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Robust Multi Variable Process Control Chart Pattern Recognition Using Neural Modeling

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Abstract: Control Chart Pattern Recognition (CCPR) is a critical task in Statistical Process Control (SPC). Abnormal patterns exhibited in control charts can be associated with certain assignable causes adversely affecting the process stability. In fact, numerous CCPR studies have been developed according to various objectives and hypotheses. Despite the research, efforts are keeping continue to increase the efficiency and recognition model simplicity. Application of different CCPR is obvious in an industrial production process where many process parameters have to monitor to meet the objectives. In this research, rather than having several numbers of CCP recognizer, a multi-process CCP recognition using a single recognition model has presented to save the solution cost. Recognition model has applied feedforward neural architecture along with gradient descent learning. In previous research over CCPR, effects of faults in recognition model have generally ignored which is very important from real-time application point of view. In this study, the effects of faults over the efficiency of CCP recognition are also presented and observed that the proposed model has very high levels of fault tolerance against different types of faults. Test simulation has applied over the huge number of control chart patterns and observed that the proposed method has delivered the superior recognition accuracy in a robust manner in comparison with other existing works in literature.

Key words: Control chart pattern, pattern recognition, neural network, fault tolerance, architecture, recognition

INTRODUCTION

Control charts are important statistical process control tools for determining whether a process is run in its intended mode or in the presence of unnatural patterns. Patterns displayed on control charts can provide information about the process. Control charts have two general uses in the maintaining the quality of the process, the most common application is as a tool to monitor process stability and control and a less common, although, some might argue more powerful, use of control charts is as an analysis tool. When a process is stable and in control, it displays common cause variation, a variation that is inherent to the process. A process is in control when based on past experience it can be predicted how the process will vary (within limits) in the future. If the process is unstable, the process displays special cause variation, non-random variation of external factors. Control charts are simple, robust tools for understanding process variability. Control Chart Patterns (CCPs) are important statistical process control tools for determining whether a process is run in its intended mode or in the presence of unnatural patterns. CCPs can exhibit six types of pattern: NoRmal (NR), CyClic (CC), Increasing Trend (IT), Decreasing Trend (DT), Upward Shift (US) and Downward Shift (DS) (Wang *et al*., 1998). Except for normal patterns, all other patterns indicate that the process being monitored is not functioning correctly and requires adjustment. Figure 1 has shown six fundamental patterns of a control chart. Interpretation of the process data still remains difficult because it involves pattern recognition tasks. It often relies on the skill and experience of the quality control personnel to identify the existence of an unnatural pattern in the process. An efficiently automated Control Chart Pattern (CCP) recognition system can compensate this gap and ensure consistent and unbiased interpretation of CCPs, leading to a smaller number of false alarms and better implementation of control charts. With this aim, several approaches have been proposed in past for CCP recognition. Some of the researchers have used rules-based possibilities like expert systems, the fuzzy clustering method and Decision Tree (DT) based classifier while other researchers have used black box approaches

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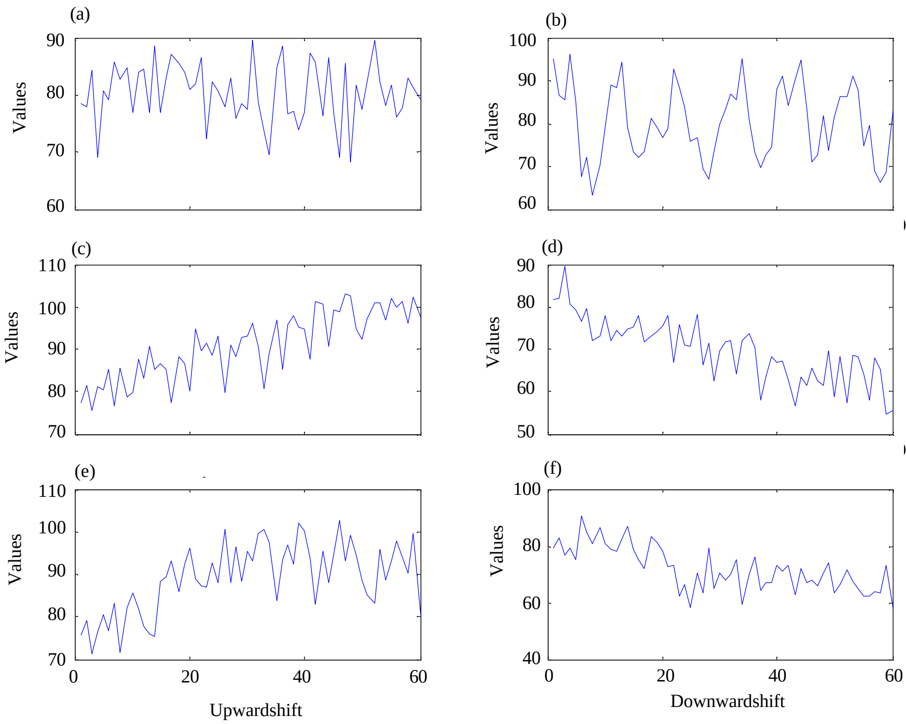

Fig. 1: Six variations of pattern in CCP: a) Normal; b) Cyclic; c) Increment; d) Decrement; e) Upwardshift and f) Downwardshift

like Artificial Neural Networks (ANNs) for recognition of CCPs. ANNs can be simply classified into two main categories: supervised ANNs and unsupervised ANNs. Literature reviews show that the techniques that use supervised neural networks as the classifier have higher performances. The advantage with a neural network is that it does not require the provision of explicit rules or templates. Most existing techniques have used the unprocessed data as the inputs of the CCP recognition system. The use of unprocessed CCP data has many additional problems such as the amount of data to be processed being large. On the other hand, the approaches which use pattern features are more flexible to deal with a complex process problem, especially when no prior information is available. If the features represent the characteristic of patterns explicitly and if their components are reproducible with the process conditions, the classifier recognition accuracy will increase. Further, if the feature is amenable to reasoning, it will help in understanding how a particular decision was made and this makes the recognition process a transparent process. Features could be obtained in various forms, including principal component analysis shape features, a correlation between the input and various reference vectors and statistical correlation coefficients.

This study has applied multilayer feedforward architecture for recognition of the fundamental six types of control chart patterns. The proposed method includes three main modules: Recognition module for a single process, effects of architecture connection faults over recognition efficiency and recognition of the multiprocess CCP through a single neural model. Performance comparison has also presented with other existing work in literature.

Literature review: Because of its significant contribution in maintaining the process quality, CCP recognition area has got lots of attention from a number of researchers. Industrial development of a pattern recognition system designed to detect and analyze various patterns that can occur on statistical quality control charts has presented by Wang *et al.* (1998). Pattern recognition techniques have been widely applied to identify unnatural patterns in control charts. The statistical correlation coefficient method has applied by Yang and Yang (2005) in the development of control chart pattern recognition system. The research by Guh (2005) has presented a hybrid learning-based model which integrates NN and DT learning techniques to detect and discriminate typical unnatural CCPs while identifying the major parameter (such as the shift displacement or trend slope) and the starting point of the CCP detected. The investigation has been given by Ebrahimzadeh and Ranaee (2010) on the design of a better system for Control Chart Pattern (CCP) recognition that includes two main modules: the feature extraction module and the classifier module. The feature extraction module uses the entropies of the wavelet packets. The possibility of parallel algorithms for fast control chart pattern recognition has explored by Wani and Rashid (2005). It addressed three major issues of control chart pattern recognition: Transparency, accuracy and fast detection of abnormal patterns. Combination of clustering and classified as a Hybrid Intelligent Method (HIM) (Ebrahimzadeh *et al*., 2012) has applied for recognition of the common types of Control Chart Pattern (CCP). Temporal coding spiking neural networks have received wider attention due to their computational power. The coincidence detection property of a spiking neuron which has no counterpart in a sigmoidal neuron is one of the reasons for that power. Application of spiking neural network for CCP recognition has been shown by Pham *et al*. (2007) and Awadalla and Sadek (2012). Enhancements to the SpikeProp learning algorithm have also given by Awadalla and Sadek (2012) which provide additional learning rules for the synaptic delays, time constants and for the neurons thresholds. To improve the pattern recognition performance of control chart, a method based on Improving Sequential Forward Selection (ISFS) and Extreme Learning Machine (ELM) has been presented by Zhang and Lin (2014). Based on Bayesian inference and maximum likelihood estimation, a statistical method of Control Chart Pattern (CCP) recognition has presented by Naeini *et al*. (2011). Fourier descriptors and neural networks have applied by Phokharatkul and Phaiboon (2011) to analyze the control chart pattern. A hybrid model for recognizing the mixture CCPs that included three main aspects: Feature extraction, classifier and parameter optimization has also exploredin (Zhang and Cheng, 2015). In the feature extraction, statistical and shape features of observation data are used in the data input to get the effective data for the classifier. A Multiclass Support Vector Machine (MSVM) applies for recognizing the mixture CCPs. Finally, the Genetic Algorithm (GA) is utilized to optimize the MSVM classifier by searching the best values of the parameters of MSVM and kernel function. By assuming that an unnatural CCP is a combination of normal pattern and process disturbance, a multi-stage control chart pattern recognition scheme which integrates Independent Component Analysis (ICA) and Support Vector Machine (SVM) is proposed by Kao *et al*. (2016). The proposed multi-stage ICA-SVM scheme first uses ICA to extract Independent Components (ICs) from the monitoring process data containing CCPs. Bag *et al*. (2012) has given focus on the design and development of an expert system for on-line detection of various control chart patterns, so as to enable the quality control practitioners to initiate prompt corrective actions for an out-of-control manufacturing process. A hybrid approach has been proposed by Yang *et al*. (2015) that integrates Extreme-point Symmetric Mode Decomposition (ESMD) with Extreme Learning Machine (ELM) to identify typical concurrent CCPs and in addition to accurately quantify the major CCP parameter of the specific basic CCPs involved. Pattern generation scheme on the accuracy of pattern recognition has been studied by De la Gutierrez and Pham (2016) using two ML algorithms: Support Vector Machine (SVM) and Probabilistic Neural Network (PNN). An attribute control chart using multiple-dependent state repetitive sampling has designed by Aldosari *et al*. (2017).

In most of the previous research, simulation performances have analyzed over small data set of control chart patterns which do not assure the reliability of obtaining performances over the long run. The obtained accuracy of recognition is another concerning issue which required attention to improve because monitoring takes place in real time and the uncontrolled process can cause the increased value of production cost and completion time. The third concern part is the robustness of the recognition module itself, especially when there is a hardware implementation of the recognition module. Any faults in the recognition module can cause serious degradation in recognition efficiency. The fourth concern issue is handling the multiple process parameters cost effectively.

MATERIALS AND METHODS

Modeling of data generation in CCP: CCPs are used to monitor the behavior of the system. Figure 1 shows the 6 main types of pattern that observed on a control chart: Normal, cyclic, downward shift, upward shift, increasing trend and decreasing trend patterns. All patterns except for normal patterns illustrate that the process being monitored is not functioning correctly and requires adjustment. For this study, the patterns of all these different types were generated using equations as shown in Table 1. Each pattern was taken as a time series of 60 data points. In the equations, η is the nominal mean value of the process variable under observation, σ is the standard deviation of the process variable, a is the amplitude of cyclic variations in a cyclic pattern (set to <15), g is the gradient of an increasing trend pattern or a decreasing trend pattern (set in the range 0.2-0.5), b indicates the shift position in an upward shift pattern and

Table 1: Modeling of CCP and associated parameters values

Control chart pattern	Pattern modeling equation	Parameters values
Normal	$p(t) = \eta + r(t)\sigma$	$\eta = 10;\ \sigma = 5$
Cyclic	$p(t) = \eta + r(t)\sigma + a \sin\left(\frac{2\pi t}{T}\right)$	$a = 10;\ T = 10$
Increasing trend	$p(t) = \eta + r(t)\sigma + gt$	$g = 0.35$
Decresing trend	$p(t) = \eta + r(t)\sigma - gt$	
Upward shift	$p(t) = \eta + r(t)\sigma + bs$	$S = 12$
		$K_1 = 12$
Downward shift	$p(t) = \eta + r(t)\sigma - bs$	$K_2 = 30$
	Where $b = \begin{cases} 0 \text{ if } t<L \\ 1 \text{ if } t \geq L \end{cases}$	
	$L = \left[U[0,1]\right]k_2 + k_1$	

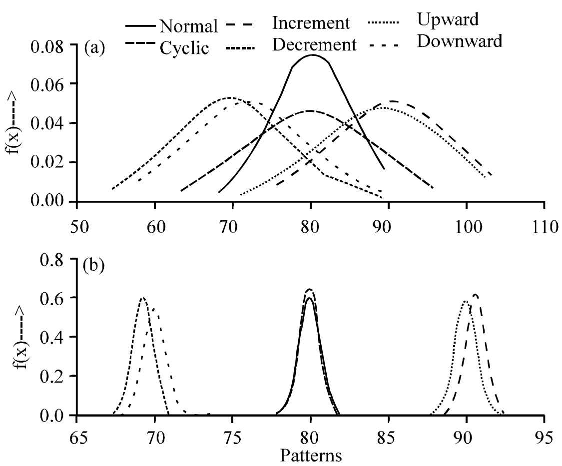

Fig. 2: Probability density function characteristics of all patterns in: a) Single data set and b) All data set

a downward shift pattern (b = 0 before the shift and b = 1 at the shift and thereafter), s is the magnitude of the shift (set between 7.5 and 20), r (:) is a function that generates random numbers normally distributed between -3 and 3, t is the discrete time at which the monitored process variable is sampled (set within the range 1-60), T is the period of a cycle in a cyclic pattern (set between 4 and 12 sampling intervals) and p (t) is the value of the sampled data point at time t .

Complexity in statistical characteristics of CCP data: To understand the complexity involved in the recognition of the control chart patterns, statistical characteristics of patterns have analyzed. Total 3000 patterns (500 of each type) were generated in total as according to modeling equations have given in Table 1. The normal Probability Density Function (PDF) of each class has computed for visualizing the statistical separability. In Fig. 2a, the PDF for a randomly selected set of 6 different patterns has shown and considered as short-run characteristic of patterns while in Fig. 2b, the PDF of all the 6000 patterns has shown and considered as long-run characteristics of patterns. It is observed from Fig. 2b, that there is a high level of overlap between normal and cyclic patterns while the combinations of increment and upward shift, decrement and downward shift, there was very significant overlap. Such overlapped characteristics of PDF show the difficulties involved in the recognition of the control chart pattern, particularly through the statistical process. Even for the short run case, there is a huge overlap observed among different classes of patterns as shown in Fig. 2a.

Applied neural model for CCP recognition: The complexity involved in the statistical separation of patterns in the control chart as shown earlier has suggested choosing the recognition model which does not consider the patterns statistical features as inputs, hence in this study, black box approach based on the artificial neural network has applied. Because of the availability of targets, feedforward architecture has considered instead of recurrent architecture. Because of objectives to meet better generalization, fault tolerance and handling multiprocess simultaneously, MLP has considered instead of other possibilities of architecture like Radial Basis Function (RBF) architecture which is more sensitive towards connection faults.

Multilayer feedforward architecture has taken as a neural model in which gradient descent based has applied on squared error surface to arrive at the minimum. The key to the use of this method on a multilayer perceptrons is the calculation of error values for the hidden units by propagating the error backwards through the network. The local gradient for the jth unit in the output layer is calculated as (assuming a logistic function for the sigmoid nonlinearity):

$$\delta_j = y_j(1-y_j)(d_j-y_j)$$

Where:

y_j = The output of unit j and
d_j = The desired response from the unit

For a hidden layer, the local gradient for neuron j is calculated as:

$$\delta_j = (1-y_j)\sum_k \delta_k w_{jk} \quad (1)$$

where, summation k is taken over all the neurons in the next layer to which the neuron j serves as input. Once the local gradients are calculated, each weight w_{ji} is then modified according to the delta rule as given in Eq. 2:

$$w_{ji}(t+1) = w_{ji}(t) + \eta\delta_j(t)y_i(t) \quad (2)$$

Where:

η = Learning-rate parameter
t = Time

Frequently modification of Eq. 2 is used that incorporates a momentum term that helps accelerate the learning process and the final equation has given in Eq. 3:

$$w_{ji}(t+1) = w_{ji}(t) + \eta\delta_j(t) + a\left[w_{ji}(t) - w_{ji}(t-1)\right] \quad (3)$$

where, a is a momentum term lying in the range $0 < a < 1$.

Fault tolerant analysis of proposed ANN system: When a system designed, quality characteristics can be defined in various ways like speed, power consumption, size, etc. Another kind of parameter which defines the reliability of the system is fault tolerance. It defines the reliability of system output if any fault happens. For a given design to know the performance value with respect to fault tolerance, it requires to analyze the system thoroughly. ANN works on parallel distributed computing, so, the expectation of fault tolerance is very high. This is a matter of interest to know how faults in ANN affect its performance with the presented principle of recognition. From a functional point of view and independently of the hardware implementation options; An ANN can have the following faults; Fault with a connection/weight or multiplier; Fault in an input; Fault in a multiplier, adder or accumulator; Fault in the activation function.

Some of these faults can mask each other in the sense that it can be indistinguishable which fault occurred. This is the case of faults of type (iii) and (iv) which produces the same type of impact in the output and can be considered as the same situation. While other faults occur in parts of the network which have connections in parallel and the impact in the output must be analyzed in this part of the circuit the connection is serial and the effect is similar. Faults of type (i) and (iii) both include the multiplier. This duplication was considered because the existence of a multiplier associated with each connection falls into fault type (i) and the existence of a single multiplier before the activation function falls into fault type (iii). Among all possible faults, faults with weights and connections are more sensitive from a practical point of view hence analysis has done over that. The global model has used consists of faults of type stuck at $+W_{max}$, $-W_{max}$ or 0 for all the connections where $+W_{max}$ is the maximum value that the weight can assume with practical effect. This model has used in the following way: Test the effect of each individual fault by setting the weight associated with each connection to $+W_{max}$, $-W_{max}$ and 0. Practically fault occurrence happens with the uniform distribution over the connection.

RESULTS AND DISCUSSION

Experimental analysis: The proposed principle has applied in this study for control chart pattern recognition with single and multiple processes. Pattern dataset which contains 3000 patterns has been generated through the model equations. Training data set contains the first 100 set of all 6 patterns (600 patterns) while the test dataset contains remaining 2400 data patterns. Feedforward architecture has developed which has a size of 60 input nodes, 10 hidden nodes and 6 output nodes (each corresponding to individual pattern). The unimodal sigmoid function has considered as activation function in all active nodes. Presence of maximum value among all 6 output nodes decides recognize patterns on the input side. Pre-processing has applied to all patterns in terms of normalization to keep the pattern variation within the range of (0 1). Bias with fixed input +1 also has applied to hidden nodes and output nodes. Initialization of all weights defined as a random number by a uniform distribution in the range of (-1 1). To increase the speed of learning momentum has also applied to momentum constant equal to 0.2. The value of learning rate is taken as 0.5 for all patterns. The objective of the learning process was to meet the mean square error of less than 0.001.

Case 1; Single process CCP recognition: Over 600 patterns, training has given and for the remaining 2400 patterns test experiment has applied. Mean square error plot for learning has shown in Fig. 3. It is clear that there

Table 2: Average performance for a single process

Trial No.	Tr. data performance	Test data performance	No.of iterations in training	Time taken (sec) in training
1	99.6667	99.8333	140	16.2970
2	99.8333	99.7917	93	10.9220
3	99.3333	99.8750	117	13.5790
4	98.8333	99.9167	226	26.5310
5	99.8333	99.8750	96	10.8910

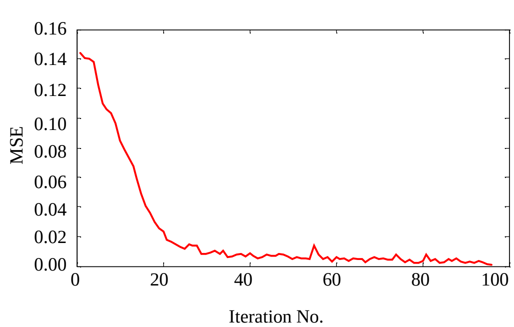

Fig. 3: Convergence characteristics in the learning mode

Table 3: Confusion matrix for a single process in all trials

Trial 1: Recognise pattern (%)						
Given test pattern	NOR [TrP TsP]	CYC [TrP TsP]	IT [TrP TsP]	DT [TrP TsP]	US [TrP TsP]	DS [TrP TsP]
NOR	[100 99.5]				[0 0.5]	
CYC		[100 100]				
IT			[100 100]			
DT				[100 100]		
US			[0 0.5]		[100 99.5]	
DS				[2 0]		[98 100]
Trial 2; Recognise pattern (%)						
NOR	[100 99.75]			[0 0.25]		[0 0]
CYC		[100 100]				[0 0]
IT			[100 100]			[0 0]
DT				[100 99.75]		[0 0.25]
US	[0 0.5]		[0 0.25]		[100 99.25]	[0 0]
DS				[1 0]	[0 0]	[99 100]
Trial 3; Recognise pattern (%)						
NOR	[100 100]					
CYC		[100 100]				
IT			[100 100]			
DT				[100 99.75]		[0 0.25]
US					[100 100]	
DS				[4 0.5]		[96 99.5]
Trial 4: Recognise pattern (%)						
NOR	[100 99.75]				[0 0.25]	
CYC		[100 100]				
IT			[100 100]			
DT				[100 99.75]		[0 0.25]
US					[100 100]	
DS				[7 0]		[93 100]
Trial 5; Recognise pattern (%)						
NOR	[100 99.75]				[0 0.25]	
CYC		[100 100]				
IT			[100 100]			
DT				[100 100]		
US			[0 0.5]		[100 99.5]	
DS				[1 0]		[99 100]

is a very sharp decline in the error value at the beginning itself. The whole process was repeated for 5 independent trials to get the understanding of experimental variation. The obtained result in the form of average recognition performance and in the form of a confusion matrix has been shown in Table 2 and 3. The required number of iterations to achieve the error below the desired value along with the time taken in the training process for each trail also has shown in Table 2. It is observed that there were very high recognition accuracy and consistency performances in the different trials over training as well as test data set. As we know, the values in the diagonal of the confusion matrix show the correct performance of the recognizer for each pattern. In other words, these values show how many considered patterns are recognized correctly by the system. The other values show the mistakes of the system. In order to obtain the Recognition Accuracy (RA) of the system, it is needed to compute the average values that are appeared in the diagonal of the confusion matrix.

Scatter diagram of recognition values for all patterns has shown in Fig. 4. The maximum value of a particular pattern class indicates the quality of the decision and its confidence over that class.

Comparison with existing work: To get the relative comparison in recognition accuracy, three different works available in the literature (Ebrahimzadeh *et al*., 2012; Zhang and Cheng, 2015; Awadalla and Sadek, 2012) have taken. Medhat etc. (Awadalla and Sadek, 2012) have applied spiking neural network architecture for a control chart recognition purpose which consists of a fully connected feedforward network of spiking neurons. The overall recognition efficiency has achieved as 98.6%. Based on statistical features and shape (Zhang and Cheng, 2015) has applied the support vector machine to recognize the patterns class. GA has applied to optimize the parameters of SVM. Different statistical characteristics of pattern like; Mean, standard deviation, mean-square value, average autocorrelation, positive cusum, negative cusum, skewness, kurtosis have applied while shape

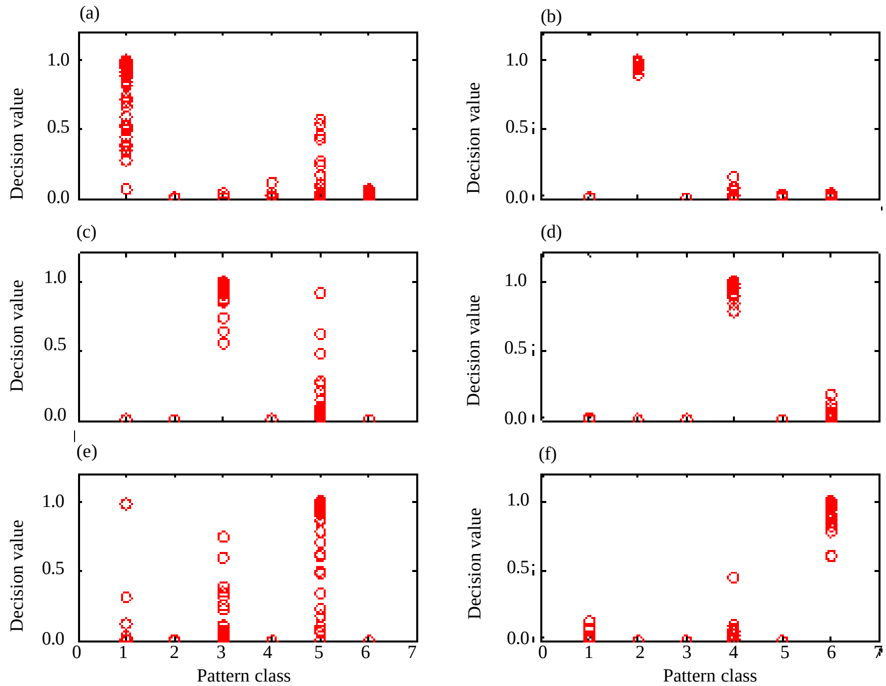

Fig. 4: a-f) Pattren class, decision value scatter diagram in single process CCP recognition

Table 4: Comparative performance for single process CCP

	Comparison in recognise pattern (%)						
Method	NOR	CYC	IN	DT	US	DS	Avg, perform
Awadalla and Sadek (2012)	99	98.2	98	98.5	99	99	98.6167
Zhang and Cheng (2015)	100	98	98	100	100	98	99.00
Ebrahimzadeh *et al*. (2012)	100	100	97.9	100	100	100	99.65
Proposed	99.75	100	100	100	99.75	100	99.9167

features of pattern like slope of the least-square line, number of mean crossing, number of least-square line crossing, the area between the pattern and its mean line, area between the pattern and its least-square line have considered. The overall achieved efficiency was 99%. To increase the accuracy (Ebrahimzadeh *et al*., 2012) has applied a hybrid approach of clustering and classifier. Different types of neural architecture, MLP (Resilient back-propagation), MLP (momentum), the PNN and the RBF have applied and obtained accuracy were 99.65, 99.23, 99.53 and 96.42% correspondingly. Obtained the best result in this study has compared with other results available in the Ebrahimzadeh *et al*. (2012), Zhang and Cheng (2015), Awadalla and Sadek (2012) as is shown in Table 4. It is clear that the proposed method has better efficiency from other considered methods. The overall recognition efficiency achieved by the proposed method is 99.91% which is superior and can be considered as an optimal status for practical purpose.

Table 5: Input-Hidden layer connection faults and achieved avg. performance

	Avg. performance (%)			Avg. performance (%)	
No.of fault (Type: Open)	Tr.	Ts	No.of fault (Type :close)	Tr.	Ts
4	99.6667	99.6667	8	99.8333	99.7083
3	99.6667	99.5417	3	99.8333	99.2083
7	99.8333	99.4583	5	99.1667	99.5000

Table 6: Hidden-Output layer connection faults and achieved avg. performance

	Avg. performance (%)			Avg. performance (%)	
No.of fault (Type: open)	Tr.	Ts	No.of fault (Type: Close)	Tr.	Ts
2	99.6667	99.0417	2	99.6667	99.7917
1	99.8333	99.8750	1	99.8333	99.8750
2	99.8333	98.9167	2	98.1667	99.1667

Robustness against faults: Faults in hidden and outer layer connections have considered in this study and the robustness of proposed system against these faults (open and short) has estimated in terms of variation in recognition efficiency by comparing of the system without faults. Probabilistic environment through uniform distribution has applied to find the position of faults in the input-hidden layer connections as well as hidden-output layer connections. Each connection has chance to be faulty as 5%. To get the more clear information about the effect of faults, performances have evaluated separately over training dataset as well as test data set. For a different number of faults over input-hidden layer connections and hidden-output layer connections, obtained performances have shown in Table 5 and 6. The average recognition

Table 7: Average performance against faults

Fault place	Fault type	Avg. No. of fault	Tr. data	Test data
I-H layer	Open	5	99.72	99.56
I-H layer	Short	6	99.61	99.47
H-O layer	Open	2	99.78	99.28
H-O layer	Short	2	99.22	99.61

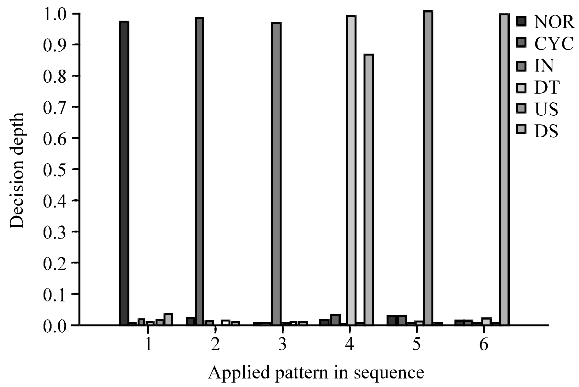

Fig. 5: Decision value in recognition for six different patterns with the fault in output connection weight

performance against average no. of faults also has shown in Table 7. It was observed that either for open connection faults or short connection faults, performance were more than 99% of all cases which is very appealing from a practical point of view and can be considered as fault-tolerant.

It is observed from performance result after faults that there is no significant effect of faults in terms of recognition efficiency but decision depth level has reduced which is very obvious. The decision depth (probability to be a pattern) for a test set of patterns has shown in the Fig. 5 in which the decision depth of each pattern has a different color. The height of decision depth indicates the confidence towards the pattern.When a test input pattern applied, the decision depth corresponding to all six patterns appeared in the output.The position of the maximum value of decision depth decides the final recognized pattern. It is observed that the pattern 4 which is decreasing trend pattern when has applied to test, there is the maximum outcome for 4th position and very close to zero for another pattern position except position 6 corresponding to downward shift. Such an outcome has appeared because of statistical similarity in both patterns as shown in Fig. 2. Technically because of a connection fault, either information passed with lesser/zeros weight in open type of faults or with more weight than actual in short type of faults.

Practical integration of proposed solution with an industrial plant has shown in Fig. 6 where neuro CCP

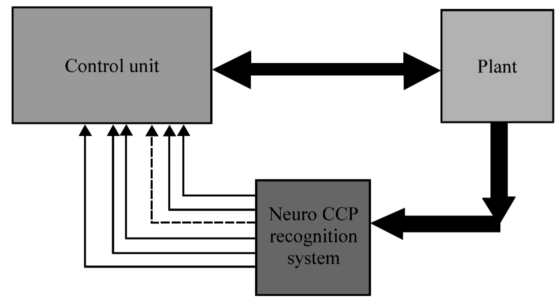

Fig. 6: Application phase of single parameter neuro system

recognition module recognized the characteristic of currently available pattern and passes this information to control unit where correct measure step is taken if needed.

Case 2; Multivariable process CCP recognition: Generally, there are a number of parameters which have to monitor to deliver the output under a satisfactory range of variation. To monitor and analyze all the parameters together, we have applied the three process parameters which have varied nature as given through the Table 1 but each process parameter has their own mean value ([80, 40, 20]) and standard deviation ([5 7 3]) in result there were 18 patterns in a set of pattern. Total 10800 patterns generated in which 1800 patterns have taken for training and remaining 9000 patterns have taken for test purpose. Preprocessing has applied to normalize the data and neural model is the same as in case of single process parameters. In Fig. 7, the different process parameters for a set of 18 patterns have shown. Error minimization characteristic in the learning process has shown in the Fig. 8. For the test point of view, five independent trials have given to understand the overall performance behavior of the proposed model and obtained performances have shown in Table 8. It is clear from the result that on average there is more than 99% efficiency has been obtained. The practical integration of the proposed model with application plant has shown in the Fig. 9. There is Time Division Multiplexing (TDM) sampling method need to apply to capture the all process parameters from the plant one by one. While the recognition of one process parameter is in progress, other process parameter information is stored in the corresponding buffer and the stored information utilized for the next time slot. Control unit collects the decision of neuro recognizer and takes the appropriate measure step as according to need.

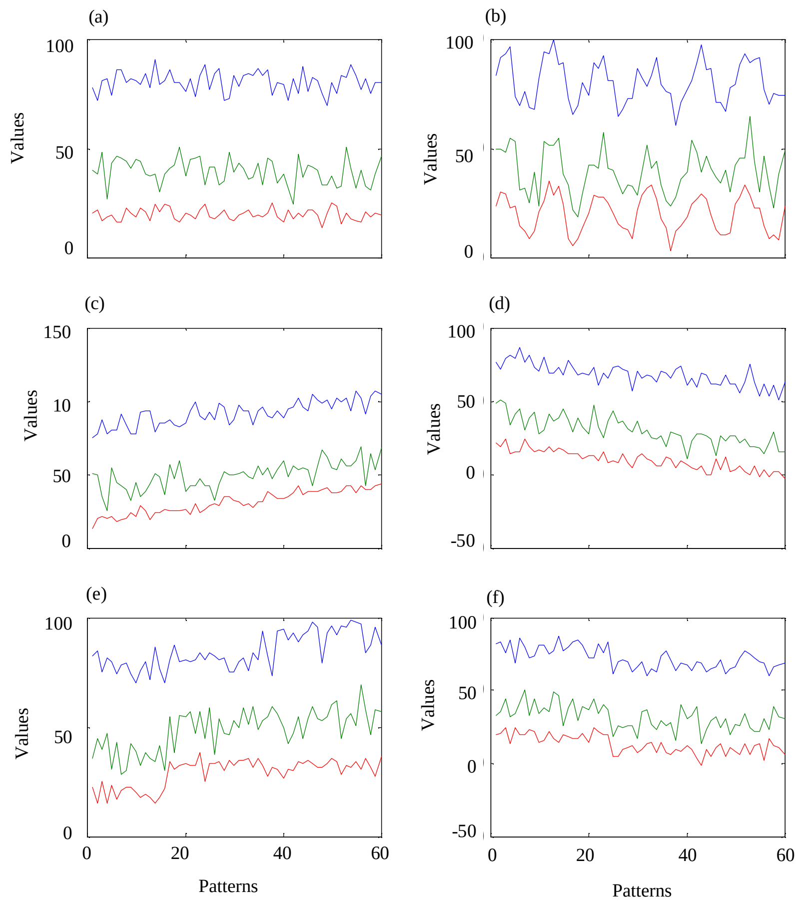

Fig. 7: Three different process patterns in single CCP: 1st process (Blue color), 2nd process (Green color), 3rd process (Red color): a) Normal pattern; b) Cyclic pattern; c) Increment pattern; d) Decrement pattern; e) Upward pattern and f) Downward pattern

Table 8: Performance efficiency (%) over training and test data set for multiprocess CCP

	Trial 1		Trial 2		Trial 3		Trial 4		Trial 5	
Pattern	Tr.	Test	Tr.	Test	Tr.	Test	Tr.	Test	Tr.	Test
NOR	100.00	098.00	100.00	099.75	100.00	099.50	100.00	099.75	100.00	099.25
	100.00	093.75	098.00	095.25	099.00	091.75	100.00	092.75	100.00	095.75
	100.00	095.75	100.00	097.50	100.00	095.50	100.00	098.00	100.00	097.75
CYC	100.00	099.75	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	099.50
	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
IT	100.00	100.00	100.00	100.00	100.00	099.75	100.00	099.75	099.00	098.00
	100.00	099.50	100.00	099.75	100.00	099.25	100.00	099.25	100.00	097.00
	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
DT	100.00	100.00	100.00	100.00	100.00	099.75	100.00	100.00	100.00	100.00
	100.00	099.25	100.00	099.75	100.00	098.50	100.00	099.25	100.00	099.75
	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
US	100.00	100.00	100.00	100.00	100.00	099.75	100.00	100.00	100.00	099.75
	100.00	097.75	099.00	096.25	100.00	095.50	100.00	099.00	100.00	098.50
	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
DS	100.00	098.75	100.00	098.00	099.00	100.00	100.00	100.00	100.00	099.50
	100.00	098.75	100.00	098.00	099.00	098.75	100.00	099.25	100.00	096.50
	100.00	100.00	100.00	100.00	099.00	100.00	100.00	100.00	100.00	100.00
Avg.	100.00	098.958	099.83	099.13	099.78	098.78	100.00	099.28	099.95	098.96

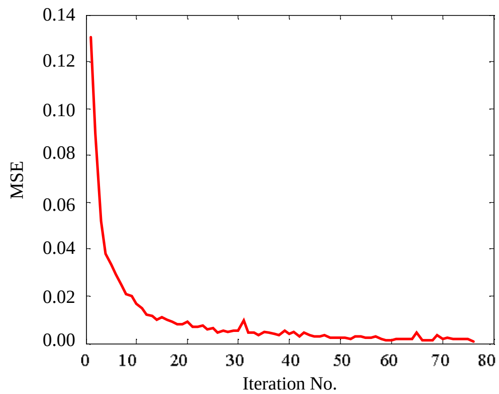

Fig. 8: Error minimization in the learning of the multiprocess parameters

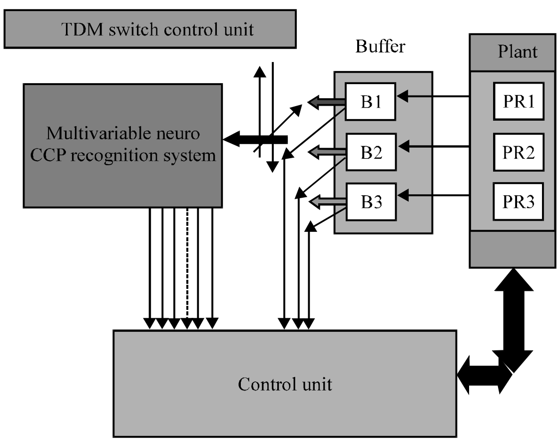

Fig. 9: Schematic diagram of integration for multivariable CCP recognition system with the plant and control unit

CONCLUSION

The need of automated control chart pattern is very important and crucial in industrial applications where the need for high efficiency and simplicity are always desired. In this research; Based on the feedforward architecture of the neural network, single process as well as multi process parameters of the CCP recognition solution has presented to meet the practical industrial need. The six fundamental patterns of control chart: normal, cyclic, incremental, decremental, upward shift and downward shift have included for recognition purpose. The proposed solution has analyzed the effect of faults which can happen in hidden and output layer connection weights and observed that the proposed solution has enough strength to tolerate these faults. The proposed solution has tested over huge number of patterns under the number of independent trials and correct recognition accuracy on average was more than 99.85% on a single process while more than 99% of multi-process. Integration of the proposed solution with a plant in the block diagram form has also presented. Finally with the outcome of experimental results, it can be stated that the proposed solution can be applied in any industrial plants where precision; Accuracy and speed are of paramount importance to monitor and analysis of the control chart pattern.

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