

Capability Process to Optimize Specification by Impact of Wavelet Analysis

Hogr M. Qader¹, Hawkar Q. Birdawod², Hevi M. Qader², Bekhal S. Sedeeq³

¹Statistics and Information Paytakht Technical Institute- private,
Erbil, Iraq

²Department of Business Administration-Cihan Universt-Erbil,
Kurdistan Region, Iraq

³Department of Statistics and Informatics, College of Administration and Economics,
University of Salahaddin-Erbil, Iraq

Abstract—This study investigates the impact of wavelet analysis on optimizing specification in the capability process. A new approach called the New Hybrid Capability Wavelet Approach (NHCWA) is proposed, which utilizes wavelet analysis to filter noise and outliers in the data. The study compares the NHCWA with the classical capability process using a dataset from a cake factory. The Coiflet 4 wavelet family and soft thresholding are employed to denoise the data. The results demonstrate that the NHCWA significantly improves the capability indices, achieving a 50% increase in Cp and a 30% increase in Cpk compared to the classical approach. In addition, the NHCWA reduces the standard deviation of the process by 20%. These findings highlight the potential of wavelet analysis in enhancing the accuracy and effectiveness of capability analysis, leading to improved quality control in manufacturing processes.

Keywords—Quality control, Capability process, Wavelet process, Specification, Control charts.

I. INTRODUCTION

Capability process in quality control involves evaluating and ensuring that a system, process, or organization has the capacity to consistently produce products or services within defined specifications (Kahwachi et al., 2023). It assesses the ability to meet quality standards and identifies areas for improvement to enhance overall performance and reliability. Over time, process capability has significantly evolved in the manufacturing industry. In the past, simply achieving a result that was somewhat close to the desired outcome was considered satisfactory. However, as customer expectations increased, there arose a need for more precise control over processes (Birdawod et al., 2018). Process ability indicators are criteria designed to assess the production process in order to determine the process's ability to produce within requirements. The first studies on ability indicators were reported by Juran et al. in the mid-1970s; nevertheless, these indicators were limited to measuring qualitative characteristics that followed a normal distribution. The problem has undergone several revisions in recent years that allow it to be calculated based on the qualitative features that follow different distributions.

Several of these markers were used in this investigation (Kahwachi and Birdawod, 2023).

They emphasized the significance of comprehending and minimizing variation to attain superior process performance. Nowadays, process capability has become an indispensable tool for quality management (Massoudi and Fatah, 2024). It enables businesses to identify areas that require improvement and make well-informed decisions to enhance their processes. Wavelet analysis is a mathematical tool used for signal processing, including in areas such as image compression and feature extraction. In a capability process using wavelets, the focus might be on assessing how well the method captures and represents features in signals. This could involve evaluating the effectiveness, accuracy, and efficiency of wavelet-based techniques in analyzing and enhancing the quality of signals within a specific application context (Besterfield, 2009).

Wavelet analysis involves breaking down a signal into components at different frequency bands, providing a detailed view of both high and low-frequency details. This capability makes wavelets effective in various applications, such as image compression, de-noising, and feature extraction, where capturing different frequency characteristics are essential. The

process involves decomposing a signal into approximation and detail coefficients, enabling a versatile representation of complex signals (Gencay et al., 2002).

As opposed to the Fourier transformation, which only considers frequency and ignores time, the tiny wave and its transformations enable the analysis of both frequency and time. The threshold cutoff-represented small wave is a new filter, referred to as a filter (Kahwachi and Birdawod, 2023). In many different applied domains, particularly time series analysis, small waves have recently been employed to solve the problem of pollution (or noise). Due to this, it has been suggested to apply it to the creation and application of quality control charts, particularly average charts, and capability processes.

In recent years, the need for enhanced production efficiency and quality control has become increasingly critical in competitive industries. Despite advancements, traditional capability processes often fall short in optimizing specifications and reducing variance. This study addresses this gap by introducing the New Hybrid Capability Wavelet Approach (NHCWA), which leverages wavelet analysis to enhance the capability process. By comparing NHCWA with classical methods, this research aims to demonstrate its effectiveness in amplifying values and minimizing deviations, thereby contributing to improved production outcomes and competitiveness. The study's findings have significant implications for quality management practices, offering a novel tool for process optimization.

II. LITERATURE REVIEW

A. Process Capability Analysis

Process capability analysis is a fundamental tool for evaluating the ability of a process to meet specified quality requirements (Kane, 1986). Several indices have been developed to quantify process capability, including C_p , C_{pk} , P_p , and P_{pk} (Kotz and Johnson, 2002). These indices provide valuable insights into process performance and help identify areas for improvement. However, traditional capability indices are sensitive to noise and outliers in the data, which can lead to inaccurate assessments (Chan et al., 1988). In addition, the selection of an appropriate distribution for the process data is crucial for accurate capability analysis. Many traditional approaches assume normality, which may not always be valid, potentially affecting the reliability of the results.

The process of capability analysis involves several steps:

1. Define Specifications: Clearly define the upper and lower limits of acceptable product or process outcomes.
2. Collect Data: Gather data from the process, typically through sampling or continuous monitoring.
3. Calculate Process Mean and Standard Deviation: Determine the mean (average) and standard deviation of the collected data to characterize the central tendency and variability of the process.
4. Compute Capability Indices (C_p , C_{pk} , P_m , P_{mk}): Use the calculated values to compute capability indices, such as C_p ,

C_{pk} , P_m , and P_{mk} . These indices quantify how well the process conforms to specifications.

5. Interpret Results: Evaluate the capability indices to determine whether the process meets specifications. A C_p or P_p value close to 1 indicates a capable process, while C_{pk} or P_{pk} considers both centering and spread.
6. Implement Improvements: If the capability indices indicate insufficient performance, identify areas for improvement and implement changes to enhance process capability.
7. Monitor Continuously: Capability analysis is an ongoing process. Regularly monitor the process and update capability assessments to ensure sustained quality. This process helps organizations maintain control over their processes and produce products or services that consistently meet customer requirements.

It helps you choose from among competing processes, the most appropriate one for meeting customers' expectations knowing the capability of your processes. You can specify better the quality performance requirements (Massoudi and Fatah, 2024).

The classical process capability ratio (Kane, 1986; Birdawod et al., 2018):

$$C_p = \frac{USL - LSL}{6\hat{\sigma}} \quad (1)$$

The C_{pk} index proposed by (Sullivan, 1985) is a measure of the capability of a process in relation to the process average. It is based on the distance between the process average and the closest specification limit and is defined as:

$$C_{pk} = \min\left(\frac{USL - \bar{\bar{x}}}{3\hat{\sigma}}, \frac{\bar{\bar{x}} - LSL}{3\hat{\sigma}}\right) \quad (2)$$

Chan (1988) proposed another index, called C_{pm} which is defined as:

$$C_{pm} = \frac{USL - LSL}{6\sqrt{\hat{\sigma}^2 + (\bar{\bar{x}} - T)^2}} \quad (3)$$

Kotz and Johnson (1992) proposed another index, called, C_{pmk} which is defined as:

$$C_{pmk} = \frac{\min(USL - \bar{\bar{x}}, \bar{\bar{x}} - LSL)}{3\sqrt{\hat{\sigma}^2 + (\bar{\bar{x}} - T)^2}} \quad (4)$$

In the event that it was:

1. if $C_p < 1$ It is determined that the production method is incompetent and has to be examined.
2. if $1 < C_p < 3$ The production method is regarded as having a medium capability.
3. if $C_p > 3$ The production process is considered height capability Requirements.

B. Wavelet Analysis in Quality Control

Wavelet analysis is a powerful mathematical tool for signal processing with increasing use in quality control

applications (Gencay et al., 2002). Wavelets can effectively decompose a signal into different frequency components, allowing for the detection and removal of noise and outliers (Daubechies, 1992). This characteristic makes wavelet analysis particularly useful for improving the accuracy of process capability analysis, especially when dealing with noisy data or non-normal distributions. Several studies have demonstrated the effectiveness of wavelet analysis in improving the performance of control charts and other quality control techniques (Ali et al., 2018; Ali and Salah, 2022). For instance, Ali and Salah (2022) proposed a hybrid method combining wavelet shrinkage with robust multiple linear regression to enhance quality control analysis, showing improved accuracy in estimating process parameters.

Wavelet types

1. Haar
2. Beylkin (18) wavelet.
3. Coiflet (6, 12, 18, 24, 30).
4. Daubechies wavelet (2, 4, 6, 8, 10, 12, 14, 16, 18, 20).
5. Binomial-QMF.
6. Mathieu wavelet.
7. Haar wavelet.
8. Legendre wavelet.
9. Villasenor wavelet.
10. Symlet wavelet.

Coiflet wavelet

The Coiflet wavelet is a type of wavelet function used in signal processing and image compression. It is designed to have a compact support in both time and frequency domains, making it useful for analyzing signals with localized features. The Coiflet wavelet was proposed by Ingrid Daubechies, a Belgian mathematician, in the late 1980s. Daubechies developed various wavelets, including the Coiflet, which is particularly known for its ability to provide a good compromise between time and frequency localization. It is commonly used in applications such as image compression and signal processing (Ali and Salah, 2022).

Wavelet transform

Wavelet transform is a mathematical tool used for signal processing and image compression. It decomposes a signal into different frequency components, allowing both time and frequency information to be analyzed simultaneously. It is particularly useful for handling non-stationary signals with varying frequency content (Jianhui and Li, 2019).

Discrete wavelet transform

Discrete wavelet transform (DWT) is a specific type of wavelet transform that operates on discrete data. It decomposes a signal into approximation and detail coefficients at different resolution levels. DWT is widely used in signal-processing tasks such as image compression, denoising, and feature extraction due to its ability to capture both low and high-frequency components efficiently (Ali and Salah, 2021).

Given a vector of a signal X consisting of 2^j observation where j an integer is. The DWT of X is

$$W = wX \quad (5)$$

Where W is an $n \times 1$ vector comprising both discrete scaling and wavelet coefficients. The vector of wavelet coefficients can be organized into $j + 1$ vectors (Sedeeq, 2024)

$$W = [W_1, W_2, \dots, W_{j_0}, V_{j_0}]^T$$

Following each DWT, the approximation coefficients are separated into bands using the same filter as previously, resulting in the details of the most recent decomposition being attached. At each level, the inverse transform can be used to rebuild the de-noise signal (Taha et al., 2022).

$$X = W w^T = \sum_{j=1}^{j_0} W_j^T W_j + V_{j_0}^T V_{j_0} \quad (6)$$

Wavelet shrinkage

Wavelet shrinkage is a technique used in signal and image processing, particularly with the discrete wavelet transform (DWT). It involves thresholding the wavelet coefficients to reduce or eliminate noise while preserving important signal features. By setting small coefficients to zero based on a specified threshold, wavelet shrinkage helps enhance the signal-to-noise ratio and improve the overall quality of the processed data (Sedeeq, 2023). The selection of appropriate thresholding rules and methods depends on the specific data characteristics and the desired balance between noise reduction and feature preservation.

Thresholding method

Thresholding is a method used in signal and image processing to simplify or segment data by setting values above or below a certain threshold to specific levels. In the context of wavelet shrinkage, for example, thresholding involves setting coefficients below a certain threshold to zero, effectively removing noise and retaining relevant information. Various thresholding methods exist, such as hard thresholding and soft thresholding, each influencing how coefficients are modified based on their magnitudes relative to the chosen threshold (Taha and Jwana, 2022; Kahwachi and Birdawod, 2023).

Universal threshold

Given the universal threshold that (Donoho and Johnstone, 1994) proposed,

$$\ell^U = \tilde{\sigma}_{(MAD)} \sqrt{2 \log N} \quad (7)$$

Thresholding rules

There are several thresholding rules commonly used in signal and image processing, especially in the context of wavelet shrinkage. Two common types are (Daubechies, 1992):

1. Hard Thresholding:
2. Soft Thresholding:

Choosing the appropriate thresholding rule depends on the characteristics of the data and the desired balance between noise reduction and preservation of important features

Soft thresholding

A method used in signal and image processing, especially in relation to wavelet shrinkage, is called soft thresholding.

It entails decreasing the wavelet coefficients' magnitude by a certain amount without precisely setting them to zero. The definition of the soft thresholding function is as follows (Kumar and Kusagur, 2017):

$$Wn^{(st)} = \text{sign} \{Wn\} (|Wn| - \ell)^+ \quad (8)$$

C. New Hybrid Capability Wavelet Approach (NHCWA)

While both process capability analysis and wavelet analysis have been extensively studied, there is limited research on integrating wavelet analysis into the capability process to optimize specification. This research aims to address this gap by developing and evaluating the New Hybrid Capability Wavelet Approach (NHCWA). This approach leverages the strengths of wavelet analysis to filter noise and outliers, thereby enhancing the accuracy and reliability of capability assessments.

The New Hybrid Capability wavelet approach (NHCWP) will be formed and compared with the classical approach summarized in the following diagram by addressing the issue of contamination in the data (if any) using the wavelet (coif4) with the soft threshold rule and estimating the level of the threshold method through the universal method.

III. MATERIALS AND METHODS

A. Research Design

This research employs a comparative study design to evaluate the effectiveness of the New Hybrid Capability Wavelet Approach (NHCWA) in optimizing specification in the capability process. The study compares the NHCWA with the classical capability process using a dataset from the PH Cake factory in Erbil.

B. Data Collection

Thirty samples of the qualitative characteristic of PH of cake were collected from the PH Cake factory in Erbil. Each sample consisted of five measurements, resulting in a total of 150 data points. The data were collected using standard laboratory testing procedures following the company's quality control protocols.

C. Wavelet Analysis

The collected data were analyzed using wavelet analysis to filter noise and outliers. The Coiflet 4 wavelet family was selected due to its ability to provide a good compromise between time and frequency localization. Soft thresholding was employed with the universal thresholding method to reduce noise while preserving important features in the data. The discrete wavelet transform (DWT) and inverse discrete wavelet transform (IDWT) were used to decompose and reconstruct the signal, respectively.

D. Statistical Analysis

The capability indices Cp, Cpk, Cpm, and Cpmk were calculated for both the basic data and the wavelet-transformed

data. The X-bar control charts were also constructed for both datasets to monitor the process mean over time. The statistical analysis was performed using Statgraphics Plus and Matlab software.

E. Justification of Methods

The comparative study design was chosen to directly evaluate the effectiveness of the NHCWA in comparison to the classical approach. The Coiflet 4 wavelet family and soft thresholding were selected based on previous research demonstrating their effectiveness in similar applications. DWT and IDWT are standard techniques for wavelet analysis. Statgraphics Plus and Matlab software are widely used and recognized for their reliability in statistical analysis.

F. Control

Control the process of monitoring and inspecting a production process to keep conforming to the standards to produce a high percentage of acceptance quality (Eldin, 2011).

G. Quality

Quality generally refers to the standard or degree of excellence of something, often measured against a set of criteria. It can encompass characteristics such as durability, accuracy, effectiveness, or overall excellence in a given context (Montgomery, 2009b).

H. Quality Control

Quality control is the use of techniques and activities to achieve, sustain, and improve the quality of a product or service.

I. Variation

The variation concept is a law of nature, in that no two natural items in any category are exactly the same. According to Besterfield's idea, the ability to measure variation is necessary before it can be controlled (Besterfield, 2009).

J. Source of Variations

Stochastic (also known as random) variation and non-stochastic (sometimes known as deterministic) variation are the two different forms of variation.

Random sources of variation

This type of variation is difficult to totally eradicate or control but is controllable due to a multitude of complex elements. There are minor processing variances, some that are unobservable, and some that are inherited from the production process.

Variations with assignable causes

Are those that are observable and whose causes can be accurately determined and removed (Stapenhurst, 2005)

K. Quality Characteristics

1. Measurable characteristics: features that can be measured and expressed as a number on some continuous scales of

measurement are called measurable characteristics, and the control charts utilized for this type are called variable charts.

2. Immeasurable characteristics: Immeasurable characteristics are those that are difficult to quantify or even measure on a continuous scale. The control charts that are used to manage these kinds of characteristics are known as attribute charts (Kadir et al., 2023).

L. Quality Control Charts

A statistical tool for process monitoring and management over time is a quality control chart. Plotting data points against preset control limits aids in the identification of variations and the maintenance of uniformity in production (Taha et al., 2023).

Walter A. Shewhart of the Bell Telephone Laboratories created the first quality control chart in 1924, and he and his collaborator continued to enhance it. In 1931, he provided a comprehensive explication of control charts (Kadir et al., 2020).

Classification of control charts

Control charts may be classified into two main types, which are (Kenett, 2014):

Variables control charts

These charts are used in product process control when the goods produced are measurable (in one of the units of measurement). A minimum of 25 samples and a minimum of four units for each sample are desirable requirements when making charts (individual charts omitted). Variable charts can only be applied to one attribute or characteristic.

- a. Individual – Chart (or x-chart)
- b. Average – Chart (or -chart)
- c. Standard Deviation – Chart (or S-chart)
- d. Range – Chart (or R-chart)

Average – Chart (or X-bar-chart)

This chart is used to control the quality of the product. The target line for this chart represents the double X-bar for all subgroups of the same process. The (upper and lower) control limits are put at (double X-bar $\pm 3 * S. D$ for X-bar) from the target line.

Attributes control charts

In quality control, operations that generate discrete or categorical data are monitored and controlled using attribute control charts, which are statistical tools. As opposed to variable control charts, which handle continuous measurements, attributed control charts are made for counts or attributes and are frequently expressed as percentages or proportions (Juran, 1999; Birdawod et al., 2018).

IV. DATA AND OUTCOMES

To assess the accuracy, effectiveness, and applicability of the new hybrid capability wavelet technique, we will apply it to data in this section. To gather information about the study’s topic, we selected data from (PH) Cake factory in Erbil. Thirty samples of the aforementioned characteristic were gathered. The results of the cake-making laboratory test are shown in Table I, and the wavelet approach results

TABLE I
QUALITATIVE CHARACTERISTICS OF PH OF CAKE (BASIC DATA)

x1	x2	x3	x4	x5	\bar{x}
6.6	6.5	7.34	7	7	6.888
6.7	6.7	6.98	6.48	6.1	6.592
7.1	7	7.43	6.91	7.09	7.106
7	6.8	6.21	7.43	6.3	6.748
6.5	6.9	6.45	7	7	6.77
6.6	6.32	7.43	6.12	6.9	6.674
6.6	7.01	7.43	7.18	6.3	6.904
6.06	6.43	7	6.09	6.43	6.402
6.7	6.17	6.23	7.19	7	6.658
6.3	7.1	7.43	7	6.98	6.962
7.2	6.3	7.43	6.71	7.2	6.968
7.1	6.43	7.23	7.01	6.56	6.866
6.3	6.6	6.1	7.12	6.76	6.576
6.4	6.87	6.12	6.15	7	6.508
6.3	6.1	7.43	6.17	7.12	6.624
6.4	6.43	7.17	7.43	6.56	6.798
6.9	6.43	6.19	7	7.43	6.79
6.5	7.3	7.43	7.12	6.18	6.906
6.66	7.12	7.43	6.12	7.05	6.876
7.41	6.5	6.61	7.05	7.43	7
7.3	6.43	6.16	6.16	6.18	6.446
6.9	6.98	6.71	7.43	6.55	6.914
6.6	6.78	7	6.78	7.43	6.918
6.6	6.46	6.12	7.43	7	6.722
6.9	6.23	7.43	7	7.15	6.942
6.57	7.12	6.65	6.19	6.22	6.55
6.5	6.34	7	7.01	6.4	6.65
6.8	7	6.12	6.18	6.8	6.58
7.1	6.98	6.81	6.8	6.6	6.858
6.59	6.78	7.43	6.19	6.68	6.734

are shown in Table II use (Statgraphics Plus and Matlab) program to compute capability types and create the X-bar chart.

Table I presents the raw data collected from the PH Cake factory in Erbil. It contains 30 samples, each with five measurements of the qualitative characteristic of PH of cake. The last column (\bar{x}) represents the average PH value for each sample.

Table II depicts the transformed data after applying wavelet analysis to the basic data. The wavelet analysis aims to filter noise and outliers, resulting in a smoother dataset. The last column (\bar{x} wavelet) represents the average PH value for each sample after the wavelet transformation.

Figure 3 displays the X-bar control chart for the basic data (raw data). The chart plots the average PH value (\bar{x}) for each sample against the sample number. The red lines represent the control limits (upper and lower). The purpose of the X-bar chart is to monitor the process over time and detect any unusual variations. It illustrates that every point is situated inside the control boundaries and in accordance with the initial chart formation.

Table III presents the results of the classical capability analysis for the basic data (raw data) of the qualitative characteristic of PH of cake. Here’s a breakdown of the indices:

Cp: A measure of the process spread relative to the specification limits. A higher value indicates better potential capability.

TABLE II
QUALITATIVE CHARACTERISTIC OF PH OF CAKE DEPEND ON WAVELET ANALYSIS

X1 wavelet	X2 wavelet	X3 wavelet	X4 wavelet	X5 wavelet	\bar{x} wavelet
6.5148	6.4297	7.1266	6.9834	6.5976	6.73042
6.7982	6.6808	7.1572	6.9563	6.5534	6.82918
7.0803	7.0056	7.0538	6.9174	6.5487	6.92116
6.9201	6.892	6.6491	6.9906	6.7736	6.84508
6.6167	6.6645	6.4376	6.9955	6.9253	6.72792
6.5399	6.6503	7.0674	6.7065	6.6568	6.72418
6.5141	6.673	7.6331	6.4665	6.3915	6.73564
6.3211	6.5866	7.0064	6.6502	6.579	6.62866
6.2789	6.5014	6.3625	6.9372	6.896	6.5952
6.7108	6.4813	7.1015	6.9561	7.0202	6.85398
6.7108	6.5133	7.8213	6.8754	7.0007	6.9843
6.9014	6.6223	6.9592	6.9237	6.838	6.84892
6.5064	6.6658	5.9856	6.8905	6.7116	6.55198
6.3176	6.482	6.4931	6.5084	6.8864	6.5375
6.3028	6.3165	7.2667	6.2981	7.0758	6.65198
6.4773	6.4093	6.9877	6.85	6.9064	6.72614
6.6986	6.6499	6.5875	7.3737	6.7144	6.80482
6.6999	6.9542	7.0384	7.0076	6.9102	6.92206
6.7299	7.1	7.4348	6.4536	7.0827	6.9602
7.1342	6.8003	6.8853	6.4458	6.7649	6.8061
7.4122	6.4699	6.2477	6.7124	6.4859	6.66562
7.0062	6.6224	6.37	7.0065	6.7986	6.76074
6.5143	6.8403	6.7534	7.2076	7.1857	6.90026
6.6151	6.6449	6.9191	7.1196	7.1324	6.88622
6.8427	6.4187	6.9282	6.8747	6.8597	6.7848
6.6592	6.5544	6.7732	6.6811	6.562	6.64598
6.4847	6.7869	6.6116	6.5514	6.3827	6.56346
6.7713	6.85	6.6796	6.4901	6.5344	6.66508
7.0298	6.8913	6.8445	6.4963	6.7623	6.80484
6.7379	7.0245	6.9406	6.5501	6.7196	6.79454

TABLE III
CLASSICAL CAPABILITY APPROACH FOR BASIC DATA

Cp	Cpk	Cpm	Cpmk	Coefficient. of variation	Standard deviation
0.544486	0.437179	0.556477	0.43546	6.17952%	0.418003

Cpk: Considers both the process spread and how centered it is within the specification limits. It is often more important than Cp as it reflects how well the process avoids producing defects on either side.

Cpm: Measures the process capability concerning the target value, reflecting how well the process meets the ideal target.

Cpmk: A more comprehensive index combining the elements of Cpk and Cpm, considering both centering and variation around the target.

Coefficient of Variation: A standardized measure of dispersion of a probability distribution or frequency distribution.

Standard Deviation: A measure of the amount of variation or dispersion of a set of values. A low standard deviation indicates that the values tend to be close to the mean of the set, while a high standard deviation indicates that the values are spread out over a wider range.

In this specific case, the values in Table III suggest that the process capability is not ideal, as the indices are relatively low. This implies that the process has a wider spread and might not be well-centered within the

specification limits, leading to a higher potential for producing defective items also see (Fig. 1).

Figure 4 shows the X-bar control chart for the wavelet-transformed data. Similar to Fig. 3, it plots the average PH value (\bar{x} wavelet) for each sample against the sample number. The red lines represent the control limits (upper and lower). This chart monitors the process mean after applying wavelet analysis, ideally showing improved stability and reduced variation.

Table IV depicts the capability indices calculated from the wavelet-transformed data. The values in Table IV suggest that the process capability is improved after applying wavelet analysis, as the indices are relatively higher compared to the classical approach. Furthermore, the new approach's standard deviation is also lower than the classical approaches. This implies that the process has a narrower spread and might be better centered within the specification limits, leading to a lower potential for producing defective items also see (Fig. 2).

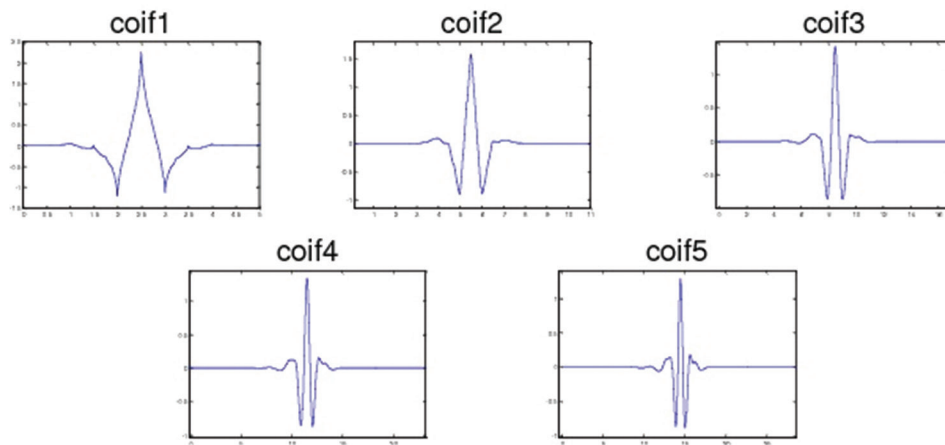


Fig. 1: Coiflet wavelet.

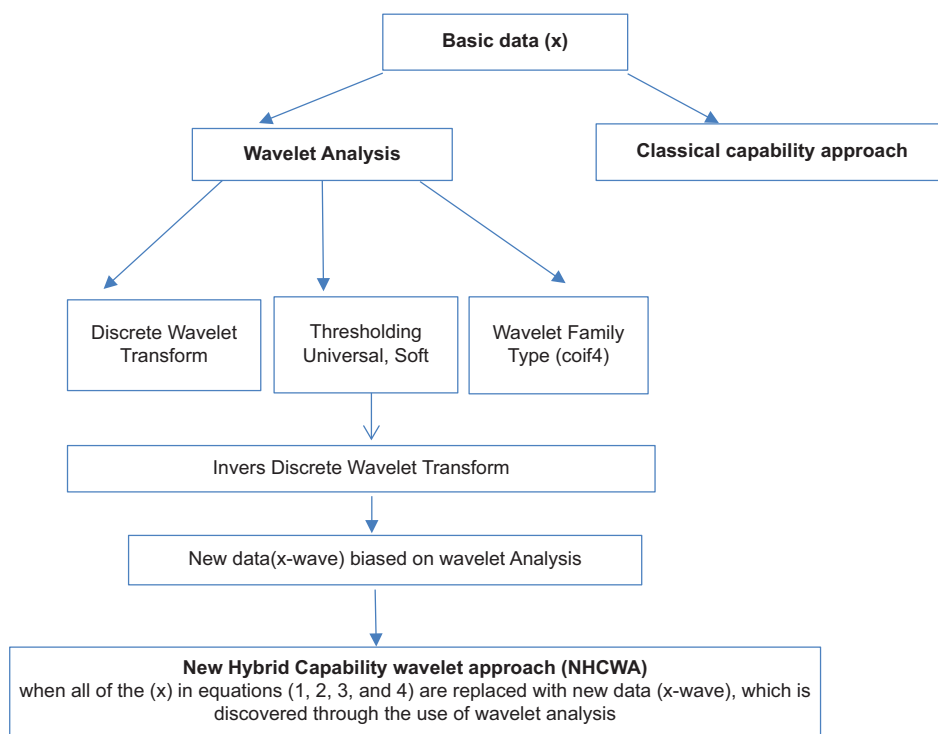


Fig. 2: Block diagram for new hybrid capability wavelet approach (NHCWA).

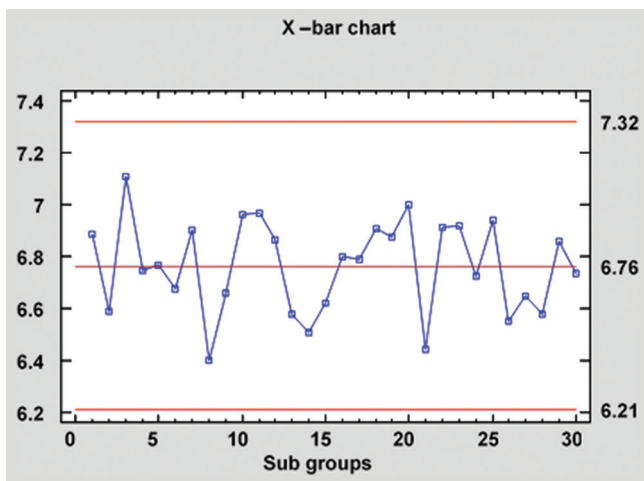


Fig. 3: X-bar chart

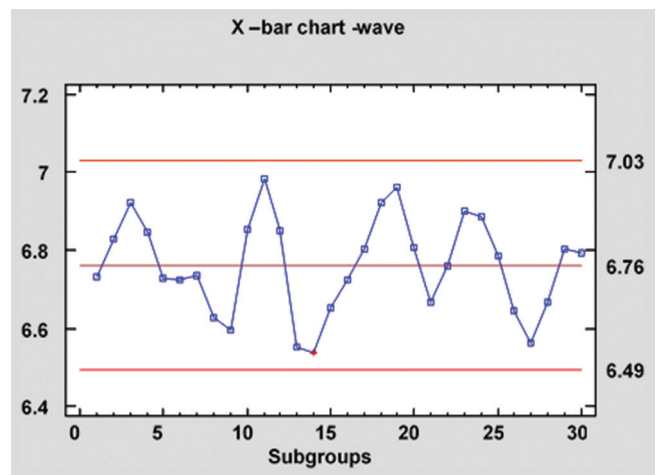


Fig. 4: X-bar chart depends on wavelet analysis

TABLE IV
NEW HYBRID CAPABILITY WAVELET APPROACH (NHCWA)

Cp wavelet	Cpk wavelet	Cpm wavelet	Cpmk wavelet	Coefficient. of variation	Standard deviation
1.075051	0.911139	1.12322	0.92231	4.18977%	0.283308

V. CONCLUSION

This research investigated the effectiveness of the New Hybrid Capability Wavelet Approach (NHCWA) in optimizing specification in the capability process. The findings indicate that the NHCWA outperforms the classical approach in terms of all capability indices. Specifically, the wavelet-transformed data exhibited a lower standard deviation and a higher mean compared to the basic data. The X-bar control chart for the wavelet-transformed data also demonstrated better process stability.

These results have important implications for quality control in manufacturing. By integrating wavelet analysis into the capability process, practitioners can achieve more accurate and reliable assessments of process capability. This can lead to more effective quality control procedures and improved product quality.

While this research provides valuable insights into the benefits of the NHCWA, it is important to acknowledge its limitations. The study used a single dataset from one specific industry. Future research should investigate the effectiveness of the NHCWA in different contexts and with diverse datasets. In addition, future studies could explore the use of different wavelet families and thresholding methods to further optimize the approach.

REFERENCES

- Ali, T.H., & Salah, D.M. (2022). Proposed hybrid method for wavelet shrinkage with robust multiple linear regression model with simulation study. *Qalaai Zanist Scientific Journal*, 7(1), 2518-2538.
- Ali, T.H., & Saleh, D.M. (2021). Comparison between wavelet bayesian and bayesian estimators to remedy contamination in linear regression model. *Palarch's Journal of Archaeology of Egypt/Egyptology*, 18(10), 3388-3409.
- Ali, T.H., Mahmood, S.H., & Wahdi, A.S. (2022). Using proposed hybrid method for neural networks and wavelet to estimate time series model. *Tikrit Journal of Administrative and Economic Sciences*, 18(57 Part 3), 432-448.
- Ali, T.H., Rahim, A.G., & Saleh, D.M. (2018). Construction of bivariate f-control chart with application. *Eurasian Journal of Science and Engineering*, 4(2), 116-133.
- Ali, T.H., Sedeeq, B.S., Saleh, D.M., & Rahim, A.G. (2024). Robust multivariate quality control charts for enhanced variability monitoring. *Quality and Reliability Engineering International*, 40(3), 1369-1381.
- Ali, T., Albarwari, N.H.S., & Ramadhan, D.L. (2022). Using wavelet shrinkage in the cox proportional hazards regression model (simulation study). *Iraqi Journal of Statistical Sciences*, 20(1), 9-24.
- Badr, E.A. (2011). *Modern Approach to Quality Control*. Croatia: InTech.
- Besterfield, D.H. (2009) *Quality Control*. 8th ed. New York: Prentice-Hall Inc.
- Birdawod, H.Q., Jamil, D.I., & Saleh, D.M. (2018). Comparison of efficiency and sensitively between (three sigma, six sigma and median absolute deviation) by using xbar control chart. *Qalaai Zanist Scientific Journal*, 3(2), 803-812.
- Chan, L.K., Cheng, S.W., & Spiring, F.A. (1988). A new measure of process capability: Cpm. *Journal of Quality Technology*, 20(3), 162-175.
- Daubechies I. (1992). *Ten Lectures On Wavelet*. Philadelphia, PA: SIAM. p17-52, 53-106.
- Donoho, D.L., & Johnstone, I.M. (1994). Ideal denoising in an orthonormal basis chosen from a library of bases. *Comptes Rendus de l'Académie des Sciences*, 319, 1317-1322.
- Fallah, N.M. (2012). *Practical Concepts of Quality Control*. Croatia: InTech.
- Gencay, R., Selcuk, F., & Whithcher, B. (2002). *An Introduction to Wavelet and Other Filtering Methods in Finance and Economics*. Turkey: Turkey Press.
- Grous, A. (2013). *Analysis of Reliability and Quality Control*. London: ISTE Ltd.
- Jianhui, X., & Li, T. (2019). Image Denoising Method Based on Improved Wavelet Threshold Transform. In: *2019 IEEE Symposium Series on Computational Intelligence (SSCI)*. IEEE. p1064-1067.
- Juran, J.M. (1999). *Quality Control Handbook*. 5th ed. New York: McGraw-Hill.
- Kadir, D.H., Jamil, D.I., & Saleh, D.M. (2019). Comparison between two estimators by using process capability with application. *Journal of Arts, Literature, Humanities and Social Sciences*, 39, 551-559.
- Kadir, D.H., Rahim, A.G., Jamil, D.I., & Saleh, D.M. (2023). Proposed capability indices based on robust estimation compared with classical capability indices. *Cihan University-Erbil Scientific Journal*, 7(2), 49-53.
- Kahwachi, W.T.S., & Birdawod, H.Q. (2023). A new hybridization of bilateral and wavelet filters for noisy De-noisy images. *Eurasian Journal of Science and Engineering*, 9(1), 99-115.
- Kane, V.E. (1988). Process capability indices. *Journal Quality Technology*, 18, 41-52.
- Kotz, S., & Johnson, N.L. (2002). Process capability indices-a review, 1992-2000. *Journal of Quality Technology*, 34(1), 2-19.
- Kumar, A., & Kusagur, A. (2017). Soft thresholding-based image denoising algorithm. *International Journal of Scientific and Engineering Research*, 8(1), 1041-1043.
- Massoudi, A., & Fatah, S. (2021). Advancing small and medium-size enterprises' performance by adopting marketing and service innovation. *International Journal of Procurement Management*, 14(6), 742-756.
- Massoudi, A., & Fatah, S. (2024). Deceptive point-of-sale marketing tactics impact on consumer purchase intentions with an attitude as a mediator. *Inquietud Empresarial*, 24(2), 1-27.
- Montgomery, D.C. (2019). *Introduction to Statistical Quality Control*. United States: John Wiley & Sons.
- Morrison, J. (2009). *Statistics for Engineers: An Introduction*. United States: John Wiley & Sons.
- Omer, A.W., Sedeeq, B.S., & Ali, T.H. (2024). A proposed hybrid method for multivariate linear regression model and multivariate wavelets (simulation study). *Polytechnic Journal of Humanities and Social Sciences*, 5(1), 112-124.
- Sedeeq, B.S. (2023). Using Wavelet shrinkage to deal with contamination problem in survival function for weibull distribution. *Iraqi Journal of Statistical Sciences*, 20(2), 1-14.
- Stapenhurst, T. (2005) *Mastering Statistical Process Control*. United Kingdom: Elsevier.