Application of a neural network to classify the out-of-control signal given by the multivariate Generalized Variance |S| control chart using real industry data.

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Abstract

Quality control techniques in the industry are used to detect changes in process dispersion, but it is necessary to monitor two or more quality variables simultaneously. The problems of process monitoring where several related variables are studied can be controlled by means of multivariate control charts. The objective of this work is to describe the implementation of the multivariate. Generalized Variance |S| control chart using real data obtained from the industry.
In the present research work the implementation of the multivariate Generalized Variance |S| control chart in the industrial field is carried out and a real multivariate case is analyzed with quality variables.

Keywords
Multivariate Statistical processes control, Generalized Variance |S| control chart.

1. Introduction

The simultaneous control of several variables in the same piece or product has received much attention in recent years Aparisi (2014). The use of a single multivariate chart for process control is a more powerful option than using several univariate charts Aparisi (2006), Montgomery (2009). However, multivariate charts do not indicate which variables or variables are being measured that have changed and current techniques are inefficient to detect the variables responsible for the change Khoo (2004), Grasman (2010). Therefore the research will be focused on finding a method based on neural networks in order to identify the variables that have changed in the process, using industrial data.
The main objective of this research is to design a generalized method based on neural networks to classify the out of control signal that the multivariate Generalized Variance |S| control chart, applied to a production process with real data obtained from the industry.

2. Approach and formulation of the research problem

Identify the variables responsible for the change in an industrial process monitored by means of a multivariate control chart. With the advent of computers in the eighties, the neural networks took great strength since they overcame the obstacle that for years prevented them from developing, the low computational capacity of computers.

This is how a large number of applications arise for neural networks; one of them is the classification and in our particular case the classification of the signal out of control, responsible for the change in the multivariate control charts.
The production processes and the quality control that are currently applied in the companies allow to detect changes in the production process that imply a loss of quality in the product. Today quality control charts are a widely used tool in the industry.
The simultaneous control of several quality variables in the same piece or product has received a lot of attention in recent years. If we want to control p variables simultaneously, we have two approaches: Use *p* univariate chartics. For example, *p* type chartics, CUSUM, or EWMA. Use a single multivariate chart. The options in this case include, among others, the Hotelling's T2 chart, the generalized variance chart |S|, Aparisi (2004), or the various options in the MCUSUM chart.
The use of multivariate charts proves to be a more powerful option, that is, it requires, on average, fewer points in the chart to detect a change in the process compared to the use of univariate charts, Lowry and Montgomery (2009). This is a cost savings for the company, since in the final production you get a better quality in the product. It seems then that the multivariate option would clearly be the choice.

3. Methodology

- Bibliochartic review of existing methods to solve the proposed problem.
- Verification of the effectiveness of these methods, measured as the percentage of hits in the case of analytical methods, and the relevance of application in the case of chartical methods. Like the analysis of the application software of neural networks that exist today to find the one of greater relevance in the industrial application proposed.
- Validation of the results obtained through statistical techniques. That is, by means of hypothesis test procedures to verify the best neural network structure found.

4. Process

For the training of the network in the case of three variables were used the variables weight, thickness and diameter of the bottles manufactured in a brewing industry.

5. Optimization of the network for 3 variables

Using the data from the bottles of the brewing industry, the values of the Generalized Variance |S| control chart were obtained through the Mathcad program and after several tests the best network structure for three variables was found.

The optimal network (see figure 1) found is a network of 4 layers in total: 11 nodes in the input layer, 12 in the first inner layer, 14 in the second inner layer and 3 nodes in the output layer. In this case the sample size, the type of point on the chart, the distance of Mahalanobis and the cut-off point were varied.

6. Application case with data from the bottling industry

The multivariate control chart | S | To determine which variable or variables are responsible for the lack of control signal. In this case a sample of size n = 4, y α = 0.003, is taken for the data obtained in a bottling industry by controlling the variables namely: weight container, thickness center and body diameter. The statistic to be plotted is:

$$|S| = \left| \frac{1}{n-1} \cdot \sum_{i=1}^{n} (x_i - \bar{x})(x_i - \bar{x})' \right|$$

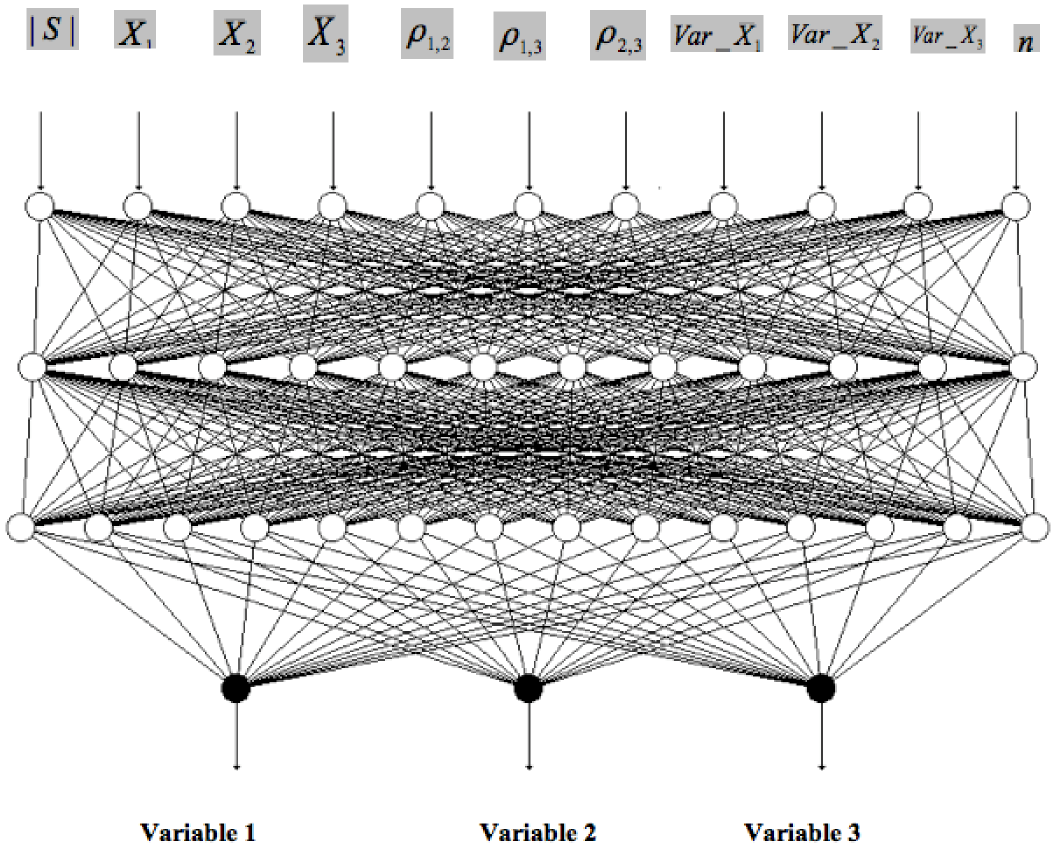

Figure 1 Structure of the neural network used, case p = 3.

The values are for 4 samples:

Table 2. 4 samples data

Bottles	Weight Container	Thickness center	Body Diameter
1	15.83	2.02	52,26
2	14.99	1.94	52.26
3	14.91	2.00	52.31
4	15.21	1,94	52.29

The upper control limit ULC = 5.0557. Aparisi (1999).

The values are:

Table 2. Input values to the network for the application case using the | S | chart

|S|	$\bar{X}_1$	$\bar{X}_2$	$\bar{X}_3$	$\rho_{1,2}$	$\rho_{1,3}$	$\rho_{2,3}$	n	Var $\bar{X}_1$	Var $\bar{X}_2$	Var $\bar{X}_3$
5.311	14.97	1.987	52.291	-0.085	-0,034	0.027	4	0,31	0,0025	0,00088

The output screen of the program is:

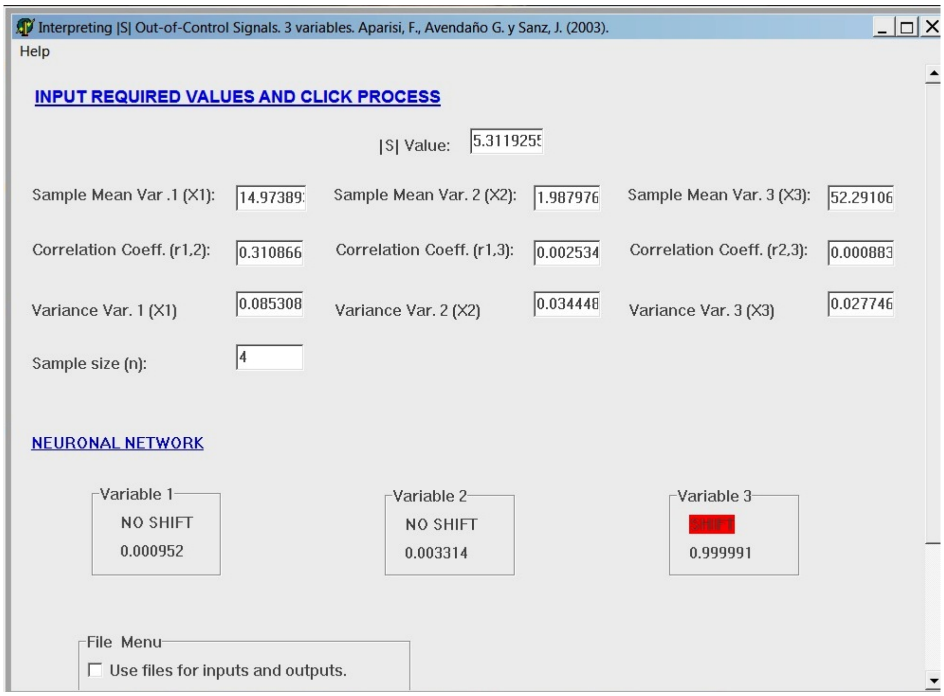

Figure 2. Neural network output for the application case using the | S | chart.

In this case the network detects that the variable responsible for the control signal is the variable assigned to node 3. That is body diameter.

7. Conclusions

In this research we have used neural networks to detect the variable or variables that cause the signal out of control in a process, when the chart detected a control output. That is, those responsible for the out of control signal found by the chart. For the case of three variables in a process of an industrial bottler.

The network design with the highest percentages of hits has, for the case of three variables, a network with an input layer of 11 nodes, a first internal layer of 12 nodes, a second internal layer of 14 nodes and an output layer of 3 nodes.

At present there is no alternative method, which detects which variable or variables are responsible for the signal of lack of control when the multivariate | S | detects a change in process. Therefore, the percentage of hits with another method can not be compared.

For the practical use of this procedure, a simple Windows program has been developed. With this program the end user does not need to have knowledge of neural networks.

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Biography

Gerardo Avendano is a full-time professor at the EAN University in Bogotá Colombia with more than 20 years of experience in teaching and research and management at prestigious universities and national and international companies. Experience in the industry in the area of production and quality, as well as in personnel management and group work. Author of scientific publications such as books, articles in indexed journals and software development. Postdoctor in Statistical Process Control SPC Penn State University (State College, USA 2007). Ph.D. Polytechnic University of Valencia (Valencia - Spain, 2003). Specialist in Advanced Statistical Methods for the Improvement of Productivity and Quality Polytechnic University of Valencia (Valencia Spain 2001). Specialist in Production Engineering of the District Francisco José de Caldas Bogotá Colombia (1998). Chemical Engineer National University of Colombia (1994).

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