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# Comparison of Some Non-Parametric Quality Control Methods

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## Abstract:

**Multivariate Non-Parametric control charts were used to monitoring the data that generated by using the simulation, whether they are within control limits or not. Since that non-parametric methods do not require any assumptions about the distribution of the data. This research aims to apply the multivariate non-parametric quality control methods, which are Multivariate Wilcoxon Signed-Rank ($SR^2$) , kernel principal component analysis (KPCA) and k-nearest neighbor ( $K^2$ $-CHART$) multivariate non-Parametric control charts. Then comparing between their performance by using average run length criterion (ARL) , based on simulation experiments with different significance levels to illustrate work of non-parametric control charts . The results show that the process of monitoring is out of control , ( $K^2 - CHART$ ) chart had better performance in the short rang and relative equality in the performance between (KPCA) and ($K^2 - CHART$) in the medium and long term .**

**Keywords:** **Quality Control , Non-Parametric Control Chart , Average Run Length, K- Nearest Neighbor , Kernel Principal Component Analysis , Wilcoxon Signed-Rank .**

## 1-Introduction:

**Quality control processes are used in different fields, including productive and service , and it is a goal for all institutions , where statistical control processes are a responsible tool for detecting changes in production processes at each stage of production in order to ensure that the estimated final results are similar results as planned . The performance of the parametric control charts is weak in the cases where the assumptions of the normal distribution are not achieved, so the nonparametric control charts are a better alternative to them in monitoring operations . The research aims to review the multivariate non-parametric quality control charts and to determine the control limits and compare the performance of the charts using Average Run Length (ARL) criterion . The researcher (Hotelling) was interested in the issue of quality control, where he wrote a book in (1947) which is one of the basic references for research and studies specialized in this subject; he depended on the theory of multivariate distributions to clarify the statistical methods used in quality control. Each (Walid , Mohamed) in (2012) used ($K^2$-CHART) on one of the industrial applications and they concluded that despite presence of some problems , the control process was carried out successfully, and the ($K^2$) chart is sensitive to shifts in the mean vector , in (2020) both of (Muhammad , Hidayatul) used the kernel PCA control chart, which depends on the kernel principal component , to monitor the quality characteristics of the mixed variables, and they concluded the good performance of the chart in discovering the out-of-control observations .**

## 2-Quality Control :

**Quality control is the procedures and activities that are implemented by all employees of the producing company or establishment to ensure that the product or service conforms to the standard characteristics pre-determined by the administration [13].**

## 3-Statistical Process Control (SPC) :

**Statistical Process Control (SPC) are one of the important tools and techniques for controlling production processes, used to improve the quality of production , ensure the availability of the required qualities in the product, examine samples, analyze the capacity of the process ... etc. Therefore, statistical qualitative control is one of the important means in the production process [14] .**

## 4-Quality Control Chart :

**The use of control panels is an indicator or early warning that detects the processes out of control for the purpose of maintaining the continuity of the production process within the limits of control [17].**

**The control charts consist of:**

**1. The lower limit represents the least acceptable percentage of defective units.**

**2. The upper limit represents the highest acceptable percentage of the number of defective units.**

**3. The central limit is the optimum level of production quality.**

## 4- Non-Parametric Multivariate Control charts:

**The control charts are based on the assumption that there is a specific form of parametric distribution, such as normal distribution, and they are called the parameter control charts used in many control applications, but there is not enough information to verify this assumption, so the performance of many of the**

**control charts in these cases may change . It leads to misleading results and false alarms . So, non-parametric dashboards are a better alternative that does not need to know the basic distribution of data and is also less affected by outliers [6] .**

## (4-1) The Multivariate Wilcoxon Signed-Rank Control Chart :

**The Wilcoxon chart is based on a multivariate formula Wilcoxon Signed-Rank Test , which is a nonparametric test that is not affected by outliers. The idea of this chart is assuming that the median values for the monitor are predetermined, in addition to assuming that the joint distribution of the variables (p) is symmetrical diagonally around the median values** $\underline{\theta} = (\theta_1, \theta_2, \dots, \theta_p)'$ **, and under this assumption that the Marginal Distributions of the variables are symmetrical around the median values for each variable .**

**Let (n) be the sample size and (p) number of variables[12] :**

$$W_i = \sum_{j=1}^{n} R(|X_{ij} - \theta_i|)Sign(X_{ij} - \theta_i) \quad , i = 1, \dots, p \qquad \dots\dots(1)$$

**Where :** $\boldsymbol{R(|X_{ij} - \theta_i|)}$ **is the rank of** $|\boldsymbol{X_{ij} - \theta_i}|$ **among** ($|\boldsymbol{X_{ij} - \theta_i}|$, $\boldsymbol{j = 1, \dots, n}$ ).

$\underline{\boldsymbol{\theta}} = (\boldsymbol{\theta_1, \theta_2, \dots, \theta_p})'$**: median vector for (p) variables .**

$W_i$ **is the sum of the Wilcoxon signed-ranks for the** $(i^{th})$ **quality characteristic . If** $\left(\underline{W} = (w_1, w_2, \dots, w_p)'\right)$ **is a vector of** ( $W_i$ ) **, the asymptotic distribution of** ($n^{-\frac{3}{2}} W$ ) **is multivariate normal with mean vector 0 and covariance matrix** ($L$) **can be consistently estimated with** $(n^{-3}\hat{L})$ **, where (** $\hat{L}$ **) defined by [2]:**

$$\hat{L}_{ii} = \frac{n(n+1)(2n+1)}{6} \quad , i = 1,2, \dots, p \qquad \dots\dots(2)$$

$$\hat{L}_{ij} = \sum_{k=1}^{n} R(|X_{ik} - \theta_i|)R(|X_{jk} - \theta_j|)Sgn\,(X_{ik} - \theta_i)Sgn(X_{jk} - \theta_j) \qquad \dots\dots(3)$$

**Then the Wilcoxon signed-rank chart statistic :**

$$SR^2 = W'\,\hat{L}^{-1}W \quad \dots\dots(4)$$

**The upper limit of the Wilcoxon chart is determined by using the** $(\chi^2)$ **distribution as follow[7] :**

$$UCL_{SR^2} = \chi^2_{\alpha,P} \qquad \dots\dots(5)$$

## (4-2) Kernel Principal Component Analysis Control Chart (KPCA-Chart)

**Kernel principal component analysis chart is based on calculating Hotelling's statistic** $(T^2)$ **for the (KPC) matrix , which is calculated by applying the (KPCA) algorithm on the covariance matrix to monitor the characteristics and discover the influence .**

**First choose the kernel function, which is based on Parameter Smothing , and then Calculate the matrix kernel by[1]:**

$$K = K_{ij} = \Omega(x_i)\Omega(x_j) \qquad i = 1, \dots, n, j = 1, \dots, n$$

**After that, calculate the (KPC) as follow :**

$$p_i = \sum_{j=1}^{n} \alpha_{ij} K\,(x_i, x_j) \qquad \dots\dots(6)$$

**From the first $l$ principal component $p$ , calculate the T2 statistics using the following equation:**

$$\tilde{T}_K^2 = \sum_{i=1}^{l} \quad p_i \lambda_i^{-1} p_i^T \qquad \dots \dots (7)$$

**where i=1,…, $l$, and $\lambda_i$ eigenvalues that correspond to i-th PCs.**
**The control limit for this panel is determined based on the kernel density estimation (KDE) .**
**Estimate the empirical density of $\tilde{T}_K^2$ statistics as follow[10] :**

$$\hat{f}_h = \frac{1}{n\hat{h}} \sum_{i=1}^{n} \quad K\left(\frac{T^2 - \tilde{T}_{K,i}^2}{\hat{h}}\right) \qquad \dots \dots (8)$$

**The cumulative distribution :**

$$\hat{F}_h(\tilde{T}_K^2) = \int_0^{\tilde{t}_K^2} \quad \hat{f}_h(\tilde{T}_K^2) d(\tilde{T}_K^2) \qquad \dots \dots (9)$$

**By using the trapezoid rule :**

$$\int_{\pi_{min}}^{\pi_{max}} \quad \hat{f}_h(\tilde{T}_K^2) d(\tilde{T}_K^2) \approx \frac{\pi_{max} - \pi_{min}}{2n} \sum_{i=1}^{n} \quad (\hat{f}_h(\tilde{T}_{K,i}^2) + \hat{f}_h(\tilde{T}_{K,(i+1)}^2))$$

**where $(\pi_{max}, \pi_{min})$ are the maximum and minimum value of $(\tilde{T}_K^2)$ .**
**So, the control limit compute as follow [11]:**

$$CL = \hat{F}_h(\tilde{t}_k^2)^{-1}(1 - \alpha) \qquad \dots \dots (10)$$

## (4-3) K-Nearest Neighbor control chart $(\mathrm{K}^2 - \mathrm{CHART})$ :

**$K^2$ chart is based on K-Nearest Neighbor algorithm which is a nonparametric supervised classification method [15] . It has been hugely used since the 1960s when computational complexities were resolved [9] .**
**Let $NN_i(x)$ be the i-th nearest neighbor training observation of data point that needs to be monitored . The local density d(x) of x can be calculated as[4] :**

$$d(x) = \frac{\frac{i}{N}}{V(\|x - NN_i(x)\|)} \dots \dots (11)$$

**Where**
**: the volume of the hypersphere containing $i$ nearest neighbor training observations**
***N*: the size of the training set.**
**Similarly, calculate the local density of $(NN_i(x))$ as follow :**

$$d(NN_i(x)) = \frac{\frac{i}{N}}{V(\|NN_i(x) - NN_i(NN_i(x))\|)} \dots (12)$$

**Where $NN_i(NN_i(x))$ ) is the $i$th nearest neighbor of $NN_i(x)$ in the same training set.**
**KNN calculates the average distances K considering (i = 1,…, k) by taking the ratio of the local density d(x) to the local density d$NN_i(x)$ which must be greater or equal to one**

$$\frac{d(x)}{d(NN_i(x))} = \frac{\sum_{i=1}^{k} \quad \|NN_i(x) - NN_i(NN_i(x))\|}{\sum_{i=1}^{k} \quad \|x - NN_i(x)\|} \geq 1$$

**$K^2$ statistics which representing the average distance between x and the k-nearest observations can be computed as follow[5] :**

$$k^2 = \frac{\sum_{i=1}^{k} \quad \|x - NN_i(x)\|}{k} \ldots (13)$$

**Determining the control limit for this chart based on a quantile estimation through the bootstrap method, a widely used resampling method .**

**So, to calculate the upper limit of control, we draw random samples (Bootstrap) whose number is B ,and it observations represent the values of $k^2$ statistics .**

$$k^2{}_{1j}, k^2{}_{2j}, \ldots, k^2{}_{Nj} \quad j = 1, \ldots, B \quad \ldots (14)$$

**Then we determine the value of the percentage $(100(1-\alpha)^{th})$ and the false alarm rate $\alpha$ , whose value ranges between (1< $\alpha$ <0) for each sample (Bootstrap), and therefore the upper control limit is calculated from the following formula [16].**

$$CL = \sum_{j=1}^{M} \quad \frac{k_{ij}^2}{B} \quad \ldots (15)$$

## 5- Average Run Length :

**Average Run Length (ARL) is one of the commonly used criteria to compare the performance of multivariate quality control charts. It is also known as the number of samples that must be determined before the process is registered as out of control [7] and the it is used to detect whether the process suffers from deviations, and ARL can be defined by the false alarm rate as it gives an indication that the process is out of control [3] . ARL is calculated from the following formula:**

$$ARL = \frac{1}{\alpha} \quad \ldots (16)$$

**$\alpha$: False Alert Rate , type error I**

**When real (ARL) value is near to default (ARL) value indicates to efficiency performance of control chart .**

## 6- Simulation :

**Simulations are used to evaluate new methods, to compare alternative methods, to validate simulation results, and to explain and support recommendations . Simulation involves generating data by sampling randomly from known probability distributions using sophisticated computer programs.**

## 7- Simulation description :

**The random variables related to the simulation experiments were generated beads on mean vector and covariance matrix for (18) variables representing the governorates of Iraq, including data on the numbers of people infected with the new Coronavirus .The control charts that were dealt with in the theoretical part of the research were found , which are the Wilcoxon map, the KPCA map with the kernel function (Gaussian), and the($K^2$ chart) map with a frequency of (B=1000) to calculate the upper limit . To analyze and compare the performance of the estimated control charts, the average run length (ARL) was estimated at the near, medium and long levels, at the levels of significance α = (0.1, ,0.02,0.01, ,0.002) and for sample (45,90,180,360) .**

## 8-Simulation results :

Tables (1),(2),(3) and (4) show the results of the (ARL) criterion for all control charts by using four different distributions; they are the multivariate normal distribution (N) and the skew multivariate normal distribution (SRN) and the t-distribution with two degrees of freedom (10,20) . The following table one contains results of default (ARL) at α = (0.1) .

**Table (1) default (ARL) at α = (0.1) $ARL_o$=10**

| | n | $SR^2$ | KPCA | $K^2$ |
|---|---|---|---|---|
| N | 45 | 8.807 | 7.903 | 8.423 |
| | 90 | 8.203 | 6.281 | 6.696 |
| | 180 | 6.829 | 6.201 | 6.445 |
| | 360 | 1.821 | 0.560 | 1.462 |
| SNR | 45 | 8.044 | 9.364 | 9.691 |
| | 90 | 6.055 | 8.154 | 8.620 |
| | 180 | 4.880 | 7.301 | 8.091 |
| | 360 | 3.794 | 6.651 | 7.602 |
| $t_{10}$ | 45 | 5.834 | 5.971 | 6.174 |
| | 90 | 4.549 | 5.804 | 5.990 |
| | 180 | 3.939 | 4.704 | 4.704 |
| | 360 | 3.425 | 3.768 | 3.768 |
| $t_{20}$ | 45 | 5.389 | 6.397 | 6.691 |
| | 90 | 4.205 | 5.765 | 6.356 |
| | 180 | 4.229 | 5.156 | 5.237 |
| | 360 | 3.939 | 5.041 | 5.218 |

Table (1) shows that at normal distribution the default (ARL) values for all control charts are less than the real (ARL) values , and $(SR^2)$ chart has the best performance , since it has the closest default (ARL) values (8.807at n=45, 8.203 at n=90 ,6.829 at n=180 ,1.821 at n=360) from real (ARL) value ($ARL_o$=10) . then $(K^2)$ chart with default (ARL) (8.423at n=45 ,6.696 at n=90 ,6.445 at n=180 ,1.462 at n=360) . At (SNR) distribution $(K^2)$ chart has best performance default (ARL) (9.961 at n=45 ,8.620 at n=90 ,8.091 at n=180 ,7.602 at n=360) then (KPCA) chart. $(K^2)$ Chart performance is still with same efficiency at t-distribution (6.174) at $(t_{10})$ and (6.961) at $(t_{20})$ , when n=45 . The following figures show the performance of charts .

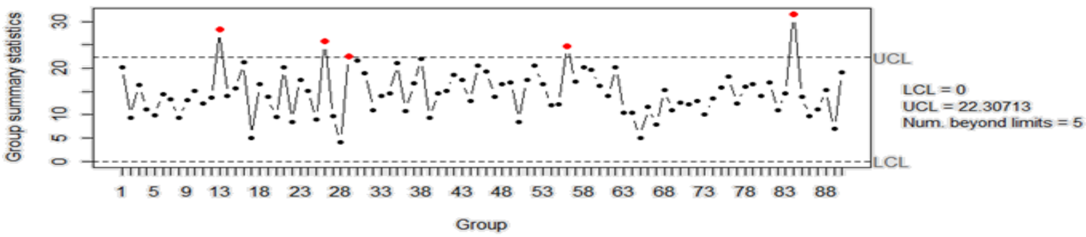


Figure (1) $(SR^2)$ chart by using simulation at α = (0.1)

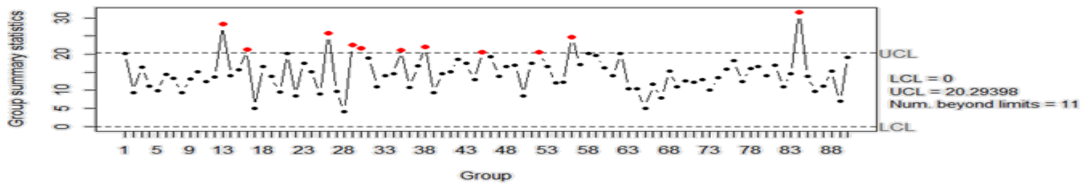


**Figure (2) $(KPCA)$ chart by using simulation at α = (0.1)**

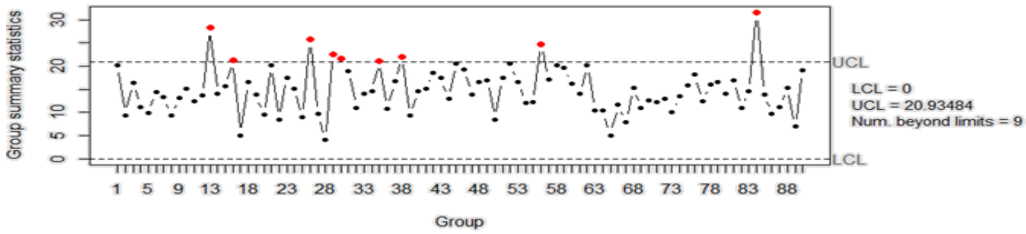


**Figure (3) $(K^2)$ chart by using simulation at α = (0.1)**

**The figures above show that some of observations are passed control limits , and the chart $(SR^2)$ has the lowest number of out-of-control observations only (5), $(K^2)$ chart has (9) out-of-control observations and (KPCA) chart has (11) observations , which means that the process of monitoring α = 0.1 is out of control . Table (2) shows results of (ARL) at α = (0.02) .**

**Table (2) default (ARL) at α = (0.02) $ARL_0$=50**

| | n | $SR^2$ | KPCA | $K^2$ |
|---|---|---|---|---|
| N | 45 | 50 | 44.039 | 44.039 |
| | 90 | 45.855 | 42.742 | 42.742 |
| | 180 | 45.75 | 41.587 | 41.587 |
| | 360 | 43.946 | 25.421 | 25.421 |
| SNR | 45 | 49.796 | 49.978 | 50 |
| | 90 | 48.333 | 49.49 | 49.805 |
| | 180 | 45.509 | 48.301 | 48.761 |
| | 360 | 44.611 | 47.74 | 47.773 |
| $t_{10}$ | 45 | 31.985 | 39.202 | 41.376 |
| | 90 | 30.413 | 31.229 | 31.229 |
| | 180 | 24.017 | 26.488 | 26.488 |
| | 360 | 18.841 | 20.959 | 21.868 |
| $t_{20}$ | 45 | 31.985 | 45.222 | 48 |
| | 90 | 31.611 | 32.26 | 37.269 |
| | 180 | 28.531 | 32.035 | 33.332 |
| | 360 | 25.784 | 26.09 | 26.09 |

**From table (2) note that $(SR^2)$ chart completely reached (50) when n=45 at the normal distribution , which means that it has best performance . At (SNR) distribution $(K^2)$ chart has best performance ; it gives default (ARL) values close to the real value and reached (50 at n=45) followed by (KPCA) chart with default value (49.978 at n=45) then $(SR^2)$ chart. At t-distribution $(K^2)$ chart has best performance with default (ARL) value (41.376 at $(t_{10})$) and (48 at $(t_{20})$) when n=45. Figures (4,5,6) represented the performance of control charts.**

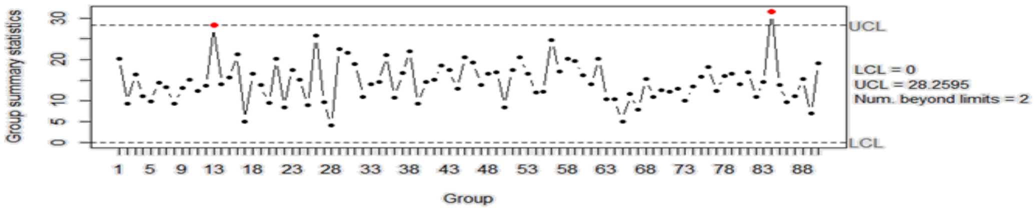


**Figure (4) $(SR^2)$ chart by using simulation at α = (0.02)**

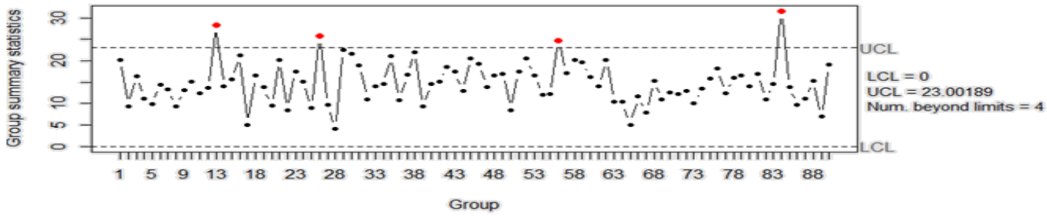


**Figure (5) $(KPCA)$ chart by using simulation at α = (0.02)**

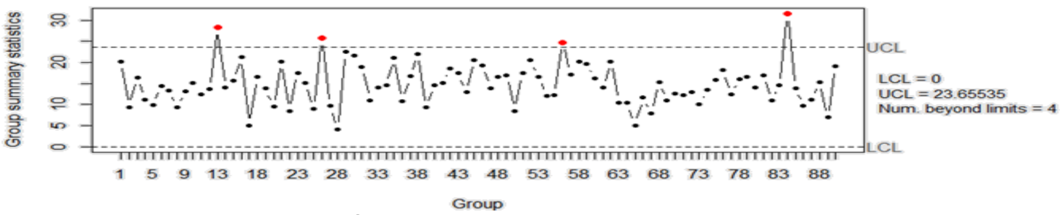


**Figure (6) $(K^2)$ chart by using simulation at α = (0.02)**

**From the figure (4) $(SR^2)$ chart has (2) observation out of control , while from figures (5) and (6) each $(K^2)$ chart and $(KPCA)$ chart have (4) observations out of control, which means that the process is out of control . Table (3) represented results of ARL for all charts at α = (0.02) .**

**Table (3) default (ARL) at α = (0.01) $ARL_o$=100**

| | n | $SR^2$ | KPCA | $K^2$ |
|---|---|---|---|---|
| N | 45 | 100 | 94.329 | 94.329 |
| | 90 | 100 | 85.485 | 87.271 |
| | 180 | 100 | 83.175 | 83.175 |
| | 360 | 98.809 | 50.41 | 50.842 |
| SNR | 45 | 99.98 | 100 | 100 |
| | 90 | 98.606 | 99.801 | 99.946 |
| | 180 | 96.59 | 98.721 | 99.321 |
| | 360 | 94.555 | 97.646 | 98.95 |
| $t_{10}$ | 45 | 66.912 | 82.752 | 90.444 |
| | 90 | 61.779 | 62.459 | 62.459 |
| | 180 | 50.357 | 53.77 | 53.77 |
| | 360 | 40.713 | 43.736 | 43.736 |
| $t_{20}$ | 45 | 66.912 | 96 | 100 |
| | 90 | 63.223 | 76.037 | 76.037 |
| | 180 | 57.65 | 65.46 | 66.665 |
| | 360 | 51.568 | 52.181 | 52.181 |

From table (3) at α = (0.02) and $ARL_o$=100 , $(SR^2)$ chart completely reached (100) when n=(45,90,180 ) and (98,809) when (n=360) at the normal distribution , so it has the best performance . At (SNR) distribution $(K^2)$ chart and $(KPCA)$ chart have reached (100 at n=45), $(K^2)$ chart performed efficiency then $(KPCA)$ chart and $(SR^2)$ chart. At t-distribution $(K^2)$ chart has the best default (ARL) value (90.444 at $(t_{10})$) and (100 at $(t_{20})$) when n=45, which mean it has best performance . Figures next represented the performance of control charts when α = (0.01) .

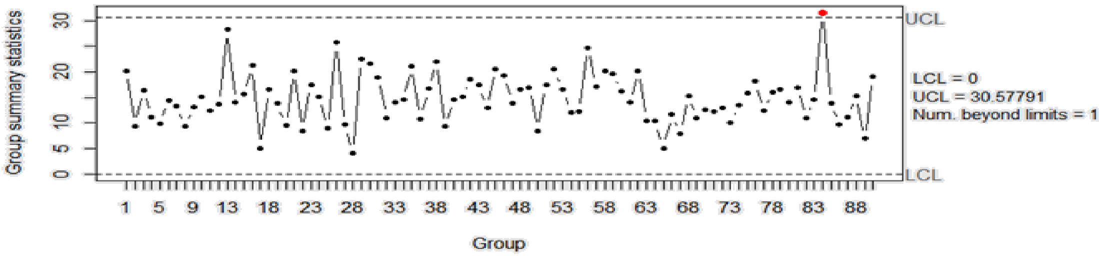


**Figure (7)** $(SR^2)$ **chart by using simulation at α = (0.01)**

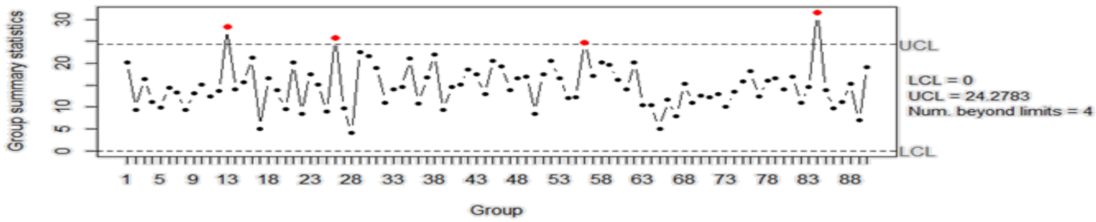


**Figure (8)** $(KPCA)$ **chart by using simulation at α = (0.01)**

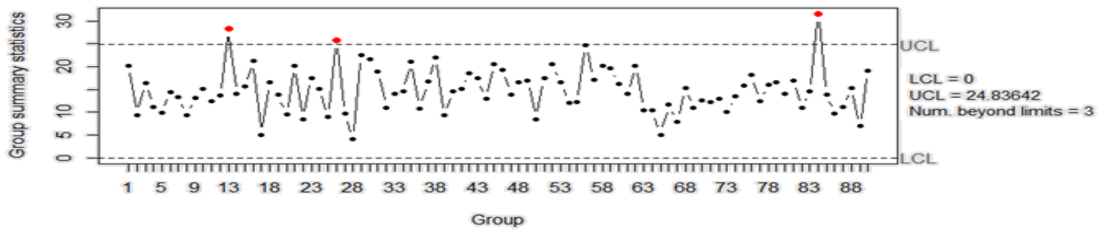


**Figure (9)** $(K^2)$ **chart by using simulation at α = (0.01)**

From the figures above note that process of monitoring is out of control at α = (0.01) , chart $(SR^2)$ has the lowest number of out-of-control observations just (1) , $(K^2)$ chart has (3) and (KPCA) has (4) observations out of control .

**Table (4) default (ARL) at α = (0.002) $ARL_o$=500**

| | n | $SR^2$ | KPCA | $K^2$ |
|---|---|---|---|---|
| N | 45 | 500 | 440.397 | 471.647 |
| | 90 | 500 | 494.047 | 494.047 |
| | 180 | 500 | 457.506 | 457.506 |
| | 360 | 500 | 448.85 | 455.108 |
| SNR | 45 | 500 | 500 | 500 |
| | 90 | 499.241 | 499.988 | 500 |
| | 180 | 495.945 | 499.138 | 499.84 |
| | 360 | 495.441 | 498.414 | 499.29 |
| $t_{10}$ | 45 | 371.188 | 428.501 | 480 |
| | 90 | 317.412 | 413.76 | 428.501 |
| | 180 | 312.296 | 331.556 | 331.556 |
| | 360 | 268.854 | 268.854 | 268.854 |
| $t_{20}$ | 45 | 372.609 | 415.021 | 421.882 |
| | 90 | 371.188 | 402.643 | 402.643 |
| | 180 | 317.843 | 333.325 | 340.394 |
| | 360 | 260.908 | 265.537 | 278.441 |

**From table (4) at the same way default (ARL) values by using $(SR^2)$ chart are close to the real (ARL) value $ARL_o$=500 it reached ( 500 at all simple size) . At (SNR) distribution $(K^2)$ chart ,$(KPCA)$ chart and $(SR^2)$ chart have reached (500 at n=45), but $(K^2)$ chart performed efficiency then $(KPCA)$ chart and $(SR^2)$ chart. At t-distribution $(K^2)$ chart has default (ARL) value (480 at $(t_{10})$) and (421 at $(t_{20})$) when n=45, it close to the real (ARL) value at all sample size , which mean it has the best performance . Figures next represented the performance of control charts when α = (0.002) .**

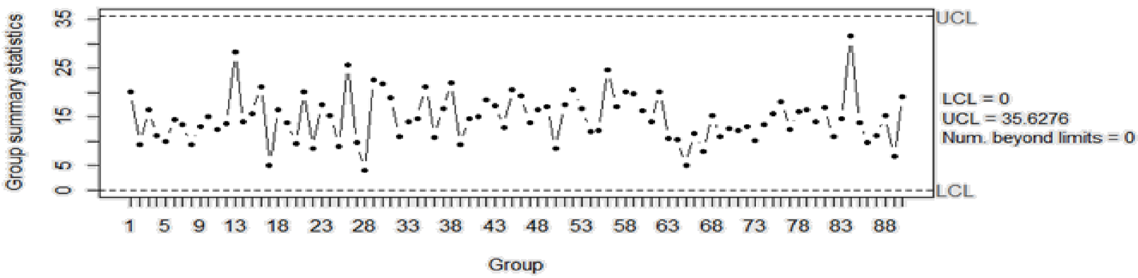


**Figure (10) $(SR^2)$ chart by using simulation at α = (0.002)**

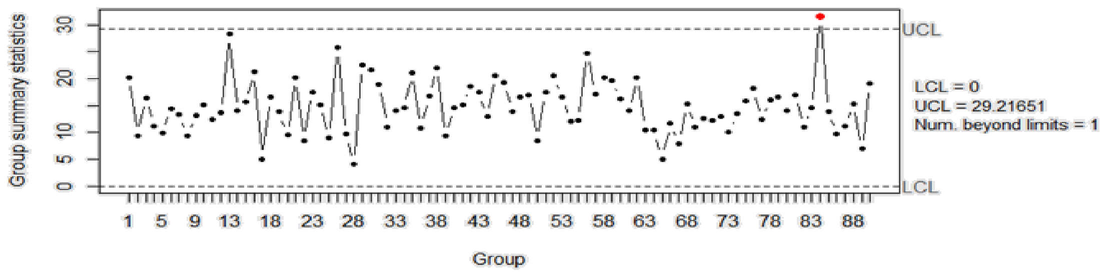


**Figure (11) $(KPCA)$ chart by using simulation at α = (0.002)**

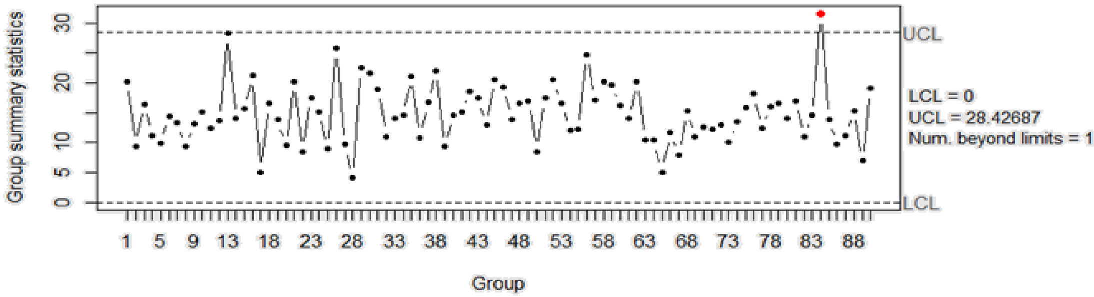


Figure (12) $(K^2)$ chart by using simulation at α = (0.002)

From previous figures note that $(SR^2)$ chart has no observations out of control; each $(K^2)$ chart and $(KPCA)$ chart have (1) observation out of control . So, there is improvement at the performance when values of (α) decrease .

## 9-Conclusion:

Through the application of simulation experiments, note that:

1. The process of monitoring was out of control, because some calculated statistics of the charts exceeds their upper limit control .
2. $(SR^2)$ Chart has the lowest number of out-of-control observations at all significant levels .
3. When values of (α) decrease default values of (ARL) for non- parametric control charts close to real (ARL) values .
4. The increase at sample size leads to diverge default values of (ARL) from real (ARL) values because increasing the sample size leads to an increase in the number of out-of-control observations at different significant level .

## 10-Further Work:

Expanding the use of multivariate non-parametric control charts due to the lack of applicable assumptions when using them . Application of other control charts in different fields to monitor deviations and changes in the control process.

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# مقارنة بعض طرائق السيطرة النوعية اللامعلميه

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**مستخلص البحث:**

تم استعمال لوحات السيطرة النوعية اللامعلميه متعددة المتغيرات لمراقبة البيانات التي تم توليدها باستعمال المحاكاة هل هي ضمن حدود السيطرة ام لا , حيث ان الطرائق اللامعلميه لا تتطلب افتراضات حول توزيع البيانات . يهدف البحث الى تطبيق طرائق السيطرة النوعية اللامعلمية متعددة المتغيرات وهي لوحة السيطرة ولكوكسن لإشارة الرتب متعددة المتغيرات ($SR^2$)) ولوحة السيطرة المركبات الرئيسة اللبية (KPCA)) و لوحة السيطرة الجار الاقرب ($K^2-CHART$) (K) اللامعلميه متعددة المتغيرات ومن ثم المقارنة بين أدائها باستعمال معيار متوسط طول المدى (Average Run Length (ARL)) وذلك بالاعتماد على تجارب المحاكاة عند مستويات معنوية مختلفة لتوضيح عمل لوحات السيطرة اللامعلميه . و اظهرت النتائج ان اعداد الاصابة بفيروس كورونا المستجد خارجة عن حدود السيطرة , وان لوحة ($K^2-CHART$) كان ادائها افضل على المدى القصير مع وجود تساوي نسبي في الاداء بين لوحة (KPCA)) و ($K^2-CHART$) على المدى المتوسط و البعيد .

**المصطلحات الرئيسة للبحث/** السيطرة النوعية , لوحات السيطرة اللامعلميه , متوسط طول المدى , الجوار الاقرب (K) , المركبات الرئيسة اللبية ، ولكوكسن لإشارة الرتب .

*البحث مستل من رسالة ماجستير