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Artificial Neural Network Model for Monitoring the Fraction Nonconforming Control Chart

S. M. Nimbale[1], V. B. Ghute[2]

[1]Department of Statistics, Solapur University, Solapur, India
Sharad_nimbale@gmail.com

[2]Department of Statistics, Solapur University, Solapur, India
vbghute_stats@rediffmail.com

Abstract: ***To be competitive in the market, it is necessary for manufacturing and service organization to fulfill costumer's demand of quality. The fraction nonconforming control chart (p-chart) is wildly used as statistical process control (SPC) tool to monitor fraction of nonconforming unit. When such chart is used it is important to quickly detect an increase or decrease in the fraction of nonconforming units. In this paper, an artificial neural network (ANN) model is developed for monitoring fraction of nonconforming units. The performance of p-chart and ANN model is evaluated through the average run length (ARL) using the simulation study. ARL performance of ANN model is found to be superior to p-chart.***

Keywords: Control chart, statistical process control, fraction nonconforming, average run length, artificial neural network**.**

1. Introduction

Today's world market has clearly verified that quality is one of the most important factors for business success and growth of organization. In many industries, Statistical Process Control (SPC) techniques are frequently used for improving the quality of product at lowest production cost. SPC techniques are also used in manufacturing process in order to reduce process and product variations. Reduction in process and product variations is very useful for industry as they result in improved financial performance and stronger competitive position. Statistical control charts are very effective in improving the quality of manufacturing and service process. One of the most commonly used statistical control chart introduced by Dr. Walter Shewhart in 1930 at Bell Laboratories. Now days, a computerized production technique is implemented in manufacturing process to achieve the increased demand product and to fulfill the customer requirements of high quality of product, which make the manufacturing process more advanced, but complicated. To be competitive in the global market, it is very important for manufacturing industry to detect process variation quickly so their causes can be found and necessary corrective action can be taken before the large quantity of nonconforming unit is manufactured. But unfortunately, SPC charts are incapable in today's manufacturing environment. In recent years, the artificial neural network (ANN) model is utilized as an efficient alternative in process control. Smith (1993) proposed a single ANN for Shewhart $\overline{X}$ and R control charts for large shifts in mean or variance detection simultaneously. Barghash (2011) compared the diverse neural network, $\overline{X}$ and CUSUM control charts in terms of ARL for small mean shift detection. Alhammadi and Adams (2013) developed the ANN for monitoring the non-conformities in a Poisson process; they also compared the performance of ANN under the varying numbers of nodes in hidden layers. The ANN model are the potential tools for recognizing shifts in process parameters as data independency is not an assumption in ANN theory.

In this paper, an artificial neural network (ANN) model is developed for monitoring fraction of nonconforming units.

2. Fraction Nonconforming Control Chart

In manufacturing or/and service organizations, many quality characteristics are not measured on a continuous scale or even a quantitative scale. In such cases, one may judge each unit of product as either conforming or nonconforming on the basis of whether or not it possesses certain attributes or we may count the number of nonconformities (defects) appearing on the unit of product. Control charts for such quality characteristics are called attributes control charts. One of most popular attribute control chart is p-chart used for monitoring the fraction nonconforming units.

If proportion of nonconforming units is p then the number of nonconforming units D in a sample of size n follows a binomial distribution with parameters n and p as long as process in stable and samples are taken independently. The sample fraction nonconforming is the ratio of the number of nonconforming units (articles, parts, specimens, etc.) to the total number of units under consideration (Montgomery 2009). Suppose m preliminary samples are selected, each of size n. Then if there are D_i nonconforming units in sample i^{th} sample of size n, we compute the fraction of nonconforming in the i^{th} sample as $\hat{p}_i = D_i/n$ where $i=1, 2, \ldots, m$ and the average of these individual sample fraction of nonconforming is

$$\overline{p} = \frac{\sum_{i=1}^{m} D_i}{mn}$$

The statistic estimates the unknown fraction nonconforming p. The upper control limit (UCL), center line (CL) and lower control limit (LCL) of the control chart for fraction nonconforming are computed as follows:

$$UCL = \bar{p} + 3\sqrt{\frac{\bar{p}(1-\bar{p})}{n}}$$

$$CL = \bar{p}$$

$$UCL = \bar{p} - 3\sqrt{\frac{\bar{p}(1-\bar{p})}{n}}$$

The chart operates by plotting $\hat{p}_i$ values on the chart with above control limits. If the plotted point goes outside the control limits the process is considered to be out-of-control.

3. Artificial Neural Network

ANN is mathematical model that tries to simulate the structure and/or functional aspects of biological neural network or system. Generally ANNs consist of three types of layers: input layers, output layers and hidden layers. The layers in a neural network are connected by links and each link has a numeric weight associated with it. ANN has great learning ability by using set of input values with respective known output values. This learning process in which weights are adjusted with respect to achieve desired output values is called training of ANN. In this study, we used the feed forward pattern recognition network because it had been proven that a feed forward neural network can learn any input-output relationship given enough neurons in the hidden layer and to be an effective system for patterns classification problems.

4. ANN Model for Control Chart

For monitoring the fraction nonconforming unit we implemented feed forward pattern recognition neural network model. This model includes fifty independent neurons in input layer, sixteen neurons in hidden layer and only single neuron in output layer with scaled conjugate gradient back propagation as network training function. ANN model is trained to classify manufacturing process as in-control state and out-of-control state. In this study, to train the ANN 10,000 simulated samples of in-control data and 10,000 out-of-control data were simulated. The simulated data was organized as input matrix and target matrix in such a way that the input matrix consist of in-control and out-of-control data together, while the target matrix has 0 value for all corresponding in-control observations in input matrix and 1 value for all corresponding out-of-control observations in input matrix. The input and target matrix defined above was taken as corresponding input and target values for ANN model. To train ANN, we divided whole data sets into training set, validation set and test sets. 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 was measured in terms of mean squared error, which was rapidly decreased as the network was trained. The trained neural network was tested with the testing samples. Which give us a sense of how well the network will perform when applied to real data. One 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. Once the network is trained sufficiently, the appropriate quantile values for in-control ANN output is used to get an UCL value, which is taken as cutoff point to decide the in-control and out-of-control state of the process (Alhammadi and Adams (2013)). That is value above the given quantile represents out-of-control state and below which represents in-control state. To monitor the performance, trained ANN was implemented to the data with shift in process of size p = 0.11, 0.12, 0.13, 0.14, 0.15, 0.16, 0.17, 0.18, 0.19, 0.2, 0.21, 0.22, 0.23, 0.24, 0.25 respectively and corresponding out-of-control points are recorded for each shift value. In SPC, ARL is mostly used to monitoring the performance of control chart. It is defined as the average number of points that must be plotted before a point indicates an out-of-control condition (Montgomery 2009). For given process the ARL was based on 10,000 simulated replications and calculated as,

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

For the purpose of comparison the cutoff values are adjusted such that ANN model shall have the ARL value approximately close to p-chart. In this work we observed that, the nominal ARL was detected for 97% quantile value.

5. Data Generation and Results

In ordered to compare the performance in terms of ARL 10,000 random numbers are simulated from binomial distribution with parameters $p=0.10$ and $n=50$. The control limits and fraction nonconforming $\hat{p}$ for each sample is calculated as mentioned in section 2. The out-of-control ARL performance under various process shifts for p-chart and ANN model for 10,000 simulations is presented in the following table. In control ARL value of both schemes is same.

Table 1: ARL performance comparison

p	*p-chart*		*ANN Model*	
	Out of Control points	*ARL*	*Out of Control points*	*ARL*
0.10	30	333.33	30	333.33
0.11	60	166.67	72	138.89
0.12	134	74.63	149	67.11
0.13	228	43.86	260	38.46
0.14	376	26.60	422	23.70
0.15	581	17.21	676	14.79
0.16	886	11.29	1001	9.99
0.17	1243	8.05	1381	7.24
0.18	1733	5.77	1830	5.46
0.19	2257	4.43	2341	4.27
0.2	2816	3.55	2888	3.46
0.21	3495	2.86	3516	2.84
0.22	4147	2.41	4184	2.39
0.23	4846	2.06	4827	2.07
0.24	5539	1.81	5478	1.83
0.25	6156	1.62	6081	1.64

From Table 1, we observe that out-of-control ARL values of ANN model for shift up to 0.21 are smaller than that of the p-chart and fro shift larger than 0.21 the out-of-control ARL values are just greater than that of the p-chart. That is, for smaller to medium shifts ANN model is efficient to detect shift in process.

6. Conclusion

In this paper, ANN model is developed for monitoring the fraction of nonconforming unit. The ANN model is found to be more efficient than the traditional p-chart in monitoring the small shift in fraction of nonconforming unit. For large shift, the ANN model is not optimal but it can compete with the traditional p-chart.

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Author Profile

Sharad M. Nimbale received the M.Sc degrees in Statistics from Department of Statistics, Karnataka University, Dharwad. For three years worked as Biostatistician and SAS programmer in the field of clinical research. Since from 2012, he is pursuing the research in Statistical Quality Control at the Department of Statistics, Solapur University, Solapur.

Vikas B. Ghute is an associate professor and head at the Department of Statistics, Solapur University, Solapur (MS), India. He received his PhD in statistics in 2008 from Shivaji University, Kolhapur, India. He is a life member of Indian Society for Probability and Statistics. He is also a life member of International Indian Statistical Association. His research interest is in statistical process control.