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PCA-WA Based Approach for Concurrent Control Chart Pattern Recognition

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ABSTRACT

Accurate and speedy automatic recognition of Statistical Process Control Chart Patterns (SPCC) is a vital task for supervising manufacturing processes. This is done for better control to produce high-quality products. The motivation of this work is to increase the recognition accuracy of concurrent patterns. In this paper, a novel approach is proposed, using neural networks (NN) with Wavelet Analysis (WA) and Principal Component Analysis (PCA) to address the (CCP) recognition problem in concurrent patterns. Eight types of concurrent patterns based on a combination of normal patterns and unnatural patterns are addressed namely; stratification, systematic, increasing trend, decreasing trend, upshift, downshift, and cyclic. Thirteen statistical and shape features are proposed as inputs to the model. The main contribution of this work is the enhancement of the performance of NN through the augmentation of the signal (control chart data) using WA and proposing better extracted statistical features through the use of PCA. Our work shows that improving the original signal and using the right features improves the accuracy of the CCP recognition significantly. The proposed approach has an overall accuracy of 96.3%. The method was compared with four other methods from the previous literature, and it outperformed these methods.

Keywords: *Adaptive Neural-Fuzzy Inference, concurrent control chart patterns, neural network, statistical features, Wavelet Analysis, wavelet transform*

1. INTRODUCTION

Statistical process control charts (SPCC) play a vital role in examining and supervising the quality parameters in manufacturing processes. In the case where a certain point is outside the control limits, or when a series of points exhibit unusual (abnormal) patterns, then the process will be considered out of control and requiring immediate intervention. Recent research has displayed that certain abnormal patterns on a statistical control chart are almost always connected with a specific set of transferable causes (Madu, 2012). The diagnosis and analysis of abnormal patterns is therefore a vital part of statistical process control charts. Abnormal patterns indicate that there is a fault in the process requiring immediate intervention. The recognition of a specific abnormal pattern can minimize the number of possible causes for investigation and thus narrow down the diagnosis timeline. This, in turn, ensures minimal process overhead to resume and improve the performance quality. Shewhart charts are used to control and monitor manufacturing processes but are limited since they provide only information about the endpoint on charts rather than trends over time. This means that the Shewhart chart will perform successfully in detecting large shifts in the process mean or standard deviation, but not so for smaller changes. From this aspect, statistical process control chart (SPCC) recognition stands a better chance to determine abnormal patterns which represent the long-term behavior in the manufacturing process. The implicit behavior causing these abnormal patterns indicates an anomalous cause has taken place requiring immediate intervention to correct the problem and revert the process to its normal state. The motivation for this work is to increase the accuracy of concurrent pattern recognition through the use of neural networks with Wavelet Analysis (WA) and Principal Component Analysis (PCA) in conjunction with a proposed set of thirteen statistical and shape features. We propose a novel method combining NN, WA, and PCA for the monitoring of control chart pattern CCP as well as detection and classification of unusual CCP.

Previous literature on the segregation of the possible SCCPs includes (Madu, 2012), wherein various rules are proposed including zone rules for detecting process instability through the inspection of the systematic patterns on the control chart; manufacturing processes for example can be made more efficient through error detection, unnatural pattern detection, quality control, and through accurate analysis of the control pattern charts. With Artificial Intelligence (AI) and the Internet of Things (IoT), the process of analysis and detection of control charts can be automated without human intervention and thus eliminating human error and false human interpretation in this very important task. With automation, other benefits standout such as cost reduction and quality performance enhancement, among others. The field of automatic recognition of pattern charts using NN is growing, and much work has been published in this field some of which will be highlighted in the literature review section, below. The use of Neural Networks (NN) for the concurrent control chart pattern recognition is well established in the extant literature. A systematic review of the work done in the field of concurrent control pattern recognition was presented by Garcia *et al*. (2022). Chiu and Tsai (2021) explored the online real-time concurrent control chart pattern recognition using singular spectrum analysis combined with a random forest classifier. Chen *et al*. (2021) studied the complete cycle control chart pattern classification using a one-dimensional convolutional neural network combined with transfer learning. The real-life applications of such systems are really important and can assist in decision-making strategies that optimize the process. Aamer *et al*. (2020) for example, review the use of machine learning demand forecasting. Yani *et al*. (2019) explore the use of machine learning in supply chain management. Huddiniah *et al*. (2019) make the case for the need of Information Technologies and the new technologies that have come out in supply chain due to the complexity of the supply chain and supply chain management.

Research into CCP recognition has existed since the late 1980s and is increasing with time. Recently, the increased interest in Artificial Neural Networks (ANN) made it a technology of choice for CCP recognition. Various research has been done on feature-based and deep learning methods with both unsupervised and supervised learning methods. Even though over 30 years of research in the field has been completed, an optimum solution for complex pattern recognition with random location, orientation, and scale remain elusive. Many different fields require automatic pattern recognition such as manufacturing processes, face recognition, cursive writing recognition, web search, and data mining. Research remains ongoing to enhance the accuracy of diagnosis and recognition of unnatural multivariate process shifts including in this work, which aims to develop an Automatic PCA-WA-based recognition technique for the concurrent control chart pattern recognition process.

The rest of this paper is structured as follows: Section II details the literature review in the area of CCP recognition and related recognition methods, section III introduces the proposed NN-based methodology, Section IV discusses the experimental results, and section V analyses the sensitivity of the proposed model, section VI adds conclusions and, finally, section VII lists references used for this work.

2. LITERATURE REVIEW

A detailed handbook of quality management is introduced which includes control pattern chart concepts as well as zone rules (Madu, 2012). The handbook details the benefits of control pattern charts and various standard rules along with an explanation of the influence on quality management. Ali *et al*. (2016) proposed a model for CCP recognition technique for multivariate autocorrelated processes; multi-layer feed-forward ANN controlled by backpropagation rules is used for the identification and classification of unnatural patterns. The authors used a dataset of 3500 simulated CCPs with Monte-Carlo simulation and obtained a recognition accuracy of 94.9%. Cheng and Cheng (2009) proposed a modified self-organizing ANN for the analysis of CCPs; they use wavelet analysis based on features as the input vector to the ANN, thereby achieving better recognition rates than the conventional approach. Woodall (2019) detailed the characteristics of total quality management (TQM) as compared to Homer Sarasohn's principles and presents the calculations used for control charts X-bar, R-chart, S-chart, and p-chart. The use of these charts is two folds; analyze the presence of a control state in the manufacturing process and retain control status.

Selvamuthu and Das (2018) explained the various statistical quality control techniques; wherein the significance of knowing the impact of the statistical characteristics and statistical estimation on production and quality control is highlighted in the development of neural networks for accurate recognition of control chart patterns. Hichacha and Ghorbel (2012) reviewed publications about classification schemes between 1991 and 2010. In addition to understanding the statistical features, it is also important to understand previous work to identify areas in need of improvement and trigger new ideas and methods in the field of automatic pattern recognition of the control charts. Pham and Wani (1997) presented a feature extraction method based on the shape of the CCP several hundreds of charts are utilized for the testing of the proposed method, and Induction, heuristic, and Neural Network models are proposed for the recognition process thus obtaining improved accuracy compared to similar methods.

A complete explanation of classification and regression trees is detailed in Loh (2011) and in Cheng *et al*. (2015). The authors propose a feature-based ANN recognition scheme with correlation analysis for feature extraction; their method also considers pattern displacement. The automatic recognition of CCPs, in particular, the nonrandom patterns can minimize the troubleshooting time through the identification of the underlying causes detailed in Yang and Yang (2005). The authors present an automatic CCP recognition system based on statistical correlation coefficients; this method bypasses the training process and produces better results in recognizing unnatural control chart patterns compared with similar methods. Al-Assaf (2004) proposed an ANN-based method with features extracted from unnatural patterns using multi-resolution wavelet analysis (MRWA) through time-frequency coefficients. A reduced set of these extracted parameters derived from the coefficients is then used as the input to ANN classifiers thus obtaining better results compared to classical ANN classifiers against Shift, Trend, and Cyclic patterns.

Masood and Hassan (2010) summarized the updated issues related to the use of ANN-based CCP recognition; the issues highlighted include input data & representation, classifier design & training, patterns, diagnosis, and multivariate process monitoring. Pham and Chan (2001) proposed an unsupervised adaptive resonance theory (ART2) ANNs for the recognition of CCPs. Three schemes were proposed: information of the changes between consecutive points in the pattern, modifying the ART2 parameters during the training, and merging the class neurons representing the same class after the training phase. Their results indicated improvement in the recognition accuracy. El-Midany *et al*. (2010) proposed a framework for multivariate CCP recognition that uses ANNs for the recognition of a set of subclasses of the multivariate abnormal patterns, identifies the variables that are responsible for the occurrence, and classifies the abnormal pattern parameters. A real case study was used in the evaluation of the method and the results indicated effective CCP multivariate pattern recognition.

Haghtalab *et al*. (2015) presented a consensus clustering method that accounts for the limitations of unsupervised algorithms and results in a robust output; their proposed method achieved a minimum of 79.10% G-Mean with a large percentage of the test instances scoring higher than 90%. Wu *et al*. (2015) presented a method that is a combination of ANN and binary tree support vector machines (BTSVM) for the recognition of unnatural control chart patterns (CCP. The proposed three-phase system used 5 statistical features and 8 shape features in the first phase, while the second phase consisted of binary class SVM for unnatural CCP detection, and the final phase used BTSVM for classification. The classification accuracy obtained in both the second and third phases was 100% and 98.5% respectively. Al-Ghanim and Ludeman (1997) presented the development and analysis of a pattern recognition system for identifying unnatural patterns in quality control charts. Correlation analysis was used to generate the optimal set of matched filters and common patterns such as systematic, trend, and cyclic patterns were used in the design. Based on exhaustive simulation runs, the system proved to be effective. Miao and Yang (2019) proposed a neural network-based method for CCP recognition.

Ali *et al*. (2016) proposed a neural network-based approach for CCP recognition as well; statistical and shape features were extracted for the first phase as well as the most suitable distinguishing features for the abnormal patterns. In the second phase, deep learning neural network was used for testing and learning, and a Monte Carlo simulation was used for verification. Zhao *et al*. (2019) used Principal Component Analysis (PCA) along with a broad learning system for fault diagnosis; ANN along with wavelet and statistical features was used in various other fields as well (Deng *et al*., 2017; Latif *et al*., 2018; Zhao *et al*., 2020; Al-Hmouz *et al*., 2017; Deng *et al*., 2017; Latif *et al*., 2018; Deng *et al*., 2019).

3. METHODOLOGY

The proposed framework is comprised of two stages, as in **Figure 1**. The first phase is related to the training stage which consists of five steps. The CCPs are generated in the first step. Using Haar Wavelet Transform (HT) the patterns are de-noised in the second step and important pattern coefficients and features are extracted and added to the original signal. In the third step, statistical and shape features of the augmented signal are extracted. Feature reduction technique using PCA is applied in the fourth step and only the most influential features are selected for the recognition. In the fifth step, a Neural Network classifier model is generated based on the selected features.

The second stage is the classification process; during this stage, a random signal containing two mixed patterns is generated. Then, using a similar process as in step two of the training stage, the signal is transformed using wavelet transform and only features selected in step two from the training stage are extracted before they are fed to the previously generated classifier model to detect the nature of the concurrent patterns.

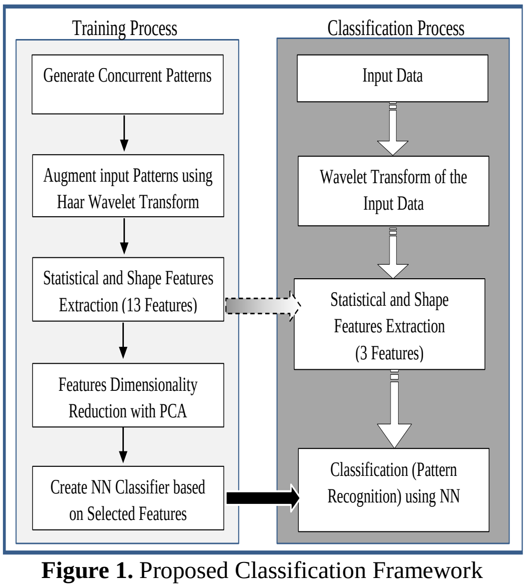

Figure 1. Proposed Classification Framework

3.1 Using Wavelet Analysis for Concurrent Process Control Chart Pattern Recognition

3.1.1 Concurrent Control Chart Patterns

In this research, one normal pattern and six abnormal patterns were considered: Normal pattern (Norm), upward shift (UShift), downward shift (DShift), cyclical pattern (Cycl), systematic pattern (Syst), upward trend (UTrend), and downward trend (DTrend). Monte Carlo simulation was used to generate training patterns based on predefined mathematical models and parameters (Cheng, 1989; Swift, 1987). In some situations, the existence of two patterns can occur simultaneously. Therefore, the first goal is to determine how the proposed method will perform when given the task of identifying concurrent patterns. **Figure 2** displays the concurrent patterns used for training the NN. These signals were simulated using Equation 1.

$$y(i,j) = a\big(\mu + (R(j) * \sigma)\big) + b(Unnatural) \quad (1)$$

The concurrent patterns individually are the weighted sum of two simple unnatural statistical process CCPs. Both a and b are what is referred to as mixing parameters whose value depends on the reliability of the sensors recording the signals.

The following assumptions were made in order to generate the concurrent patterns:

1. Patterns are generated based on a normal distribution following Equation 1 with $(\mu = 80, \sigma = 5)$
2. The shift magnitude (s) in (UShift) or (DShift) depends on the value of σ where $1 \leq s \leq 3$.
3. The cyclical effect seen in (Cycl) is created using ($a \times \sin(2\pi i/T)$)
   where:
   $$1 \leq a \leq 3 \; in\; terms\; of\; \sigma, T = 8$$
4. The systematic effect seen in (Syst) is generated by ($d \times (-1)^i$)
   where:
   $$1 \leq d \leq 3 \; in\; terms\; of\; \sigma$$
5. To simulate a trend in (UTrend) and (DTrend) the following term (ig) was added to (Norm)
6. where:
   $$0.10 \leq g \leq 0.26 \; in\; terms\; of\; \sigma$$

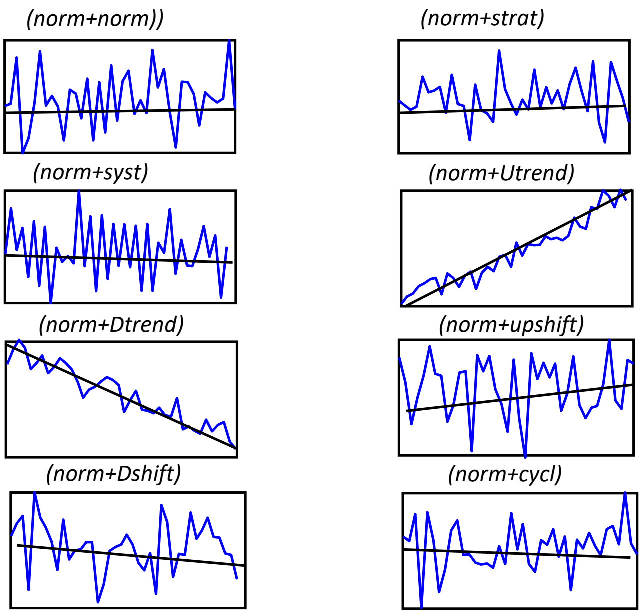

Figure 2 Concurrent Patterns

Normalization of the patterns is performed used equation 2 in order to ensure the comparability of the patterns regardless of the magnitude differences.

$$s_n = \frac{s_i - \mu}{\sigma} \quad (2)$$

Where s_i is the i^{th} data point, σ and μ are the standard deviation and mean respectively.

3.1.2 Wavelet Transform (WA)

Pattern recognition relies heavily on Fourier Transform (FT) which is considered one of the main signal processing analytical tools. The FT of a time varying signal is an independent function of time. That is, it does not record frequencies varying with time. Thus, the introduction of WA was done for this purpose. WA can cut parts of the signal at varying time scales. The Wavelet Transform (WT) of a function $f(t)$ is a decomposition the function into a set of basic wavelets, equation 3:

$$W(a,b) = \int_{-\infty}^{+\infty} f(t)\, \psi^*{}_{a,b}(t)\, dt \quad (3)$$

Wavelets are derived from one single source wavelet $\Psi(t)$ through translation and dilation:

$$\Psi^*{}_{a,b}(t) = \frac{1}{\sqrt{a}} \Psi\left(\frac{t-b}{a}\right) \quad (4)$$

Where a is a scale parameter and b is a translation parameter.

In this paper, wavelet coefficients are extracted from the CCPs, using Haar Transform (HT) (Walker, 2008) shown in **Figure 3** and are added to the input vector before the extraction of statistical and shape features. The advantage of using the WT is in its capability to compute the spectral analysis of a certain signal over a time domain by cutting small waves of the signal at various time scales.

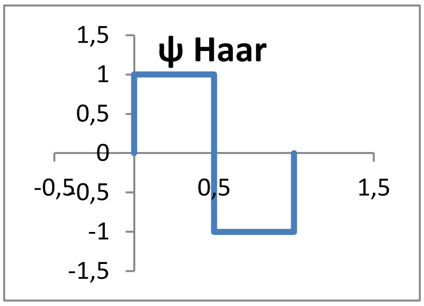

Figure 3 Haar Function

3.1.2.1 Wavelet Analysis (WA) to Extract Features

The patterns produced in this paper were a results of time series of 32 data points. The patterns can be viewed as a vector of 2^5 numbers, $w_0(v)$, where $1 \leq v \leq 2^5$. From this, two new vectors can then be generated as follows in Equation 5 and Equation 6.

for any $1 \leq l \leq 5$, the following results:

$$w_l(v) = \frac{1}{2}[w_{l-1}(2v-1) + w_{l-1}(2v)] \quad (5)$$

$$y_l(v) = \frac{1}{2}[w_{l-1}(2v-1) + w_{l-1}(2v)] \quad (6)$$

Where $l \leq v \leq 2^{l-1}$and both $w_l(v)$ & $y_l(v)$ have 2^{l-1} components.

3.1.3 Control Charts Features Extraction

In this research, 13 shape and statistical features are proposed. Mean (μ), Mean Square Error (MSE), Kurtosis (Ku), Skewness (Sk), Slope of the Least Square line (SLP-LS), Sum of Least Square regression error (SE-LS) (Besterfield, 2004), Slope (Sp) (Brook and Arnold, 2018), Area between the mean line and the Pattern (APM), Area between the Least Square line and the Pattern (APS), the number of crossings of the pattern with the mean line (nc1), the number of least-square line crossings (nc2) (Pham and Wani, 1997), Ratio between the variance of data points and the mean sum of square errors of the least square line (RVE) (Gauri, 2009), and Mean Absolute Deviation (MAD) (Allen, 2018). **Table 1** provides the equations/description of all these features. These features were carefully selected in order to identify all the CCPs.

Feature	Formula / Description
an	$\sum_{i=1}^{n} y_i \big/ n$ (7)
MSE	$\frac{1}{n}\sum_{i=0}^{n}(\widehat{y_i} - y_i)^2$ (8)
Slope	$\widehat{\beta_1} = \sum_{i=1}^{n}(t_i - \bar{t})(y_i - \bar{y}) \big/ \sum_{i=1}^{n}(t_i - \bar{t})^2$ (9)
Kurtosis	$\sum_{i=1}^{n} f_1(y_i - \bar{y})^4 \big/ ns^4$ $\quad Where\ s\ is\ Sample\ Standard\ Deviation$ (10)
Skew	$\sum_{i=1}^{n}(y_i - \bar{y})^3 \big/ ns^3$ $\quad Where\ s\ is\ Sample\ Standard\ Deviation$ (11)
LS-SLP	$\sum_{t=1}^{n}(t - \bar{t})\,(y_t - \bar{y}) \big/ \sum_{t=1}^{n}(t - \bar{t})^2$ (12)
LS-ERR	$\sum_{t=1}^{n}(y_t - \widehat{y_{LS}})$ (13)
nc1	The number of mean crossings, crossings of the pattern with the mean line
nc2	The number of least-square line crossings
APM	The area between the mean line and the pattern
APS	The area between the least square line and the pattern
RVE	$\left[\frac{1}{n-1}\sum_{i=1}^{N}(y_i - \bar{y})^2\right] \Big/ \left[\left[\frac{1}{n-2}\left\{\sum_{i=1}^{N}(y_i - \bar{y})^2 - \frac{(\sum_{i=1}^{N} y_i(t_i - \bar{t}))^2}{\sum_{i=1}^{N}(t_i - \bar{t})^2}\right\}\right]\right]$ (14)
MAD	$\frac{1}{n}\sum_{i=1}^{n}\lvert y - \hat{y}\rvert$ (15)

Table 1 Feature Equation And Desctiption

3.1.4 Principal Components Analysis (PCA)

To minimize the complexity of the classifier and to prevent overfitting, the number of features used in the training and classification process should be minimized. One of the methods used for this purpose is Principal Components Analysis (PCA), which is a multivariate statistical analysis technique used to minimize data dimensionality by eliminating redundancy and focusing on the most vital variables referred to as Principal Components (PCs) while still retaining maximum information. The minimization from a d-dimensional dataset to an m-dimensional subset (where m < d) is performed if there is a correlation between the variables. The PCA method in dimensionality reduction (Jackson, 2005) is detailed in the following steps:

Step 1: Standardization of Data

$$y_{ij} = \frac{x_{ij} - \overline{x_j}}{c_j} \in Y \quad (16)$$

Where c_j represents characteristics, and $\overline{x_j}$ is the mean characteristics.

Step 2: Generate the covariance matrix C and calculate the PCs (eigenvectors e_i) and eigenvalues(λ_i).

$$C = \frac{1}{N}\left[Y - \bar{Y}l\right]\left[Y - \bar{Y}l\right]^T \quad (17)$$

Step 3: Solve for the characteristic value of C and corresponding V value:

$$(\lambda l - C)V = 0. \quad (18)$$

The number m of PCs is selected if the cumulative contribution rate exceeds 85%. This transformation will minimize the data dimension without losing much information. The 13 features are extracted from the different control chart patterns and through the use of PCA analysis the list of features is minimized to the three most significant ones namely, Mean, MAD and APM. As can be seen in **Figure 4**, the cumulative contribution rate of these three features is more than 92%; in fact, Mean and MAD alone can theoretically achieve more than 85% accuracy in classifying CCPs. It can also be noticed from the plot that there is a small confusion between normal + normal, normal + cyclic, and normal + systematic patterns due to the similarity of the signals of these patterns in the time domain. **Figure 5** is a parallel coordinate plot where the features are laid out horizontally, and each pattern of the three previously mentioned patterns is represented by the median and quartiles (25% and 75% points). The figure shows that the three features (Mean, MAD, and APM) have the capability of distinguishing between the three patterns.

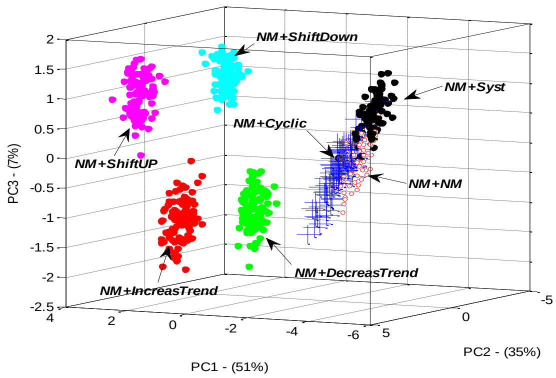

Figure 4 PCA Separation of Patterns Based on Mean, MAD, and APM

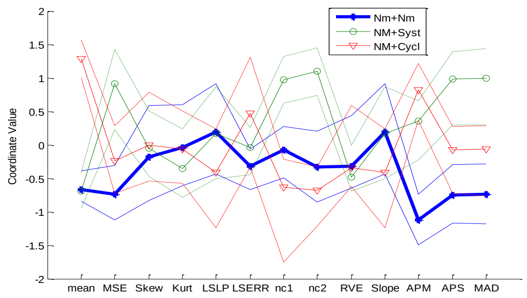

Figure 5 Correlation Analysis Between Different Features

4. EXPERIMENTS AND RESULTS

In order to demonstrate the contribution of the proposed method in this paper, various results are generated to compare the proposed method and show the improvement achieved. In order to test the performance of the approach, five NN classifier models were trained using the backpropagation gradient descent method. The first classifier model, Test model 1, is generated based on the original thirteen statistical and shape features. To reduce the complexity of the NN and to decrease confusion about the training and recognition processes a second model is generated, Test model 2, which is based on three randomly selected features (Mean, RVE and Slope). Third, in order to increase the accuracy of the NN by selecting the influential set of features that provide a better representation of all the input combinations, a third classifier model, Test model 3, is generated based on PCA selected features (Mean, MAD, and APM).

A fourth model, Test model 4, is generated based on the enhancement of the original signal with the WA coefficients and the extraction of 13 statistical and shape features which represent the inputs of the NN classifier. The fifth classifier model, the PCA-WA model, is based on the proposed approach. It is generated based on PCA selected features (Mean, MAD and APM) after the original signal was augmented with WA coefficients. The models are then tested with input data generated based on a normal distribution. 2100 control chart samples were generated, 300 of each type of pattern. 1470 samples were used for the training phase, 315 for validation, and 315 for testing. The performance of the neural network was measured using the mean squared error and the percent error. The lower the value of these two indicators, the better the performance of the neural network. These values correlate with the accuracy values shown in the result tables.

Table 2 shows a comparison between the four test models. It is apparent that Model 4 (WA) shows a noticeable improvement over the other models. **Table 2** also shows that Model 2 (three features only) is slightly better than Model 1 (13 features) which is due to reduced confusion during the training and testing phases. The use of the PCA approach, in Model 3, improves the recognition process even further over Model 2 due to a better selection of the statistical features.

Figure 6, **Table 3** to **Table 6** show the comparison between the proposed approach (PCA-WA) and the four other test approaches. As seen in the results, the proposed approach is significantly much better than other approaches with an improvement of up to 26% over Test Model 1, 27% over Test Model 2, 15% over Test Model 3, and 8% over Test Model 4. This improvement is due essentially to the enhancement of the original signal through the use of WA which adds extra unique information to each CCP pattern that is captured in the statistical and shape features selected by the PCA.

Table 2 Comparison Of Results and Improvement Percentages Between the fourr test Model

					% improvement of Test Model 4 Over		
	Model-1	**Model-2**	**Model-3**	**Model-4**	**Model-1**	**Model-2**	**Model-3**
Training	75.40%	77.50%	84.60%	89.35%	19%	15%	6%
Validation	75.60%	76.40%	87.20%	89.26%	18%	17%	2%
Testing	76.20%	75.80%	83.50%	89.10%	17%	18%	7%

The proposed approach shows that pattern recognition may be enhanced if the original data is enhanced through different methods. We are proposing the use of Wavelet Analysis to capture the particularity of each data set (pattern) at the frequency plane and then add it to the original data set to distinguish it from other data sets. Then, using any machine learning classifier, the patterns can be identified with certain accuracy. It has been proven in the literature the importance of using statistical or shape features of the original patterns. Therefore, to improve the recognition process even further we selected thirteen statistical and shape features and used them as input to the classifier model instead of the original data. However, the statistical features used in this study were randomly selected, and some of them may be negatively correlated which slows down convergence yielding in low accuracy of the model. Through the use of PCA, we were able to reduce the number of features from thirteen to three which resulted in an improvement of the model performance of about 9.6% over Test Model 1 and about 10.2% over Test Model 1. Combining signal enhancement of WA and feature reduction of PCA resulted in an accuracy of 96.3%.

Table 3 Comparison between PCA-WA Approach and Test Model 1

	Test model 1	PCA-WA Approach	% Improvement
Training	75.40%	94.00%	25%
Validation	75.60%	94.60%	25%
Testing	76.20%	96.30%	26%

Table 4 Comparison between PCA-WA Approach and Test Model 2

	Test model 2	PCA-WA Approach	% Improvement
Training	77.50%	94.00%	21%
Validation	76.40%	94.60%	24%
Testing	75.80%	96.30%	27%

Table 5 Comparison between PCA-WA Approach and Test Model 3

	Test model 3	PCA-WA Approach	% Improvement
Training	84.60%	94.00%	11%
Validation	87.20%	94.60%	8%
Testing	83.50%	96.30%	15%

Table 6 Comparison between PCA-WA Approach and Test Model 4

	Test model 4	PCA-WA Approach	% Improvement
Training	89.35%	94.00%	5%
Validation	89.26%	94.60%	6%
Testing	89.10%	96.30%	8%

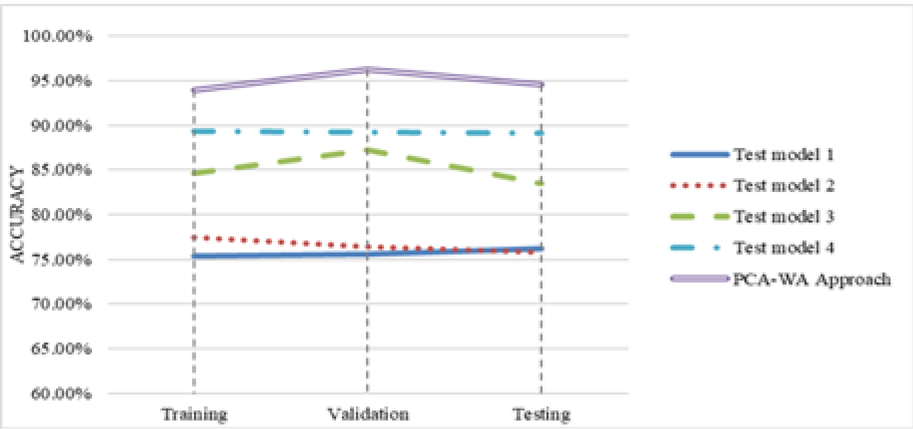

Figure 6 Comparison Results Chart Between The Four Test Models and The Proposed Approach (PCA-WA)

Figure 6 and **Table 7** show the comparison between the proposed PCA-WA method with the four models used for comparison in this paper. It is clear from both the chart and the table that the proposed method showed significant improvement compared with the four models.

Table 7 Comparison results of the four test models and the proposed approach (PCA-WA)

						% improvement of Test Model PCA-WA Over			
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model PCA-WA**	**Model 1**	**Model 2**	**Model 3**	**Model 4**
Training	75.40%	77.50%	84.60%	89.35%	94.00%	25%	21%	11%	5%
Validation	75.60%	76.40%	87.20%	89.26%	94.60%	25%	24%	8%	6%
Testing	76.20%	75.80%	83.50%	89.10%	96.30%	26%	27%	15%	8%

A clear comparison can be seen when presenting all the results to show the improvement obtained from the proposed method. It is apparent from the results that the PCA-WA approach outperformed the other approaches used for comparison here in this paper and outperforms similar approaches in the previous literature.

5. SENSITIVITY ANALYSIS

In order to examine the validity of this study, we need to perform a sensitivity analysis. Some of the inputs to the model (PCA-WA) must be varied and their impact on the accuracy of the model will be analyzed. We focused on two types of inputs, initial weights and the distribution of the data samples. The weights initialization process is done randomly. Each time the training process starts, a new set of weights is assigned to neurons, which may have an impact on the performance or the training time of the model. The weights are then, updated after each iteration until all the conditions are satisfied. As for the second type of input, we used 70% (1470 samples) for training, 15% (315 samples) for validation, and 15% (315 samples) for testing. A different distribution may have an impact on the performance of the model.

Thus, we ran multiple training sessions with different initial weights using the original distribution. Then, we ran other training sessions using one set of weights but with different data sample distributions. Finally, we ran more training sessions with a different sample distribution and a random initialization of weights. **Table 7** and **Figure 8** show the variation of the model performance based on the different initial weights. **Table 8** and **Figure 7** show the variation of the model performance based on the different sample distributions using the same initial weights Training/Validation/Testing ([60% / 20% / 20%], [60% / 30% / 10%], [65% / 20% / 15%], [70% / 20% / 10%], [75% / 15% / 10%], [80% / 10% / 10%]). **Table 9** and **Figure 10** show the variation of the model performance based on the different sample distributions using different initial weights.

Table 8 PCA-WA Performance Using Different Weight Sets

	Set-1	**Set-2**	**Set-3**	**Set-4**	**Set-5**	**Set-6**	**Variation**
Training	94.40%	94.20%	94.44%	95.03%	94.11%	94.56%	0.98%
Validation	94.80%	94.80%	94.52%	94.46%	94.38%	94.72%	0.45%
Testing	96.22%	96.21%	96.10%	96.15%	96.02%	96.30%	0.29%

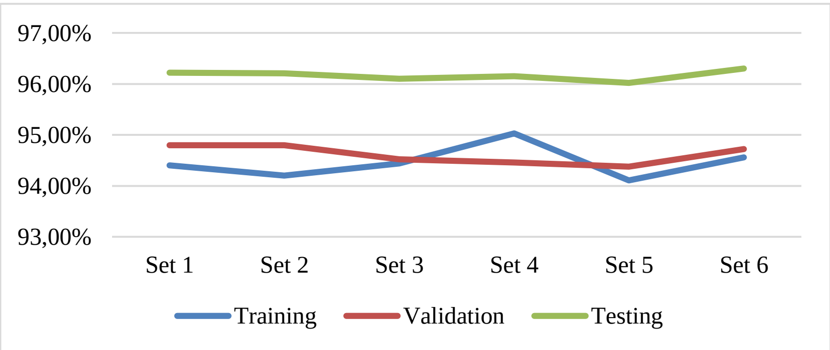

Figure 7 PCA-WA Performance Using Different Weight Sets

Table 9 PCA-WA Performance Using Different Sample Distributions with The Same Initial Weights

	60/20/20	**60/30/10**	**65/20/15**	**70/25/10**	**75/15/10**	**80/10/10**	**Variation**
Training	93.10%	93.42%	93.89%	94.15%	94.20%	95.12%	2.17%
Validation	94.12%	94.28%	94.53%	94.81%	94.63%	94.31%	0.73%
Testing	95.80%	95.96%	96.14%	96.25%	96.28%	96.25%	0.50%

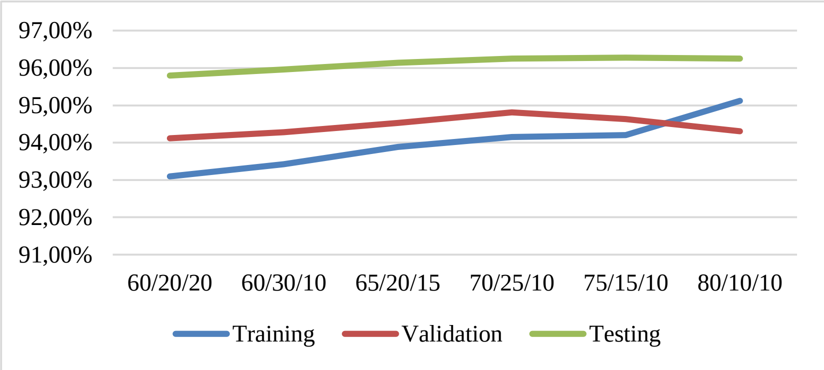

Figure 8 PCA-WA Performance Using Different Sample Distributions with The Same Initial Weights

Table 10 PCA-WA Performance Using Different Sample Distributions with Different Initial Weights

	60/20/20	60/30/10	65/20/15	70/25/10	75/15/10	80/10/10	Variation
Training	94.69%	95.30%	94.44%	94.23%	97.11%	96.33%	3.06%
Validation	93.80%	93.61%	95.87%	95.66%	93.51%	94.21%	2.52%
Testing	95.64%	95.35%	96.12%	96.23%	96.30%	95.88%	1.00%

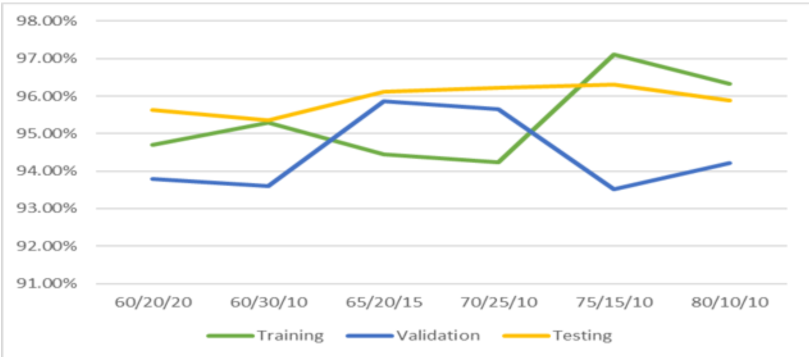

Figure 9 PCA-WA Performance Using Different Sample Distributions with The Different Initial Weights

As we can conclude from the sensitivity analysis results, the variation of the model performance using the testing data is very small especially when only one input varies. For instance, the variation of the performance is about 0.29% when we varied the initial weight values. Also, when the distribution of the data samples varied, we noticed a small change in the performance of the model during the testing phase. The only time there is a noticeable variation is when the initial weights are different and the distribution of the data changes.

6. CONCLUSIONS

The work in this article proposed new methods and techniques to enhance the recognition accuracy for concurrent CCPs. The proposed method consisted of using WA before extraction of the statistical and shape features. However, in order to avoid overfitting and confusion, PCA was used to reduce the features to the 3 most significant ones. The PCA-WA approach using artificial neural networks resulted in a significant increase in the recognition accuracy rate over similar approaches compared to this work and those reported in previous literature. 96.3% accuracy rate was achieved using the PCA-WA proposed technique. It is anticipated that with a larger pool of statistical and shape features even higher accuracy rates can be realized.

The results presented in this paper showed that the combination of NNs, WA, and PCA methods offers the optimum potential for pattern recognition compared to similar approaches. For future work, we plan to use the same model to detect and classify other types of concurrent statistical process control chart patterns, using both simulated data and real data generated from manufacturing processes. We are also in the process of evaluating novel methods in Neural Network classifiers that would further enhance the recognition rate and recognize various concurrent patterns. Deep learning based on newer networks such as recurrent neural networks (RNN) and long short-term memory (LSTM) will be explored in future research. This work provides a guide for engineers, faced with the problems encountered in CCP recognition of manufacturing processes; in fact, the application of this approach is not limited to manufacturing processes, it can potentially be applied to predict problems in any process, manufacturing, or service, resulting from variations.

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