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Monitoring Process Mean and Variability Using Artificial Neural Networks

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Abstract— In today's modern market quality of product is most preferable parameter for customers. In order to fulfill the customer requirements manufacturing industries implementing the advanced technology in order to improve and maintain high quality of product. Consequently its real time need that process variation is to be controlled in very advanced approach.The Shewhart $\overline{X}$ chart is usually used to monitor shifts in process mean, whereas, the R and S charts are most widely used in industry to monitor process variability. In this paper, artificial neural network based approach is developed for monitoring the mean and variability of the process. The ARL performance of the proposed approach is evaluated by using simulation and is compared with traditional Shewhart $\overline{X}$ and S charts under normal process distribution. The proposed study indicates that ANN scheme is effective than $\overline{X}$ and S charts for monitoring the process mean and variability.

Keywords*— Artificial neural network; Statistical process control; $\overline{X}$ chart; S chart; Average run length*

I. INTRODUCTION

Control charts are statistical process control tools that are widely used to monitor the process parameters. The basic purpose of implementing control charts is to detect abnormal variations in the process. The control charts are used to detect changes in process with respect to some quality characteristic. The changes may occur in mean as well as in the variability of a relevant quality characteristic. It is therefore necessary to control both of them using suitable control charts, one for process mean and another for process variability. The Shewhart $\overline{X}$ chart is used to detect shifts in process mean, whereas, the R and S charts are most widely used in industry to detect the occurrence of shifts in the process variability. In any production process it is very important to detect quickly the occurrence of shifts in process mean and variance so that their causes can be found and necessary corrective action can be taken before a large quantity of non-conforming product is manufactured. In some cases, statistical process control charts have insufficient ability to determine quickly the occurrence of a fault in process. Therefore, it is necessary to suggest commutative method for monitoring processes, which can overcome the limitations of traditional control charts and have the more efficiency to detect the shifts in the process parameters.

As artificial neural network technique is an attractive alternative for efficient monitoring of process parameters and such improved monitoring of process parameters is always desirable for monitoring processes, the purpose of this study is to contribute the development of ANN techniques for monitoring the process parameters. In this study, we have used the ANN technique with back propagation method to monitor process parameters. We have trained ANN to be used in statistical process control charts to monitor process mean and process variability. By investigating the performance of trained artificial neural network under normal distribution, we have comparisons of the traditional $\overline{X}$ and S charts and ANN based $\overline{X}$ and S charts to gain the precision of the process.

The rest of the paper is organized as follows. In section 2 presents the literature review. In Section 3, Shewhart type $\overline{X}$ chart for monitoring process mean, Shewhart type S chart for monitoring the process variability under normal process distribution also concept of artificial neural network is discussed. Section 4 discusses the application of artificial neural network techniques for monitoring the changes in the process mean and process standard deviation. Data generation and performance comparison of proposed scheme is presented in Section 5. Some conclusions are given in Section 6.

II. RELATED WORK

Recently, many researchers have been devoted to the application of artificial neural networks in monitoring process parameters due to the superior performance of artificial neural networks in comparison with traditional control charts. Pugh [13] proposed a three layered feedforward neural network with back-propagation training algorithm to determine the shifts in the process mean. He compared the performance of proposed ANN scheme with traditional $\bar{X}$ chart and concluded that the ARL performance of ANN is about equal to $\bar{X}$ chart for monitoring large shifts in the process mean. Smith [16] trained the feed forward back-propagation NN models with sigmoid activation function which can be comparable to Shewhart $\bar{X}$ and R charts. He demonstrated that the single NN can model Shewhart $\bar{X}$ and R charts simultaneously for determining shift in the mean and/or variance respectively. Stutzle [17] trained ANN with back-propagation algorithm to classify the process into in-control and out-of-control state. He compared performance of $\bar{X}$ and S charts with ANN model in terms of ability to classifying the process as in-control or out-of-control state and concluded that ANN seems to be used for special tasks such as the classification of the kind of shift. Ho and Chang [4] proposed a combined neural network control scheme for monitoring process mean and standard deviation simultaneously. Their proposed network shows better results in comparison to classical control charts in most situations. Cheng [3] developed an ANN model for detecting changes in the process mean. His proposed approach shows higher performance in detecting small to moderate shifts in comparison to the combined Shewhart-CUSUM scheme. Junsub *et al.* [5] used the neural network method for a non-normal data to detect the process control shifts for location parameter. They compared the performance of proposed neural network model with that of the traditional $\bar{X}$ control chart under nine skewness and kurtosis cases. Their simulation study indicates that the ARL performance of the neural network model is superior to the traditional $\bar{X}$ chart when the normality assumption is violated. Barghash [2] developed a diverse neural network. His simulation study compared the performance of the traditional $\bar{X}$ and CUSUM control charts in terms of ARL for the detection of small shifts in the process mean. Psarakis [12] presented an overview of the literature in neural networks for statistical process control charts. Nimbale [9] proposed ANN chart as alternative for fraction non-defective control chart. Also Nimbale [10] developed ANN chart for monitoring individual measurements.

III. CONTROL CHARS AND ANN

1. *Shewhart $\bar{X}$ Control Chart for Process Mean*

The Shewhart $\bar{X}$ control chart has been most popular and widely used control chart for monitoring the mean of a process distribution (usually a normal distribution) of quality characteristics of items produced by a certain process.

Let X_{ij} be the j^{th} observation in i^{th} sample (i = 1, 2, ...) of size n from a quality characteristic of interest X. The sample mean of i^{th} sample is given by

$$\bar{X}_i = \frac{1}{n}\sum_{i=1}^{n} X_{ij} \tag{1}$$

We assume that the samples are independent and the characteristic X is normally distributed with mean μ and standard deviation σ. Let μ_0 and σ_0 be the in-control values of μ and σ respectively. In practice, in-control process parameters are usually unknown and are estimated from the samples taken when process is assumed to be in-control. An out-of-control process mean is denoted by $\mu_1 = \mu_0 + \delta\sigma_0$. Thus, when $\bar{X}$ chart is employed, the shifts in the process mean are measured through $\delta = \frac{\mu_1 - \mu_0}{\sigma_0}$. When $\delta = 0$, process is in-control, otherwise, the process is shifted. The mean of the process is monitored by plotting the sample means $\bar{X}_i$ on the Shewhart control chart with upper control limit (*UCL*) and lower control unit (*LCL*) given by,

$$\begin{aligned} UCL &= \mu_0 + L\,\frac{\sigma_0}{\sqrt{n}} \\ LCL &= \mu_0 - L\,\frac{\sigma_0}{\sqrt{n}}, \end{aligned} \tag{2}$$

Where *L* is control limit coefficient. *L* is usually set to 3 for a standard Shewhart $\bar{X}$ control chart under normality. If $LCL < \bar{X}_i < UCL$ the process is regarded as in-control otherwise indicating that there has been a change in process mean and the process is deemed out-of-control.

2. *Shewhart S Control Chart for Process Variability*

Let X_{ij} be the j^{th} observation in the i^{th} random sample (i =1, 2, …) of size n from a quality characteristic X. The sample standard deviation of i^{th} sample is given by

$$S_i = \sqrt{\frac{1}{n-1}\sum_{j=1}^{n}(X_{ij} - \bar{X}_i)^2} \tag{3}$$

We assume that samples are independent and that the characteristic X is normally distributed with mean μ and standard deviation σ. Let μ_0 and σ_0 be the in-control values of μ and σ respectively. Also, we assume that the mean of the quality characteristic remains unaffected as its in-control level μ_0 by the presence of assignable causes in the production line. An out-of-control process standard deviation is denoted by $\sigma_1 = \lambda\sigma_0$ $(\lambda > 1)$. Thus $\lambda = \sigma_1 / \sigma_0$ is the ratio between the out-of-control and the in-control process standard deviation. Therefore, when S chart is employed, the process shifts are measured through λ. An increase (decrease) in the process standard deviation corresponds to $\lambda > 1\,(0 < \lambda < 1)$. For $\lambda = 1$, the process is considered to be in-control.

The control limits of S chart are obtained using the asymptotic property of S. Then the limits of the S chart will be:

$$UCL = c_4\,\sigma_0 + L\,\sigma_0\sqrt{1-c_4^2} = (c_4 + L\sqrt{1-c_4^2}\,)\sigma_0$$
$$LCL = c_4\,\sigma_0 - L\,\sigma_0\sqrt{1-c_4^2} = (c_4 - L\sqrt{1-c_4^2}\,)\sigma_0 \quad (4)$$

Where $L > 0$ is the control limit coefficient of the S chart. The value of L depends on the desired in-control ARL. The process standard deviation is then monitored by plotting the sample the values of S_i on the Shewhart control chart with control limits given by Eq. (4). LCL is replaced with zero if calculated value is negative. If $LCL < S < UCL$ the process is regarded as in-control otherwise indicating that there has been a change in process standard deviation and the process is deemed out-of-control.

3. *Artificial Neural Network Approach*

Artificial neural network (ANN) is a computing system consisting of a number of interconnected processing elements called neurons. A neuron in a neural network is sometimes called a node or unit and which are interchangeable. Generally, ANN model is constituted by three types of layers; input, hidden, and output.

The layers in a neural network are connected by links and each link has a numeric weight associated with it. In ANN, an activation function is used as threshold device to restrict the output of each processing node to pre-defined limits. The activation function transforms or converts the value of input for given output values. This learning process in which weights are adjusted with respect to achieve desired output values is called training of ANN. Usually, determining the number of input units and output units is clear from interest of application. However, determining the number of hidden units is a bit of an art form, and requires experimentation to determine the best number of hidden units (Parker [11]). The most well known supervised technique is back-propagation. The steps of back propagation training process are as follows:

i) Calculate the output for given existing weights. ii) Determine the error between the desired output and the actual output. iii) Feed the error back through the system to adjust the weights. iv) Continue until the error is minimized across all training patterns.

In literature, several adoptive learning algorithms for feed forward neural network have recently been developed. However, ANN with the scaled conjugate gradient (SCG) back propagation yields the best performance among the other learning algorithms. For more about SCG refer Moller [7] and Sandhu *et al.* [15]. The performance of network is measured in terms of mean squared errors, which are rapidly decreases as the network is trained. The trained neural network is tested and validated with another sets of sample. It gives us a sense of how well the network will perform when applied to real data. The measure of how well the neural network has fit the data is the confusion matrix. The confusion matrix shows the percentages of correct and incorrect classifications of proposed network. For trained network the misclassifications percentages should be very small. If this is not the case then further training, or training a network with more hidden neurons, would be advisable.

IV. Proposed ANN Approach for Monitoring Process Mean and Variability

In this section, the structure and the training procedure of artificial network scheme for monitoring the process parameters is described. To design the scheme, feed forward pattern recognition neural network with scaled conjugate gradient back-propagation network training function is implemented. It consists of n neuron in input layer, ten neurons in hidden layer and one neuron in output layer. In order to train the neural network, 10000 sets (subgroup samples of size n) of simulated in-control and out-of-control samples from $N(\mu,\sigma^2)$ distribution are used. The simulated data is then organized as input matrix and target matrix. The input matrix consists of set of in-control data followed by set of out-of-control data. The target matrix has value 0 for all corresponding in-control set in input matrix and the value 1 for all corresponding out-of-control set in input matrix. The input and target matrices defined above are taken as the corresponding training data set for feed forward pattern recognition neural network. To train the neural network, the whole data set is divided into training set, validation set and test set. The training set is used to coach the network for desire classification. Training continues as long as the network continues improving on the validation set. The performance of network is measured in terms of mean squared errors, which can rapidly decreases as the network is trained.

The trained neural network is tested with the testing samples, which give us a sense of how well the network will perform when applied to real data. The confusion matrix is used to evaluate how well the neural network has fitted for given data. The confusion matrix shows the percentages of correct and incorrect classifications of proposed network. For trained network, the misclassifications percentages should be very small. If this is not the case then further training or training a network with more hidden neurons would be advisable. In the present study of network with confusion matrix, the percentage of incorrect classification less than or equal to 5% is accepted as trained network. Once the network is trained sufficiently, the appropriate quantile is taken to determine the upper control limit (UCL) of ANN outputs. In order to determine the *UCL* of ANN outputs, first to generate pure in-control state data and then the trained neural network is applied to this data. Network generates the output within interval [0, 1]. As per the training, ANN gives the output values close to 0 for in-control state and close to 1 for out-of-control state. A suitable quantile values for the in-control ANN output is used to get an *UCL* value. An intensive search is conducted to find the appropriate quantile value which gives nominal in-control ARL_0. The value above the given quantile represents out-of-control point and below which represents in-control point. In this work we observed that, the nominal *ARL* was detected for greater than 95% quantile values.

V. DATA GENERATION AND PERFORMANCE MEASURE

To evaluate the performance of the proposed neural network methodology extensive simulation study is conducted using programming in MATLAB. The performance of the proposed ANN schemes are compared with the corresponding conventional control charts. The average run length (*ARL*) is used as performance criteria. The *ARL* is defined as the average number of sample points plotted before a chart gives an out-of-control signal. The *ARL* for in-control process is denoted as ARL_0 and for out-of-control it is denoted as ARL_1. A desirable property of any monitoring process is that it should detect any out-of-control situation as quickly as possible and leave the production process alone when it is in-control. In other words, the monitoring process should generate signal as quickly as possible (smaller ARL_1) if the production process is out-of-control and as late as possible (larger ARL_0) if the production process is in-control. In this study, for a process under normal distribution the *ARL* values are based on 10,000 simulated replications and calculated as,

$$ARL = \frac{Total\ points}{Total\ number\ of\ out\ of\ control\ points}$$

Since the proposed neural network schemes are designed to detect shifts in process mean and process standard deviation, it is appropriate to compare the performance of these schemes with the traditional Shewhart $\overline{X}$ and S control charts. For the comparison to be unbiased, the ARL for both control methods are kept the same (ARL_0 =370) when the process is in-control.

For the purpose of comparison of proposed ANN schemes with the conventional control charts, data is generated from normal process distribution. To find the nominal 370 in-control *ARL* value for ANN based chart the appropriate *UCL* value is detected by extensive searching method. The exhaustive quantile range [95, 99.8] is used as *UCL* of ANN based charts for normal process distribution so that in-control *ARL* is 370 approximately.

To examine the ability of proposed ANN based charts to detect shift in a process mean and process standard deviation, we consider underlying process distribution is normal *with* mean μ and standard deviation σ. Let μ_0 and σ_0 be the in-control values of μ and σ respectively. When shift in process mean occurs, we have change from the in-control value μ_0 to the out-of-control values $\mu_1 = \mu_0 + \delta\sigma_0$. When a shift in process standard deviation occurs, we have change from the in-control value σ_0 to the out-of-control values $\sigma_1 = \lambda\ \sigma_0\ (0 < \lambda \neq 1)$. Without loss of generality we assume $\mu_0 = 0$ and $\sigma_0 = 1$. For a fixed ARL_0 = 370 of the conventional $\overline{X}$ chart and the ANN-$\overline{X}$ chart, ARL_1 values of detecting shifts in process mean of size δ = 0.10, 0.15, 0.20, 0.25, 0.30, 0.35, 0.40, 0.50, 0.75, 1.00, 1.25, 1.50, 2.00, 2.25, 2.50 and 3.00 are calculated for sample size *n* = 3, 5, 10 and 15. The results of detecting various shifts in process mean in terms of average run length criteria are given in Table 1

Table 1: ARL performance of $\overline{X}$ chart and ANN-$\overline{X}$ chart

Shift δ	*n* = 3		*n* = 5		*n* = 10		*n* = 15	
	$\overline{X}$	ANN-$\overline{X}$	$\overline{X}$	ANN-$\overline{X}$	$\overline{X}$	ANN-$\overline{X}$	$\overline{X}$	ANN-$\overline{X}$
0.00	370.37	370.37	370.37	370.37	370.37	370.37	370.37	370.37
0.10	344.83	188.68	238.10	172.41	208.33	131.58	157.27	159.49
0.15	312.50	153.85	217.39	113.64	147.06	86.96	128.21	104.17
0.20	256.41	125.00	185.19	89.29	94.34	57.80	83.33	62.11
0.25	232.56	96.15	138.89	69.44	70.42	40.00	50.25	39.37
0.30	185.19	70.92	104.17	52.08	47.39	28.09	32.26	23.58
0.35	153.85	60.98	72.46	39.84	33.00	20.92	21.41	16.29
0.40	106.38	50.25	55.87	30.03	22.17	15.87	14.10	10.96
0.50	62.50	34.97	33.44	20.08	11.72	9.17	7.06	5.99
0.75	21.93	13.28	10.73	7.23	3.61	3.08	2.18	1.98
1.00	9.29	6.32	4.53	3.37	1.71	1.61	1.24	1.20
1.25	4.85	3.60	2.41	1.98	1.19	1.16	1.03	1.03
1.50	2.90	2.28	1.57	1.40	1.03	1.03	1.00	1.00
2.00	1.48	1.32	1.08	1.05	1.00	1.00	1.00	1.00
2.25	1.23	1.15	1.02	1.01	1.00	1.00	1.00	1.00
2.50	1.10	1.06	1.00	1.00	1.00	1.00	1.00	1.00
3.00	1.01	1.01	1.00	1.00	1.00	1.00	1.00	1.00

The *ARL* profiles in Table 1 clearly show that as the magnitude of shift increases, the *ARL* value decreases, and hence the chart signal faster. For example, the *ARL* profile for the ANN based chart with *n* = 5 in Table 1 is {370.37, 172.41, 113.64, 89.29, 69.64, . . . , 1.00} as δ increases from 0.0 to 3.0. It can be seen that the ARL_1 values in detecting different shifts in the process mean of the ANN-$\overline{X}$ based control chart are adequately smaller than that of the conventional $\overline{X}$ chart. From numerical comparisons, it is clearly shown that the ANN-$\overline{X}$ chart always outperforms the conventional $\overline{X}$ chart for all the given shifts. For example, ANN-$\overline{X}$ chart with n = 5 gives an *ARL* of 89.29, whereas the conventional $\overline{X}$ chart gives an *ARL* of 185.29 in detecting shift of magnitude $\delta = 0.20$. This shows that there is a reduction of $\left(\frac{185.19 - 89.29}{185.19}\right) \times 100\% = 51.78\%$ in terms of the out-of-control ARL when the process is monitored by ANN-$\overline{X}$ chart instead of the conventional $\overline{X}$ chart.

For a fixed ARL_0 = 370 of the conventional *S* chart and the ANN-*S* chart, ARL_1 values of detecting shifts in standard deviation of size λ = 1.00, 1.05, 1.10, 1.15, 1.20, 1.30, 1.40, 1.50, 1.60, 1.70, 1.80, 1.90, 2.00, 2.50, 3.00, 3.50 and 4.00 are calculated for sample size n = 5, 10 and 15. The results of detecting various shifts in process standard deviation in terms of average run length criteria are provided in Table 2. The *ARL* profiles in Table 2 clearly show that as the magnitude of shift increases, the *ARL* value decreases, and hence the chart signal faster.

Table 2: ARL performance of S chart and ANN-S chart.

Shift	n = 5		n = 10		n = 15	
λ	*S*	ANN-S	S	ANN-S	S	ANN-S
1.00	370.37	370.37	370.37	370.37	370.37	370.37
1.05	192.31	181.82	161.29	160.29	125.00	124.25
1.10	108.70	94.34	68.03	66.92	52.91	51.10
1.15	63.69	53.76	37.31	35.67	26.53	22.15
1.20	40.49	34.48	22.78	21.62	14.95	13.66
1.30	20.53	17.86	10.44	10.45	6.28	6.64
1.40	11.81	11.00	5.79	5.22	3.57	3.73
1.50	7.83	7.34	3.71	3.81	2.40	2.07
1.60	5.69	5.26	2.74	3.36	1.83	1.28
1.70	4.42	4.05	2.15	2.59	1.51	1.81
1.80	3.50	3.25	1.80	1.12	1.32	1.53
1.90	2.89	2.71	1.56	1.81	1.21	1.36
2.00	2.47	2.36	1.40	1.61	1.13	1.24
2.50	1.56	1.53	1.10	1.17	1.02	1.04
3.00	1.28	1.26	1.03	1.05	1.00	1.01
3.50	1.16	1.14	1.01	1.02	1.00	1.00
4.00	1.10	1.09	1.00	1.01	1.00	1.00

It can be seen that the ARL_1 values in detecting different shifts in process standard deviation in ANN-*S* control chart are adequately small than that of the traditional *S* chart for small to moderate shifts in the process standard deviation. For large shifts, the performance of the proposed ANN-S chart is similar to that of the S chart. For Sample size n = 15, the performance of both charts is similar. It indicates that the proposed ANN-*S* chart is more efficient than the *S* chart in detecting shifts in the process standard deviation. From numerical comparisons, it is clearly shown that the ANN-S chart always outperforms the conventional S chart for many instances. For example, ANN-S chart with n = 5 gives an *ARL* of 34.48, whereas the conventional S chart gives an *ARL* of 40.49 in detecting shift of magnitude $\lambda = 0.20$. This shows that there is a reduction of $\left(\frac{40.49 - 34.48}{40.49}\right) \times 100\% = 14.84\%$ in terms of the out-of-control *ARL* when the process is monitored by ANN-S chart instead of the conventional S chart.

VI. CONCLUSION

In this paper, process monitoring methodology based on artificial neural network is presented for monitoring the process parameters. The proposed neural network schemes are used for detecting shifts in the process mean and process standard deviation. The *ARL* performances of these schemes are investigated using simulation and are compared with the corresponding $\overline{X}$ and *S* control charts under normal process distribution. The comparative study shows that the performance of neural network based monitoring scheme is superior to that of the existing control charts for monitoring process mean and process standard deviation. The capability of the neural network to identify the shifts in the process mean and process variability has shown a substantial improvement over the conventional control charts. The improvement in the ANN-$\overline{X}$ chart's ability under normal distribution to detect shifts is about 51% as compared to $\overline{X}$ chart for small to moderate shifts in the process mean. The improvement in ARL for the ANN-S chart under normal distribution is about 15% as compared to S chart for the small shifts in the process standard deviation. The neural network approach presented in this paper offers a competitive alternative to the existing $\overline{X}$ and *S* charts. The advantage of neural network scheme to detect the shift in process parameter quicker than traditional control chart is useful for manufacturing unit to take corrective action before the large quantity of defective units are manufactured.

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