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Construction of the Daubechies Wavelet Chart for Quality Control of the Single Value

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Abstract

In this paper, it was proposed to create a new quality control chart for the single value of the Daubechies wavelet to address the problem of data contamination before creating the single value chart and comparing it with the classical Shewhart single value chart. The proposed charts are an application of wavelet shrinkage and a universal threshold estimation method with a soft threshold rule to address the contamination problem and de-noise data to obtain a more efficient chart in controlling the single value and increasing the sensitivity of the chart in detecting minor changes that may occur in the production process. Accordingly, a single chart for the Daubechies wavelet with orders (1, 2, and 3) was proposed and applied to randomly generated data (simulated) for several cases, then real data and some efficiency indicators of the proposed charts were calculated and compared with the classical chart based on the MATLAB program. The paper results showed that all proposed charts were better than the classical chart for single values for all simulation cases and real data.

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1. Introduction

Wavelet analysis hybrid control charts offer a sophisticated approach to process monitoring and quality control by integrating wavelet analysis with traditional control chart techniques. This hybrid approach enables the detection of both abrupt and gradual changes in process behaviour across multiple scales or frequencies [1]. By decomposing process data into different levels of resolution, wavelet analysis enhances the sensitivity of control charts to detect subtle shifts or patterns that may go unnoticed with conventional methods. The integration of wavelet analysis into control charting processes provides a comprehensive framework for early anomaly detection, leading to more proactive and effective process management, improved product quality, and enhanced productivity [2]. Wavelet control charts are a powerful tool used in statistical process control to monitor and detect deviations or abnormalities in processes. Unlike traditional control charts, which rely on fixed time intervals or sample sizes, wavelet control charts adaptively analyze data at multiple resolutions, allowing for the detection of both large and small shifts in the process. This introduction explores the principles, advantages, and applications of wavelet control charts in ensuring the quality and stability of manufacturing and industrial processes. Control charts play a crucial role in production by providing real-time insights into process variability and performance [3]. By continuously monitoring key process parameters, control charts allow production teams to detect deviations from the desired target or specifications [4]. This early detection enables prompt corrective actions, minimizing defects, reducing waste, and optimizing product quality. Ultimately, control charts contribute to enhancing efficiency, consistency, and reliability in production processes, leading to improved customer satisfaction and competitiveness in the market [5].

2. Quality Control Charts

Quality control charts, also known as statistical process control (SPC) charts, are tools used in manufacturing and other industries to monitor and control processes over time [6]. They help identify variations or abnormalities in a process that may lead to defects or deviations from desired outcomes. Common types of quality control charts include [7]:

I. X-Bar and R Charts: Used for monitoring the central tendency (mean) and variability (range) of a process.
II. Individuals and Moving Range (I-MR) Charts: Suitable for monitoring individual data points and their moving ranges, especially when the sample size is one.
III. P Charts: Used for monitoring the proportion of defective items in a sample over time.
IV. NP Charts: Similar to P charts but used when the sample size remains constant.
V. C Charts: Used for monitoring the count of defects per unit.
VI. U Charts: Similar to C charts but used when the sample size varies.

These charts typically consist of plotted data points along with control limits that indicate the expected variation in the process. When data points fall outside these limits or display non-random patterns, it suggests that the process may be out of control and require investigation and corrective action. Quality control charts are essential for ensuring consistent product quality and process improvement [8].

2.1. The Shewhart Control Chart for Individual Values

The Shewhart Control Chart for Individual Values is a quality control tool used to monitor processes where the sample size is one [9]. This chart plots individual data points against time or sequence order. It helps detect shifts or trends in the process over time.

- Center Line (CL): Represents the process mean for the individual chart.
- Upper Control Limit (UCL) and Lower Control Limit (LCL): These lines are typically set at ±3 standard deviations from the center line for the individual's chart, and they indicate the range of variation expected from common causes of variation in the process.

2.2. Kolmogorov–Smirnov Test

The Kolmogorov-Smirnov test is a statistical method used to determine if a sample comes from a specific probability distribution. It compares the cumulative distribution function (CDF) of the sample data with the CDF of the theoretical distribution.
There are two versions of the test [10]:

I. One-sample Kolmogorov-Smirnov test: This version is used when you want to test if a sample follows a specific distribution. It compares the empirical distribution function of the sample with the theoretical distribution function.

II. Two-sample Kolmogorov-Smirnov test: This version is used to test if two independent samples come from the same distribution. It compares the empirical distribution functions of the two samples.

The test produces a test statistic, D, which represents the maximum absolute difference between the two CDFs. The null hypothesis assumes that the sample is drawn from the specified distribution. If the calculated D statistic exceeds a critical value from the Kolmogorov-Smirnov distribution, then the null hypothesis is rejected, indicating that the sample does not follow the specified distribution.

The Kolmogorov-Smirnov test is non-parametric, meaning it makes no assumptions about the underlying distribution of the data. However, it is sensitive to differences in both location and shape of the distributions being compared [11].

3. Wavelet Shrinkage

Wavelet shrinkage is a technique used in signal, data and image processing for denoising and compression. It’s based on wavelet transforms, which decompose signals into different frequency components, allowing for both localizations in time and frequency.

In wavelet shrinkage, noisy data are decomposed using a wavelet transform, typically into wavelet coefficients at different scales. Then, a thresholding operation is applied to these coefficients to remove or shrink those that are considered to be noise, while retaining those that represent the de-noise data or important features [12].

Wavelet shrinkage offers advantages over classical denoising methods by being able to adaptively remove noise while preserving data features at different scales [13]. It has applications in various fields such as medical imaging, audio signal processing, and de-noise data (dealing with contamination problems).

3.1 Daubechies Wavelet

The Daubechies wavelet, named after the Belgian mathematician Ingrid Daubechies, is a family of orthogonal wavelets used in signal processing and de-noise data. These wavelets are known for their compact support, symmetry, and orthogonality, making them popular choices in various applications [14]. Key features of Daubechies wavelets include:

I. Orthogonality: Daubechies wavelets form an orthogonal basis for data decomposition, meaning they preserve energy and information during transformation.

II. Compact Support: Unlike some other wavelet families, Daubechies wavelets have finite support, which means they are non-zero over a finite interval. This property is advantageous for localized signal analysis.

III. Variability: The Daubechies wavelet family includes several members, such as Daubechies D2, D3, D4, D5, and so on, each characterized by a different number of vanishing moments. More vanishing moments typically allow for better time-frequency localization and smoother scaling functions.

IV. Wavelet Transform: The discrete wavelet transforms (DWT) using Daubechies wavelets decompose a signal into approximation and detail coefficients at different scales [15]. This decomposition facilitates signal analysis, denoising, compression, and feature extraction.

Daubechies wavelets find applications in diverse fields such as image and signal processing, de-noise data, feature extraction, and pattern recognition. Their properties make them well-suited for tasks requiring efficient representation of data with localized features [16].

3.2 Universal Thresholding

Universal thresholding is a method commonly used in wavelet shrinkage for denoising data or images. It’s a thresholding technique that aims to automatically select an optimal threshold value based on the statistical properties of the data [17].

The idea behind universal thresholding is to estimate the noise level in the data and then apply a threshold that adapts to this noise level. One popular method for universal thresholding is Stein’s unbiased risk estimate (SURE), which provides an unbiased estimate of the mean squared error (MSE) of the denoised signal [18]. The threshold value is then chosen to minimize this estimated MSE.

The SURE threshold is often referred to as the “universal threshold” because it works well across a wide range of data and noise types without requiring prior knowledge of the noise characteristics [19]. By adaptively selecting the threshold based on the data itself, universal thresholding can effectively remove noise while preserving important data features.

Universal thresholding is particularly useful in applications where the noise level may vary across different parts of the data, or when the noise characteristics are not known in advance. It has been successfully applied in fields such as image and de-noise data, where accurate denoising is crucial for subsequent analysis or visualization [20]. Given the universal threshold that [21] Proposed:

$$\lambda^{U} = \hat{\sigma}_{(MAD)}\sqrt{2\log N} \tag{1}$$

Where N is the number of observations, and is the estimator of the standard deviation of details coefficients, which is estimated as [22]:

$$\hat{\sigma}_{(MAD)} = \frac{MAD}{0.6745} \tag{2}$$

The wavelet coefficients' median absolute deviation at the finest scale [23], or MAD, is defined as.

$$MAD = median\left[\left|W_{1,0}\right|, \left|W_{1,1}\right|, \ldots, \left|W_{1,\frac{N}{2}-1}\right| \right] \quad (3)$$

$W1 = W1,0,\ W1,1,\ \ldots,\ W1,\ N/2-1$ which represents the discrete wavelet transformation coefficients at the first level for observation while the constant (0.6745) is the median of the standard normal distribution [24].

3.3 Soft Threshold Rule

Soft thresholding is a technique used in signal and image processing, particularly in the context of wavelet shrinkage. It involves shrinking or reducing the magnitude of wavelet coefficients by a certain threshold without setting them exactly to zero. The soft thresholding function is defined as follows [25]:

$$Wn^{(st)} = sign\ \{Wn\}\ \left(\left|Wn\right| - l\right)+ \quad (4)$$

Where l represents the threshold value and:

$$Sign\{Wn\} = \begin{bmatrix} +1 & if\quad Wn > 0 \\ 0 & if\quad Wn = 0 \\ -1 & if\quad Wn < 0 \end{bmatrix} \quad (5)$$

and

$$\left(\left|Wn\right| - l\right)_{+} = \begin{bmatrix} \left(\left|Wn\right| - l\right) & if\quad \left(\left|Wn\right| - l\right) \geq 0 \\ 0 & if\quad \left(\left|Wn\right| - l\right) < 0 \end{bmatrix} \quad (6)$$

4. Proposed Chart

The proposed method is to use a Daubechies Wavelet (1, 2, and 3) to de-noise data (even if it does not include adding contamination to it) with a Universal thresholding type and a soft threshold rule to obtain the filtered data that will be used in the construction proposed chart for Quality Control of the single value (use de-noise data in determining quality control limits). Then compare it with the classical chart.

5. Application aspect

In the simulation study, a single quality control chart was simulated and then applied to the real data based on variance and difference to compare the effectiveness and precision of the estimated variance and the difference between the upper and lower control limits between the proposed and classical charts. A program in MATLAB (version 2022a) language was created specifically for this purpose application (Appendix).

5.1. Simulation study

For the first experiment from simulation, with a variance (4), and a total number of observations of 25. The classical chart and the proposed chart of Daubechies (1, 2, and 3) wavelets are shown in Figure 1.

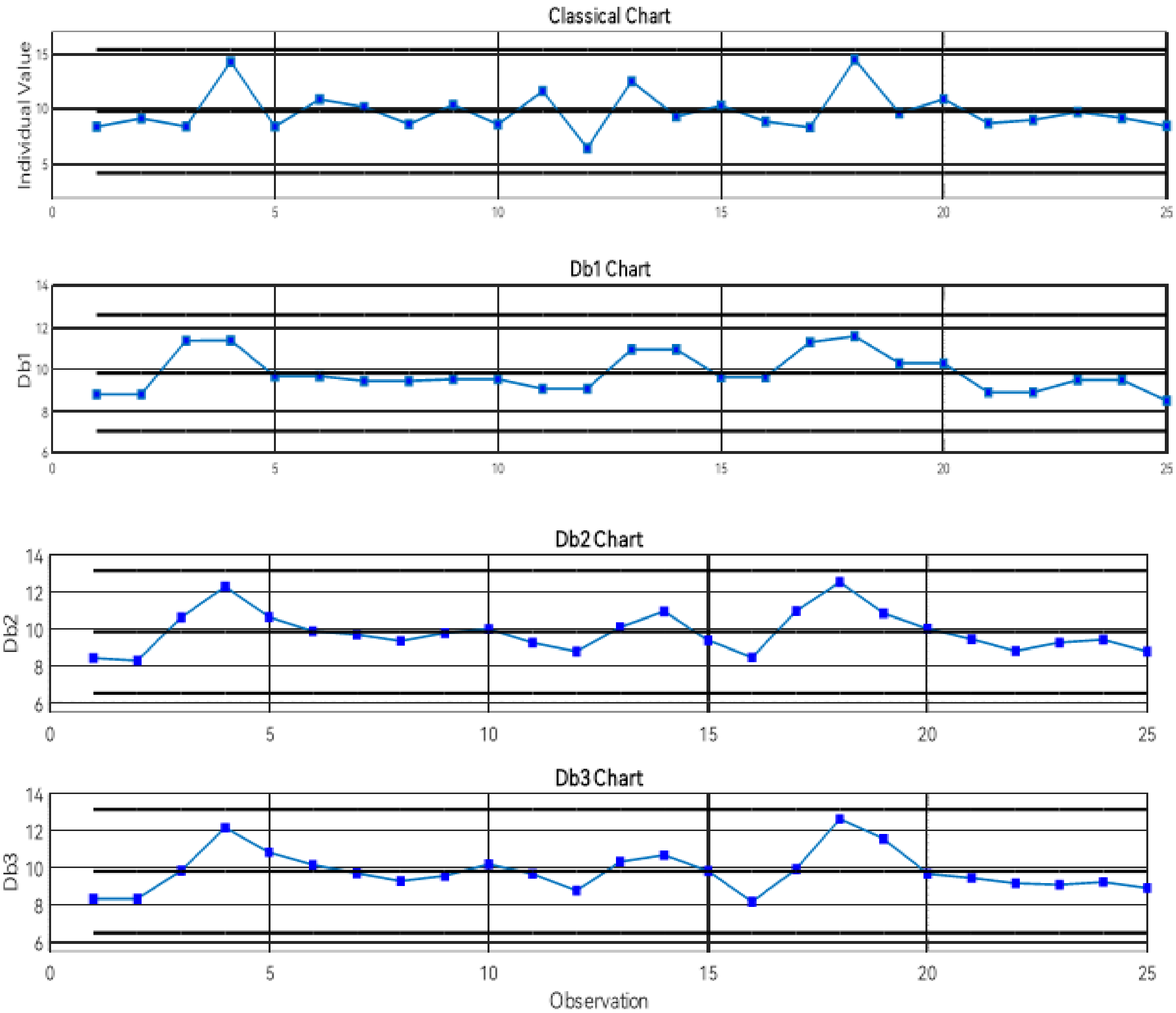

Figure 1. Classical and Proposed Chart for the First Experiment

Figure 1 shows that in Phase I, all points lie within the control limits for all four charts and can therefore be relied upon in the future (Phase II) to control the qualitative characteristic of the single value. The simulation results of the first experiment for the classical and proposed charts are summarized in Table 1:

Table 1. Results of the First Experiment (m = 25, Mean = 10, and Variance = 4)

Chart	LCL	CL	UCL	Difference	Variance	p-value
Classical	4.2360	9.8126	15.3892	11.1532	3.4554	0.3676
Db1	7.0358	9.8126	12.5893	**5.5535**	**0.8567**	0.0840
Db2	6.5041	9.8255	13.1469	6.6428	1.2257	0.7852
Db3	6.4845	9.8110	13.1375	6.6530	1.2295	0.6401

Table .1 shows that all the proposed charts were better than the classical chart, depending on the difference and variance, while the first proposed chart (Db1) was the best compared to the rest of the proposed charts. The original and de-noise data followed a normal distribution based on the Kolmogorov–Smirnov test, which has a p-value greater than the significant level (0.05). That is, the de-noise data maintained the normal distribution generated from it.

The experiment was repeated (1000) times generated for the normal distribution, m = 25 and 30 observations (number of sub-samples), 4 and 25 variances. The average of the difference, variance, p-value and control limits was calculated, and the results are summarized in Tables 2-5:

Table 2. Average Results of the Simulation (m = 25, Mean = 10, and Variance = 4)

Chart	LCL	CL	UCL	Difference	Variance	p-value
Classical	3.9892	9.9839	15.9788	11.9896	4.0712	0.7858
Db1	5.7929	9.9839	14.1750	8.3821	2.0304	0.4985
Db2	5.8884	9.9832	14.0780	**8.1896**	**1.9374**	0.7435
Db3	5.8774	9.9836	14.0898	8.2125	1.9491	0.7499

Table 3. Average Results of the Simulation (m = 25, Mean = 10, and Variance = 25)

Chart	LCL	CL	UCL	Difference	Variance	p-value
Classical	-5.0271	9.9599	24.9470	29.9741	25.4452	0.7858
Db1	-0.5177	9.9599	20.4376	20.9553	12.6897	0.4985
Db2	-0.2789	9.9581	20.1951	**20.4740**	**12.1088**	0.7435
Db3	-0.3066	9.9590	20.2246	20.5312	12.1822	0.7499

Table 4. Average Results of the Simulation (m = 30, Mean = 10, and Variance = 4)

Chart	LCL	CL	UCL	Difference	Variance	p-value
Classical	3.9962	9.9861	15.9760	11.9799	4.0535	0.7842
Db1	7.0955	9.9861	12.8767	5.7811	0.9982	0.2172
Db2	7.0221	9.9853	12.9484	5.9262	1.04712	0.6110
Db3	7.1599	9.9860	12.8122	**5.6522**	**0.94847**	0.6458

Table 5. Average Results of the Simulation (m = 30, Mean = 10, and Variance = 25)

Chart	LCL	CL	UCL	Difference	Variance	p-value
Classical	-5.0096	9.9652	24.9401	29.9497	25.3345	0.7842
Db1	2.7388	9.9652	17.1916	14.4528	6.2389	0.2172
Db2	2.5554	9.9632	17.3710	14.8156	6.5445	0.6110
Db3	2.8998	9.9651	17.0304	**14.1306**	**5.9279**	0.6458

All the proposed charts were better than the classical chart for all cases because the averages of the variance and difference for the proposed charts were less than the classical chart. The proposed chart (Db2) was better than the other proposed charts for 25 observations, while the proposed chart (Db3) was better than the other proposed charts for 30 observations, also the de-noise data maintained the normal distribution generated from it since all p-values were greater than the significant level (0.05).

6.2. Real data

This part uses an actual dataset from [26] to evaluate the efficacy of the recommended charts. The costs associated with processing loan applications are tracked by a bank's home loan processing unit. Calculated by dividing the total weekly costs by the number of loans processed in a given week, the quantity tracked is the average weekly processing costs.

Table 6. Costs of Processing Mortgage Loan Applications

Week	1	2	3	4	5	6	7	8	9	10
Cost	310	288	297	298	307	303	294	297	308	306
Week	11	12	13	14	15	16	17	18	19	20
Cost	294	299	297	299	314	295	293	306	301	304

Construction of the individual value and proposed charts for the first time (Phase I) is explained in Figure 2.

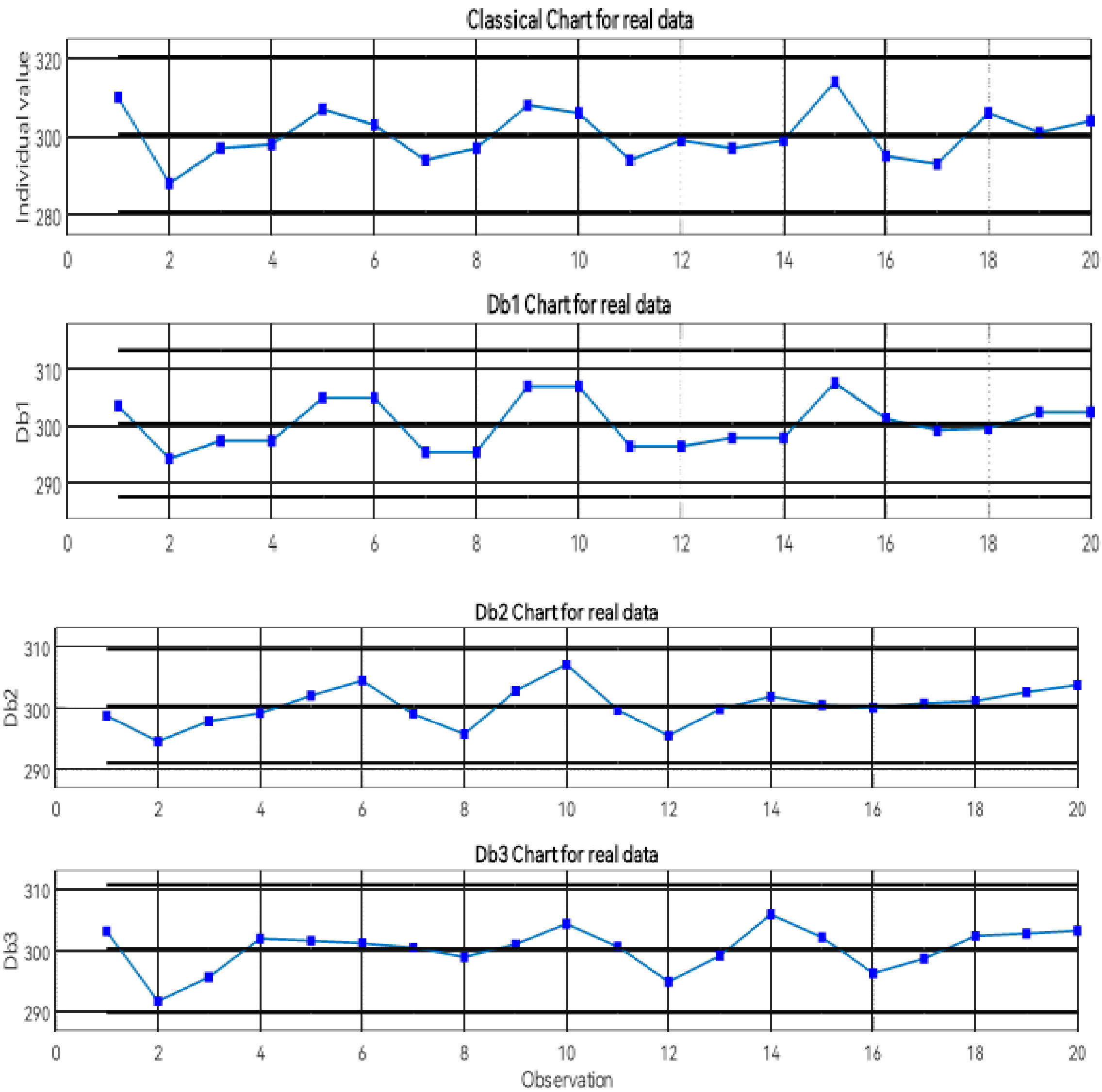

Figure 2. Classical and Proposed Chart for the First Experiment

Figure 2 shows that in Phase I, all points lie within the control limits for all four charts and can therefore be relied upon in the future (Phase II) to control the qualitative characteristic (the costs of processing loan applications) of the single value. The real data results for the classical and proposed charts are summarized in Table 7:

Table 7. Results of real data

Chart	LCL	CL	UCL	Difference	Variance	p-value
Classical	280.7316	300.5000	320.2684	39.5368	43.4211	0.7777
Db1	287.6774	300.5000	313.3226	25.6453	18.2689	0.5482
Db2	291.0379	300.2943	309.5507	**18.5128**	**9.5201**	0.9666
Db3	289.8782	300.2982	310.7182	20.8399	12.0640	0.5501

Table .7 shows that all the proposed charts were better than the classical chart, depending on the difference and variance, while the second proposed chart (Db2) was the best compared to the rest of the proposed charts. The original and de-noise data followed a normal distribution based on the Kolmogorov–Smirnov test (not rejecting the null hypothesis), which has a p-value greater than the significant level (0.05). That is, the de-noise data maintained the normal distribution.

6. Conclusion & Recommendations

Through the study of simulation and real data, the following main conclusions and recommendations were summarized:

6.1. Conclusions

1. All the proposed (Db 1, 2, and 3) charts were better than the classical chart for single values for all cases simulation and real data.
2. The Db2- chart was better than the other proposed charts with 25 observations and real data.
3. The Db3- chart was better than the other proposed charts with 30 observations.
4. The de-noise data maintained the normal distribution for generated and real data.

6.2. Recommendations

1. Using Daubechies Wavelet Chart for Quality Control.
2. Conducting a prospective study on the use of the Daubechies Wavelet with a multivariate Single Value chart.
3. Conducting a prospective study on the use of the other wavelets with a Single Value chart.

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Appendix

```
clc
clear all
randn('seed',1234); n=30;
for j= 1:1000
x=randn(n,1)*5+10; T(j)=mean(x); V(j)=var(x);
UCL(j) = T(j)+3*sqrt(var(x));
LCL(j) = T(j)-3*sqrt(var(x)); D(j)=UCL(j)-LCL(j);
y = (x-mean(x))/sqrt(var(x)); [h p(j)]=kstest(y); p(j)=p(j);
xd = wdenoise(x,'Wavelet','db1', 'DenoisingMethod','universal','ThresholdRule','soft');
Tw(j)=mean(xd); V1(j)=var(xd);
UCLw1(j) = Tw(j)+3*sqrt(var(xd));
LCLw1(j) = Tw(j)-3*sqrt(var(xd)); D1(j)=UCLw1(j)-LCLw1(j);
yd = (xd-mean(xd))/sqrt(var(xd)); [h p1(j)]=kstest(yd); p1(j)=p1(j);
xd2 = wdenoise(x,'Wavelet','db2', 'DenoisingMethod','universal','ThresholdRule','soft');
Tw2(j)=mean(xd2); V2(j)=var(xd2);
UCLw2(j) = Tw2(j)+3*sqrt(var(xd2));
LCLw2(j) = Tw2(j)-3*sqrt(var(xd2)); D2(j)=UCLw2(j)-LCLw2(j);
yd2 = (xd2-mean(xd2))/sqrt(var(xd2)); [h p2(j)]=kstest(yd2); p2(j)=p2(j);
xd3 = wdenoise(x,'Wavelet','db3', 'DenoisingMethod','universal','ThresholdRule','soft');
Tw3(j)=mean(xd3); V3(j)=var(xd3); UCLw3(j) = Tw3(j)+3*sqrt(var(xd3));
LCLw3(j) = Tw3(j)-3*sqrt(var(xd3)); D3(j)=UCLw3(j)-LCLw3(j);
yd3 = (xd3-mean(xd3))/sqrt(var(xd3));
 [h p3(j)]=kstest(yd3); p3(j)=p3(j);
end
r=[mean(LCL) mean(T) mean(UCL) mean(D) mean(V) mean(p)]
r1=[mean(LCLw1) mean(Tw) mean(UCLw1) mean(D1) mean(V1) mean(p1)]
r2=[mean(LCLw2) mean(Tw2) mean(UCLw2) mean(D2) mean(V2) mean(p2)]
r3=[mean(LCLw3) mean(Tw3) mean(UCLw3) mean(D3) mean(V3) mean(p3)]
```

Conflict of interest

The author has no conflict of interest.

تكوين لوحة المويجة دوبشيز لمراقبة جودة القيمة المفردة

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الخلاصة:تم في هذا البحث اقتراح تكوين لوحة سيطرة نوعية جديدة للقيمة المفردة للمويجة دابشيز وذلك لمعالجة مشكلة تلوث البيانات قبل تكوين لوحة القيمة المفردة ومقارنتها مع لوحة شيوارت للقيمة المفردة التقليدية. إن اللوحات المقترحة هي تطبيق لانكماش المويجات وطريقة تقدير قطع العتبة الشاملة مع قاعدة قطع العتبة الناعمة لمعالجة مشكلة التلوث وتقليل ضوضائية البيانات للحصول على لوحة أكثر كفاءة في السيطرة على القيمة المفردة وزيادة حساسية اللوحة في الكشف عن التغييرات الطفيفة التي ربما تحدث في العملية الإنتاجية. وبناءً على ذلك، تم اقتراح اللوحة المفردة للمويجة دابشيز ذات الرتب (1، 2، و3) وتطبيقها على بيانات مولدة عشوائياً (محاكاة) لعدة حالات ومن ثم بيانات حقيقية وحساب بعض مؤشرات كفاءة اللوحات المقترحة ومقارنتها مع اللوحة التقليدية اعتماداً على برنامج ماتلاب. بيَنت نتائج البحث أن جميع اللوحات المقترحة كانت أفضل من اللوحة التقليدية للقيمة المفردة لجميع حالات المحاكاة والبيانات الحقيقية.

الكلمات المفتاحية: لوحة السيطرة شيوارت للقيمة المفردة، المويجات، الانكماش، المويجة دابشيز ، قطع العتبة الشاملة .