition 2** $(L \ge r)$	**State of the process**
0.01	9	37.1	212	92.2	9	$X_{27:200} \le Y_{5:9} \le X_{174:200}$	$9 \ge 3$	In Control
	17	42.4	177	80	12	$X_{40:200} \le Y_{9:17} \le X_{161:200}$	$12 \ge 5$	In Control
	27	53	160	159	12	$X_{51:200} \le Y_{14:27} \le X_{150:200}$	$12 \ge 4$	In Control
0.005	9	37.1	212	42.4	8	$X_{23:200} \le Y_{5:9} \le X_{178:200}$	$8 \ge 2$	In Control
	17	42.4	194	89	12	$X_{37:200} \le Y_{9:17} \le X_{164:200}$	$12 \ge 4$	In Control
	27	42	197	118	17	$X_{35:200} \le Y_{14:27} \le X_{166:200}$	$17 \ge 11$	In Control
0.0027	9	35	227	159	6	$X_{20:200} \le Y_{5:9} \le X_{181:200}$	$6 \ge 2$	In Control
	17	42	200	95.4	13	$X_{34:200} \le Y_{9:17} \le X_{167:200}$	$13 \ge 3$	In Control
	27	42.4	169.6	105	15	$X_{43:200} \le Y_{14:27} \le X_{158:200}$	$15 \ge 7$	In Control

In order to graphically compare the traditional Shewhart $\overline{X}$ chart with the distribution-free control chart used in this paper, $\overline{X}$ charts are plotted for all data sets, but only the one for $m = 200$ is given in the text. As it is shown in Figure 4, the in-control process seems to be out-of-control with two points exceeding the upper control limit. The reason for this misleading result is that; this is a non-normal process and the traditional $\overline{X}$ chart has normality assumption. In such situations where the assumptions are not satisfied, the control charts may mislead the practitioners. It is said to be inconvenient to analyze a non-normal process as if it is normally distributed.

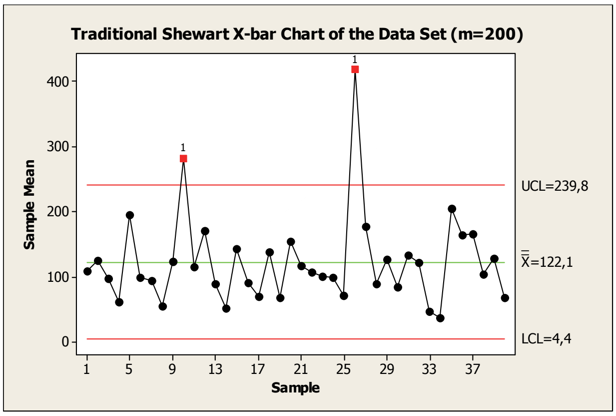

Figure 4. Traditional Shewart $\overline{X}$ chart of the data set ($m = 200$)

6. CONCLUSIONS

The distribution-free quality control chart is performed when the underlying distribution is unknown or normality assumption is not satisfied. This study shows FAR and ARL values for different design parameters for the distribution-free quality control chart proposed by (1).

This chart is applied to 3 data sets obtained from a textile production mill. First, normality of each data set is tested with Anderson-Darling normality test and it is seen that none of the data sets are distributed normally. Therefore, as traditional quality control charts would not be suitable for them, distribution-free quality control chart is used with the aim of analyzing whether the process is in control or not. For all test samples of different sizes, the process is concluded to be statistically in control.

Also, the processes are evaluated with both distribution-free and traditional $\overline{X}$ charts. The results of two charts are compared to each other. Here, the distribution-free charts show that the data sets are under statistical control. But, as the normality assumption is violated, $\overline{X}$ charts show the process to be out-of-control. This misleading condition may cause many disadvantages for the organizations such as; suspending an actually in-control process, increasing the production costs, and etc. This is called producer's risk (Type I error) in statistical quality control, which is undesired by all producers. Therefore, the control chart used in this study would be useful to practitioners for controlling the quality of processes.

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