Control Chart Pattern Recognition of Multivariate Auto-correlated Processes Using Artificial Neural Network

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Abstract

The objective of this study is to model a control chart pattern recognition method for multivariate auto-correlated processes. The model development process uses a multi-layer feed forward Artificial Neural Network (ANN) architecture governed by back-propagation learning rule to identify and classify a set of sub-classes of abnormal patterns. Network training was conducted using simulated Control Chart Patterns (CCP) with Monte-Carlo simulation technique. A total of 3500 CCP examples (500 CCPs for each type of pattern) were generated and all CCPs data are normalized (standardized) before being employed as input to the neural network for better performance of the network. With this the study proposes a model for control chart pattern recognition of multivariate auto-correlated statistical process control to identify and classify seven types of typical control charts patterns: i.e. normal, downward shift, upward shift, decreasing trend, increasing trend, cyclic, and systematic patterns. The proposed framework is effective in control chart pattern recognition of multivariate auto-correlated processes with 94.9% recognition accuracy. Furthermore, the Control Chart Pattern Recognition (CCPR) model is validated by the data which is obtained from in-control process of a factory producing Alcohol and Liquor which demonstrates the accuracy of the CCPR. Pattern recognition for multivariate processes is common in the literature. But, this study proposed a new model for multivariate auto-correlated processes.

Key Words: *Multivariate Statistics, Control Chart, Neural Network, Process control*

Introduction

Control charts developed by Shewhart (1924) have been widely used in the quality control of manufacturing processes. They are still one of the most important tools of statistical process control. They are also useful in determining whether a process is behaving as intended or if there are some unnatural causes of variation. A process is out of control, if a point falls outside the control limits, or a series of points exhibit an abnormal pattern. These abnormal patterns provide important information regarding opportunities for process improvement. The presence of abnormal patterns indicates that a process is affected by assignable causes, and corrective actions should be taken (El-Midany et al., 2009). Therefore; identifying or analyzing abnormal patterns and diagnose the causes of out of control conditions are an important aspect of statistical process control. However, most of the studies in the pattern recognition of control charts emphasized on the pattern recognition of a single process variables or individual process variables (Chen & Zhou, 2009; Guh & Hsieh, 1999).

In many quality control settings, the manufacturing process may have two or more quality characteristics or quality variables to be controlled and monitored. The conventional practice in monitoring and controlling process variables has been to maintain a separate chart for each quality characteristic.

Individual process variable monitoring would result in some false out-of-control alarms when the characteristics are highly correlated, especially when one variable is dependent on the other and the correlations between variables result in degrading the statistical performance of the charts (Montgomery, 2009).

Multivariate Statistical Process Control (MSPC) is a set of techniques to deal with correlated variables. Commonly used techniques are Hotelling's T^2 chart, Multivariate Exponential Weighted Moving Average (EWMA) and Multivariate Cumulative Sum (MCUSUM) charts (Montogomery, 2009). Among these methods, Hotelling's T^2 chart is extensively applied in practice. However, dealing with multivariate data under the influence of auto-correlation requires additional considerations or modifications in designing the control schemes so as to ensure the control schemes are valid and robust; otherwise false alarm rate in the controlling process will appear (Hwarng & Wang, 2010). In the implementation of MSPC, control chart pattern recognition is the most important step in the process.

Different rules and methods have been developed to detect abnormal control chart patterns –runs test, zone test, geometric moving average test, and recently artificial neural network. The first three rules or tests indicate the presences of unnatural pattern in the process, but do not explicitly show the type of patterns (Hachicha & Ghorbel, 2012). Recent development in the field is the application of artificial neural network which has a capability to learn control chart patterns from a noisy data and recall during the real application of pattern recognition processes. Therefore, various artificial intelligence approaches have been applied into SPC. Neural networks (NNs) have an excellent noise tolerance in real time, requiring no hypothesis on statistical distribution of monitored measurements (Yu & Xi, 2009).

In a normally distributed univariate process data control chart pattern recognition using artificial neural network has been widely applied (Guh & Hsieh, 1999; Cox, 2005; Zobel, 2004; Addeh et al., 2011; Wang et al., 2008; Hwarng & Wang, 2010; and Salehi et al., 2012). In spite of its utility, research in the field of control chart pattern recognition of multivariate processes is limited. Wang and Chen (2002) proposed a neural fuzzy model for detecting mean shifts and classifying their magnitude in multivariate process. Salehi et al, (2011) proposed a hybrid learning-based model for on-line analysis of out-of-control signals in multivariate manufacturing processes. Zorriassatine, (2003) has developed a model for identification of abnormalities caused by mean shifts in bivariate process. El-Midany et al., (2010) proposed a framework to recognize a set of sub- classes of multivariate abnormal pattern (only for the pattern types of shift and trend), identify the responsible variables and classify the abnormal pattern parameters.

Their model used T^2 statistics (values) of the process variables as an input to their model structure of ANNs to recognize selected sub-classes of multivariate abnormal patterns in the process data. A survey on control chart pattern recognition by Hachicha & Ghorbel (2012), however, shows that there is no research made on multivariate auto-correlated process for detecting the types of abnormal patterns and pinpointing the variable or group of variables source that cause the out-of-control signal in more realistic processes. The purpose of this paper is to develop a control chart pattern recognizer model using an Artificial Neural Network for manufacturing industries with multivariate auto-correlated processes.

Research Methodology

In order to achieve the objective of this research, first, a control chart pattern recognition model using an artificial neural network was designed; second, the seven patterns were defined and the network has been trained and tested with simulated data; and third, the control pattern recognition model has been validated by taking a real data from a processing industry. A software package MATLAB® R2013a was used for designing and training the neural network, and also for generating MATLAB code of CCPR procedure and running the application to evaluate process data. Monte-Carlo simulation technique was used for generation of example control chart patterns, and for training and testing the neural network.

During the pattern generation, a programming code was coded on python programming file, and 'Enthought Canopy®' was used to run the program file. In addition, the pattern generation was supported by a 'Spread sheet'.

Minitab 17® was used to standardize the simulated training data set and real process data which helps the neural network for better training performance, and also statistics like distribution estimation and auto-correlation coefficient determination of the collected process data has been done through Minitab.

Furthermore, Qualstat® software is applied for plotting multivariate T^2 control chart of the process data to ensure that the process is in control, which is used for comparison during the validation process of the result of the proposed CCPR model against the in-control process data.

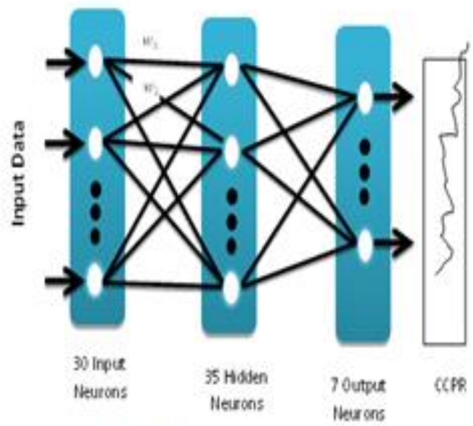

Figure.1 The Network Architecture

Artificial Neural Network Modeling

The neural networks proposed for this research are multilayer feed forward networks governed by back-propagation learning algorithm. It consists of three layers comprising input, hidden, and output layers. The number of input and output nodes was designated by the total number of inputs required to successfully represent a specified pattern and the number of pattern classes to be identified respectively.The input layer comprises 30 neurons which are used to put in 30 data (one control chart pattern example), these are taken from T^2 values of 30 consecutive observations (i.e. window size) in a control chart to the network. The seven (7) neurons in the output layer yield the type of the input pattern vector. The hidden layer consists of 35 neurons.

Although the more hidden neurons provide the better learning results, previous studies show that increasing hidden neurons could not improve the learning results, but will increase the total learning time. In this research, the hidden neuron was determined through trial and error; therefore, once the number of hidden neurons exceeds 35, it is not helpful for learning results. The input layer, hidden layer, and output layers are fully connected, and the connection weights are determined through the learning process. The network architecture adopted in this study is demonstrated in Figure 1. Additional parameters and features of the neural network design are summarized below: Let $X = \{x_1, x_2, . . ., x_I\}$ be an arbitrary input sample vector, $Z = \{z_1, z_2, . . ., z_O\}$ be the actual output vector, $D = \{d_1, d_2, . . ., d_O\}$ be the desired output vector, w_{ij} $(1 \leq i \leq I, 1 \leq j \leq H)$ be the connection weight values between the input and hidden layers, v_{jk} $(1 \leq j \leq H, 1 \leq k \leq O)$ be the values between the hidden layer and the output layer, θ_j $(1 \leq j \leq H)$ be the output threshold of each neuron in the hidden layer.

Activation or transfer function: Sigmoid transfer function is employed for both hidden and output layers. This function is frequently used in neural network applications primarily due to its function features, its continuous derivatives, and its insensitivity to noise (Hwarng and Hubele, 1993 and Perry et al., 2001).

This function is mathematically expressed as: $Y = f(I) = \frac{1}{1+e^{-\alpha I}}, 0 \leq f(I) \leq 1$, where α is the learning rate (α=0.01)

Error function: The mean square error (MSE) is used.

Initial connection weight and Learning rate: Initial connections weights are set in the range [-1, 1]. The learning rate α is the most important parameter. It scales the magnitude of weight adjustments and, thus can dramatically affect the rate of learning. In this study it is set at 0.01.

Training algorithm: When training large networks, and when training pattern recognition networks, scaled conjugated gradient learning algorithm is preferred since memory requirements are relatively small, and yet much faster than standard gradient descent algorithms. As an illustration of how the training works, consider the simplest optimization algorithm gradient descent. It updates the network weights and biases in the direction in which the performance function decreases most rapidly, the negative of the gradient. One iteration of this algorithm can be written as: $\mathrm{W}_{\mathrm{ij}}^{\mathrm{k+1}} = \mathrm{W}_{\mathrm{ij}}^{\mathrm{k}} - \alpha * \mathrm{Xi}$, when output is increased from the target value and $\mathrm{W}_{\mathrm{ij}}^{\mathrm{k+1}} = \mathrm{W}_{\mathrm{ij}}^{\mathrm{k}} + \alpha * \mathrm{Xi}$ when the output is decreased from the target value; otherwise $\mathrm{W}_{\mathrm{ij}}^{\mathrm{k+1}} = \mathrm{W}_{\mathrm{ij}}^{\mathrm{k}}$. Where, W_{ij}^{k+1} is the new adjusted weight, W_{ij}^{k} is the old weight, Xi is the input value, and α is the learning rate. This equation is iterated until the network converges.

Learning termination conditions:
The training of the Backward Propagation Network (BPN) is terminated when they reach a predetermined learning number or if the error does not improve in consecutive 6 epochs. In this study, the maximum learning number of BPN is set to be 1000.

Pattern Generation

In the real application of the result of this study the T^2 value obtained from the process data will be used as an input to the network in order to identify and/or classify abnormal patterns in the process. Therefore, the data generated has a univariate data value in which different data noises that can exhibit various abnormal patterns is introduced in order to imitate the real time patterns of process data. This simulation of various types of control chart patterns is useful for training the neural network so that the neural network can detect and/or classify patterns during the real time application of the neural network.

In generating such complex and large data, Monte-Carlo simulation technique is an efficient method. Pattern generation in several previous works of neural network approaches to control chart pattern recognition tasks has been successfully accomplished by the process mean and two noise components (eq. (1)).

$$X(t) = \mu + r(t) + d_t \qquad (5)$$

Where, $X(t)$ is the observation at time t, μ represent a known process mean of the data series when the process is in control, $r(t)$ is a random normal noise or variation (it is taken as being a random number in the range between -3 and 3, and d_t is a special disturbance due to some assignable cause.

The following expressions were used to generate data sets for the special disturbance due to some assignable causes of the different patterns of a control chart. Together with the normal pattern, this study addresses seven types of control chart patterns including normal, upward shift, downward shift, increasing trend, decreasing trend, cycle, and systematic pattern.

All the detail consideration for the generation of d_t of all the abnormal control chart patterns are expressed below: Notably, a normal pattern is one in which only common cause variations (background noise) are present in the control chart so that the process is considered to be in control.

Normal pattern
$d_t = 0$;

Upward Shift Pattern
$d_t = u * s$eq.
(6)
Where, u represents parameter to determine the position of shifting;

$u = \begin{cases} 0, & beforeshifting \\ 1, & aftershifting \end{cases}$ $s$is a shift magnitude

(1.0 ≤ s ≤3.0).

Down ward Shift Pattern

$d_t = u * s$the same as the upward shift, however the shift magnitude has negative value.

$u = \begin{cases} 0, & beforeshifting \\ 1, & aftershifting \end{cases}$ $s$is a shift magnitude

(-3.0 ≤ s ≤-1.0).

Table1 : Parameters of Generated Process Data

Types of Control Chart Pattern	Parameters	Descriptions of patterns	Quantity generated
Normal		In control process data μ=0 & σ=1	500
Downward shift	$s =$ (-3.0 ≤ s ≤ -1.0)	Shift magnitude from process mean	500
Upward shift	$s =$ (1.0 ≤ s ≤ 3.0)	Shift magnitude from process mean	500
Decreasing trend	$\theta =$ (–0.30 ≤ θ ≤ –0.10)	Slope	500
Increasing trend	$\theta =$ (0.10 ≤ θ ≤0.30)	Slope	500
Cyclic	$k =$ (1.0 ≤k ≤3.0), $T = 10$	Amplitude, Period	500
Systematic	$a =$ (1.0 ≤ a ≤3.0)	Magnitude of process fluctuation	500

Increasing trend pattern

$d_t = \theta * t$ (7)

Where, θ represents trend slope taken as being in the range and t is time of observation.

Decreasing trend pattern

$$d_t = \theta * t$$

Here in decreasing trend, θ the trend slope has negative value (–0.30 ≤ θ ≤–0.10).

Cyclic pattern

$d_t = k * \sin(\frac{2\pi t}{T})$

(8)

Where, k represents cycle amplitude taken as being in the range (1.0 ≤k ≤3.0);

$T$is the cycle period in this research it is fixed at $T = 10$; and$t$ is the time of observation.

Systematic pattern:

$d_t = a * (-1)^t$eq. (9)

Where,a is the magnitude of the systematic pattern it is taken as being (1.0 ≤ a ≤3.0), determining the fluctuations above or below the process mean and$t$ is the time of observation.

To simulate the control chart patterns using Monte-Carlo simulation technique, first, control chart pattern generation program were coded on python program. Enthought Canopy® Software was used to run the python code. The data generated by the python program was used for training and the performance of the neural network could not be improved above 85% of successful classification of the testing sets. Therefore, in order to improve the network performance additional new data were generated using Microsoft Excel® (Spread Sheet).

A special cause disturbance for both upward and downward shift has been introduced at the middle of the recognition window. The summary of pattern parameters used for data generation is described in Table 1.

Network Training

Once the network has been designed, the network is trained (by optimizing the error function). This process determines the best set of weights and biases for training data set. In the training process of the network module, a total number of 3500 control chart training examples were used. Each types of pattern consists of an equal number of training examples, 500 control chart pattern examples for each type of abnormal patterns including a normal pattern. All the generated data are standardized (scaled) for better performance of the network training. During the training of the ANN CPR model the following methodology was implemented.

1) Data generated using Monte-Carlo simulation technique. 2) The generated data will be standardized for better performance of the neural network.3) Divide samples into training set (70%), validation set (15%) & testing set (15%) in random fashion. 4) Conduct the training on the designed ANN. 5) Validate the training using validation data sets, If the intended training goal is not met, go the next step, or else go back to train by adjusting the connection weights (an epoch). 6) During the training when the network performance

goal is met, test the trained network using testing data set. If the result is acceptable, finalize the training and trained ANN is ready for use; otherwise go back to modify the network or increase and/or change the training data set. In this training, the output calculation, back-propagation and updates of weight is conducted. The initial connection weights, the learning rate, and momentum factor of the back-propagation network are set to the MATLAB's standard configuration of the training rules. All the training examples were presented to the neural network in a random fashion. The desired outputs for the network are defined by the following categories as shown in Table 2. Table 3 summarizes the classification results of the proposed control chart pattern recognition model on the testing example set using a confusion matrix that shows the distribution of the misclassification. Here, a type I error occurs when a normal testing control chart pattern example is wrongly predicted (classified) as an abnormal control chart pattern by the proposed control chart pattern recognition model. A type II error occurs when an anormal testing control chart pattern example is wbrongly classified as a normal control chart pattern by the proposed model. For instance, for the normal pattern, the type I error of the proposed model was 10.4%, while the type II errors were 2.7%, 2.7%, 0.0%, 0.0%, 0.0%, and 0.0% for pattern types of downward shift, upward shift, decreasing trend, increasing trend, cycle, and systematic respectively. Most of the misclassification was observed to happen in the recognition of downward shift, upward shift, and increasing and decreasing trend patterns. With the presence of downward shift patterns, most of the misclassified patterns are classified as decreasing trend and less frequently as a normal pattern. In the presence of upward shift patterns, most misclassifications were classified as increasing trends and less frequently as normal patterns. In increasing trend patterns all of misclassifications were upward shift patterns, whereas in decreasing trend all misclassifications were a downward shift pattern. The misclassification between shift and trend patterns indicates that patterns with small shift magnitudes resemble with trend patterns and vice versa. Both cyclic and systematic patterns were not misclassified. The overall testing result (94.1%) indicates that the training was successful and the neural network performance is accurate.

Model validation

Multivariate statistical process control using residual hotelling T^2 control chart is integrated with the proposed control chart pattern recognition model to make the process monitoring and controlling activity effective. Data will be taken from the online manufacturing process and T^2 control chart plotted. If the process is in-control go to the next process monitoring. If the process is out of control the T^2 values of the observed data standardized and input to CCPR model to determine an abnormal pattern. If there is an abnormal pattern, with good process knowledge the assignable cause will be diagnosed and online action will be taken to the manufacturing process. If the result from the CCPR is normal pattern, the process is out of control because of an outlier/s. Therefore, the possible assignable causes will be diagnosed with good process knowledge; otherwise further action for diagnosing the assignable cause will be conducted by using MYT decomposition method or principal component analysis. Validation of the control chart pattern recognition model based on data collected form a company processing Alcohol and Liquor products. Characteristics which are serially dependent determine the successful outputs of the manufacturing process. The production process of alcoholic liquor involves several sequenced processes starting from molasses several process variables and quality syrup preparation up to liquor packaging and distributing. Previous studies conducted in process monitoring and controlling indicates that there are 20 critical process variables and quality characteristics in the production process (Lemma, 2014). These process variables and quality characteristics are described in **Table 4**. These process variables (multivariate auto-correlated process variables) are serially dependent and exhibit correlation either strongly or moderately among each other. For the purpose of this research, 93 sample data were collected from each type of process variables and quality characteristics as seen in **Table 5**. These data were processed and presented to the control chart pattern recognizer model to identify the types of patterns exhibited from this collected data. At the early stage of the process monitoring and controlling, the collected auto-correlated data treated for removal of auto-correlation using time series predicting model and then using this predicted data T^2 control chart is developed.

Table 2: Representation of Output Categories

Control chart pattern type	Outputs category						
	1	2	3	4	5	6	7
Normal	1	0	0	0	0	0	0
Downward shift	0	1	0	0	0	0	0
Upward shift	0	0	1	0	0	0	0
Decreasing trend	0	0	0	1	0	0	0
Increasing trend	0	0	0	0	1	0	0
Cyclic	0	0	0	0	0	1	0
Systematic	0	0	0	0	0	0	1

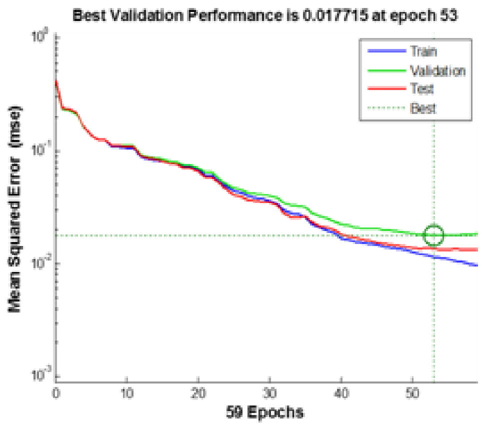

Figure 2: The network Training Performance

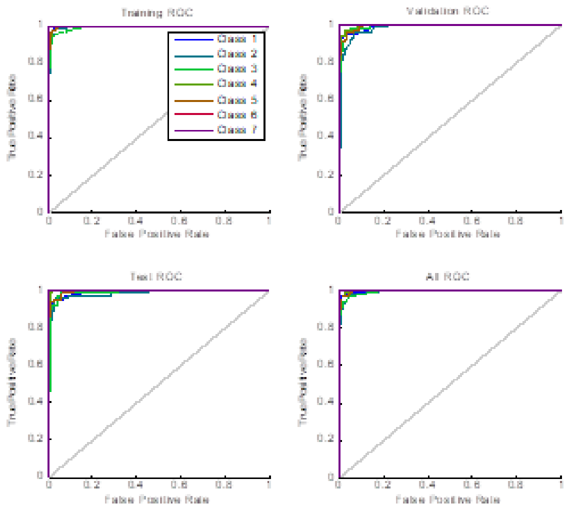

Figure 3: Network Training Receiver Operating Characteristics (ROC) Curve

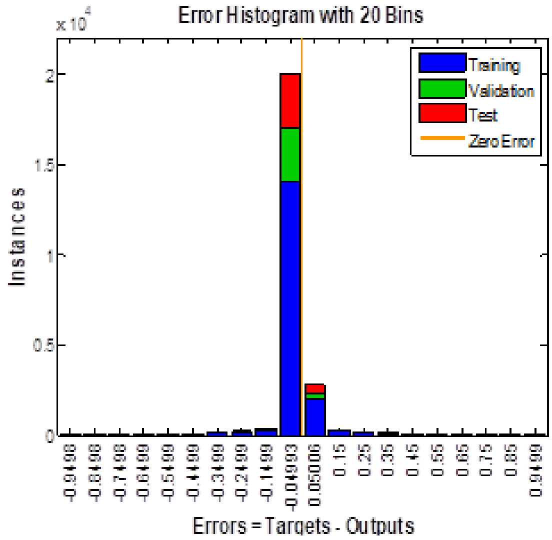

Figure 4: Error Histogram

Table 3: Matrix Showing the Classification of the Testing

		Predicted pattern						
	Types of patterns	Normal	Downward shift	Upward shift	Decreasing trend	Increasing Trend	Cyclic	Systematic
True Patterns	Normal	89.6%	5.97%	2.98%	0	1.49%	0	0
	Downward shift	2.7%	90.5%	0	6.76%	0	0	0
	Upward shift	2.7%	0	91.9%	0	5.4%	0	0
	Decreasing trend	0	6.4%	0	93.6%	0	0	0
	Increasing Trend	0	0	7.14%	0	92.86%	0	0
	Cyclic	0	0	0	0	0	100%	0
	Systematic	0	0	0	0	0	0	100%

Table 4: Critical Process Variables and Quality Characteristics

Process/stage	Variable	Variables Representation
1.Fermentation process	Fermented wine Brix	FWB
	Fermented wine temperature	FWT
	Fermented wine GL	FWGL
2. Distillation process	Fermented wine feed rate	FWFR
	Rectification column temperature	RCLT
	Pre-heater column temperature	PHCLT
	Fusel oil column temperature	FOCLT
	Filter column temperature	FCLT
	Rectification condenser temperature	RCNT
	Fusel oil condenser temperature	FOCNT
	Acidity condenser temperature	ACNT
	Distillation condenser temperature	DCNT
	Filter condenser temperature	FCNT
	Rectification column reflux rate	RCLR
	Fusel oil column reflux rate	FOCLR
	Filter column reflux rate	FCLR
3. Pure alcohol product	Pure alcohol extraction rate	PAE
	Pure alcohol grade	PAG
	Permenganent time	PT
4.Liquor product	Liquor Grade	LG

Table 5: Collected Data for 20 Critical Variables of NALF

Obsv No.	FWB	FWT	FWGL	FWFR	.	.	.	FCLR	PAE	PAG	PT	LG
1	7.3	31.8	6.0	3200.0	.	.	.	300.0	237.4	96.4	2.5	39.6
2	7.3	30.5	5.5	3200.0	.	.	.	300.0	237.4	96.4	2.5	39.9
3	7.3	31.5	7.0	3200.0	.	.	.	280.0	240.0	96.4	2.5	39.8
4	7.7	31.0	6.8	3200.0	.	.	.	370.0	233.2	96.4	2.5	40.2
.	.	.	.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.	.	.	.
90	8.9	32.5	7.5	3200.0	.	.	.	420.0	230.0	96.5	2.0	40.2
91	8.2	31.0	7.5	3200.0	.	.	.	440.0	220.0	96.5	2.0	39.8
92	9.1	33.5	7.5	3200.0	.	.	.	440.0	220.0	96.5	2.0	39.9
93	8.2	33.0	7.5	3200.0	.	.	.	440.0	230.0	95.0	2.0	40.4

Table 6: T^2 Values of the Collected Process Data

	Observation No.	**T^2 Values (data1)**	**Observation No.**	**T^2 Values (data2)**	**Observation No.**	**T^2 Values (data3)**
Control chart Pattern Recognition Window	1	20.81035	31	12.81919	55	21.30466
	2	21.80719	32	11.43592	56	25.91325
	3	26.90726	33	12.42666	57	28.7044
	4	19.40346	34	12.49176	58	22.19562
	5	16.33248	35	10.13335	59	13.31291
	6	16.36439	36	9.989161	60	7.240752
	7	37.21674	37	14.63964	61	11.52447
	8	33.8086	38	15.45348	62	20.90234
	9	32.18515	39	15.52241	63	7.983093
	10	15.16282	40	23.63752	64	22.81666
	11	22.83228	41	18.64971	65	27.13319
	12	17.99016	42	17.27818	66	12.43383
	13	22.50832	43	26.66137	67	14.50844
	14	21.21474	44	28.48098	68	18.51175
	15	31.52029	45	18.72264	69	11.88646
	16	29.44914	46	23.96568	70	12.32784
	17	37.62803	47	13.50697	71	16.71864
	18	26.15612	48	16.74802	72	12.77594
	19	20.0743	49	20.04498	73	20.10003
	20	12.48489	50	17.62342	74	22.74139
	21	25.66959	51	14.25	75	26.10231
	22	18.47132	52	23.67614	76	14.4545
	23	19.55558	53	18.94915	77	17.72669
	24	34.93054	54	15.65261	78	9.51546
	25	25.52647	55	21.30466	79	26.9718
	26	18.4959	56	25.91325	80	10.80547
	27	26.8129	57	28.7044	81	20.8425
	28	12.57247	58	22.19562	82	9.103688
	29	18.4959	59	13.31291	83	15.74605
	30	26.8129	60	7.240752	84	11.73663

From this data, the T^2 values are used as an input to the neural network model developed, to identify and classify the control chart patterns exhibited by the collected process data. The T^2 values of the collected process data are listed in Table 6. To apply the proposed model, the T^2 values of the collected data are calculated (**Table 2**.), that is obtained from hotelling's T^2 control chart of a controlled process was taken and standardized to values (μ=0, σ=1), and presented to the neural network control chart pattern recognizer. The trained network starts to recognize the type of pattern exhibited by the data presented based on the window size of 30 consecutive observations and the output of the recognition is presented as follows:

The size of recognition window (window length) can significantly affect the performance of the control chart pattern recognizer (Lin et al., 2011 and Guh & Shiue, 2008). The window length is defined as the number of sample points to be considered at a time in detecting an unnatural pattern. Since the number of network inputs affects the size of the network, emphasis should be given to the selection and representation of the data in the training set. For quick computation in process control, lesser window size is efficient; however, as previous studies indicated, too small window size detects control charts quickly that means it has a shorter Average Run Length (ARL). This situation might generate higher Type I error due to insufficient information to represent the features of data. On the other hand, if the window size is too large, it might generate higher Type II error and may consume significant computation time. In this study, a window size of 30 were selected through trial and error in order to obtain good generalization performance of the neural network. The T^2 control chart which shows the in control process generated by Qualstat software application was presented in **Figure 5**. As it is seen in the control chart, all the data points are distributed below the upper control limit of the process which shows the process being in control.

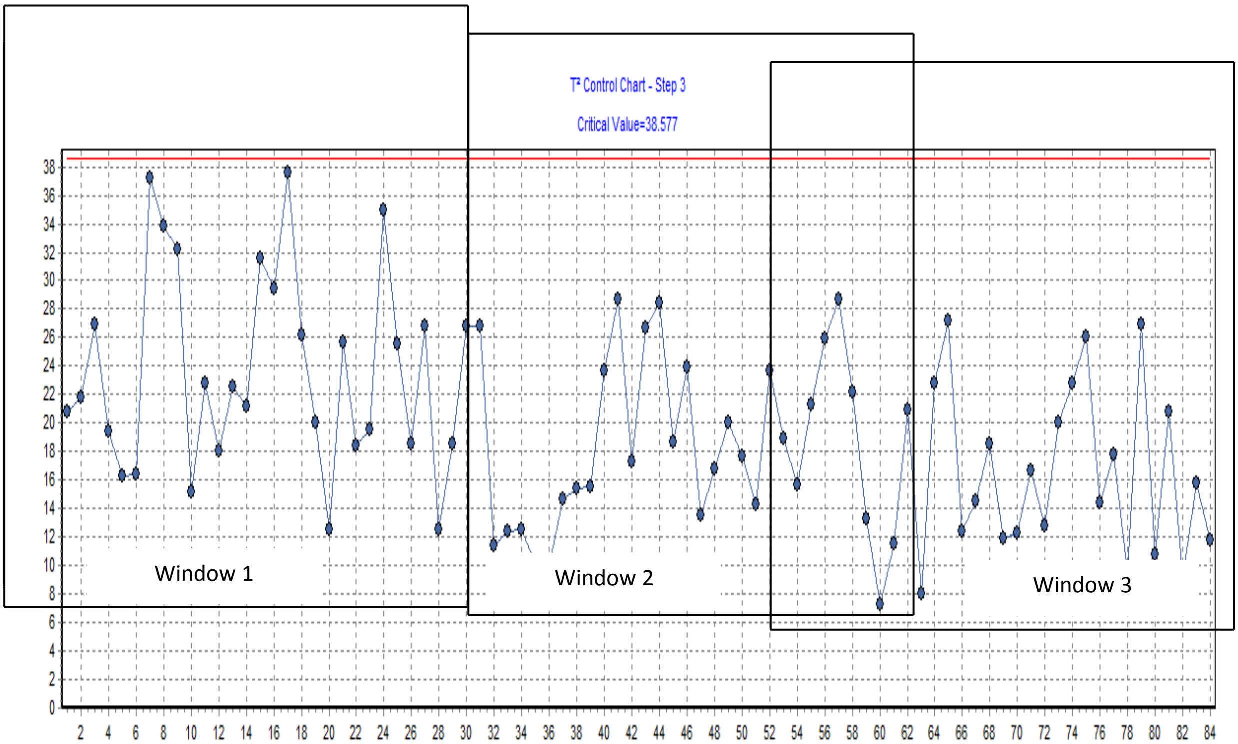

Figure 5 : T^2 Control Chart for Observations

As any window of data is applied to the trained network, one of the predefined pattern classes (normal, downward shift, upward shift, decreasing trend, increasing trend, cyclic, and systematic pattern) is determined. In this aspect when the given observation of the above window sizes of the standardized T^2 values for observation No. 1-30 (data1), 31-60 (data2), and 55-84 (data 3) are applied in a separate window to the proposed CCPR, the following output were identified: The control chart pattern recognition model classifies all the three control chart patterns presented from the in control process as a normal pattern. Therefore, this result shows that the control chart pattern recognition model performs very accurately by generating the same results with the predefined state of the process.

CONCLUSIONS

The training result shows that, the neural network has a very good performance in recognition of control chart patterns with overall recognition accuracy of 94.9%. In the network testing results, it was observed that most of the misclassification to happen in the recognition of downward shift, upward shift, and increasing and decreasing trend patterns. With the presence of downward shift patterns, most of the misclassified patterns are classified as decreasing trend and less frequently as a normal pattern. In the presence of upward shift patterns, most misclassifications were classified as increasing trends and less frequently as normal patterns. In increasing trend patterns all of misclassifications were upward shift patterns, whereas in decreasing trend all misclassifications were a downward shift pattern. The misclassification between shift and trend patterns indicates that patterns with small shift magnitudes resembles with trend patterns and vice versa. It is also found that both cyclic and systematic patterns were not misclassified (recognized with 100% accuracy). From the presented testing data though there are both type I type II errors, the overall testing result (94.1%) indicates that the training was successful and the neural network performance is accurate. The proposed methodology was evaluated using the controlled process data from a company process and accurate results were obtained as the control chart pattern recognition model signals an output of a normal control chart pattern. This result shows that the integration of control chart pattern recognition model and multivariate statistical process control technique can give a better performance of process monitoring and controlling activity.Hence, the proposed model can be adapted to various process settings of manufacturing industries. In the adoption of the model proposed by this study to reduce the misclassification rate among different classes of control chart patterns, one should increase the number of training examples with those patterns that exhibit higher confusion rate in this study. In the application and effective use of this model, manufacturing industries should also determine the possible association of assignable causes with specific control chart pattern exhibited by their process.Further research shall be done on the magnitude of special cause disturbance like shift magnitude, trend slope, cycle amplitude and period, and process fluctuation magnitude that are important activity in control chart pattern recognition, the task of estimation of this parameter magnitudes were not included in this study. This study considers seven types of control chart patterns. Hence, future study shall also address the situations when multiple (mixed) abnormal patterns exist concurrently in multivariate process control charts.

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