An Approach for Control Chart Pattern Recognition using the Fuzzy ARTMAP Artificial Neural Networks with Improved Efficiency

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ABSTRACT

The use of Control Charts (CC) in manufacturing processes is a common technique to monitor the quality of the production. The production variables are monitored to preserve the process under statistical control and also to detect any special variation. Causes for special variation are diverse such as change in material processing, changing the machine operator, changing the machine itself, etc. These changes are typically showed in CC and interpreted by trained personnel to take appropriate actions to get the process under statistical control. In this paper we introduce an approach to recognise and analyse statistical patterns using Artificial Neural Networks (ANN's). The approach is based on the FuzzyARTMAP (FAM) network whose parameters are selected on-line depending on the encountered probability distribution and whether special or non-special patterns are encountered; hence, the mechanism for selection is driven by the type of probability distribution. In terms of the network parameter selection, their value is not predefined but established a priori based on a sensitivity analysis for improved the efficiency. Experimental results showed that the range selection of these parameters is very important to improve the efficiency of the FAM network and to establish a robust method to effectively recognise CC patterns in Statistical Process Control (SPC).

Keywords: Process Control, Control Charts, Neural Networks Applications.

1. Introduction

In manufacturing processes, the use of Control Charts (CC) is a common technique used to monitor the quality of the production. Control charting is the key point in Statistical Process Control (SPC) implementation. The correct application of these Control Charts requires satisfying statistical assumptions such as the independence of the random variable and symmetry in its probability distribution (Montgomery, 2009). Variables are monitored to preserve the process under statistical control and also to detect any special variation. Causes for special variation are diverse such as change in material processing, changing the machine operator, the machine itself, etc. Such changes are typically showed in CC and interpreted by trained personnel to take appropriate actions to get the process back in control. By using CC it is possible to know when the process presents a special behaviour by monitoring its upper and lower control limits. However, it is not always possible to determine the type of pattern and other methods are preferable. An alternative approach to recognise CC patterns is the creation of Artificial Neural Network-based Control Chart Pattern Recognition schemes overcoming disadvantages with traditional interpretation methods.

The effective use of ANN in CC pattern recognition has been effectively used by several authors (Guh, 2005). Several advantages can be appreciated such as the clustering capability of ANN's to classify several process patterns and also the incremental learning capability with some ANN's. However, some serious disadvantages are recognised as well, such as the correct selection of ANN parameters (Masood I and Hassan, A., 2010) which is still recognised as a challenging work. The complexity of the problem increases if we consider that in most of the cases a normal data distribution is assumed; if non-normal probability distribution data is present, then another scheme has to be considered. To overcome these limitations, a novel approach to recognise and analyse statistical quality patterns using ANN based on the Fuzzy ARTMAP (FAM) Artificial Neural

Network is proposed. The FAM parameters are determined by using a Fractional Factorial Design for maximum efficiency as developed by (Vazquez-Lopez, et al., 2010). The system is able to recognise the pattern type and the FAM parameters can be selected on-line depending on the nature of the input data, depending if special or non-special patterns have been encountered. In general, this scheme establishes a robust method to recognise effectively CC patterns based on the best network parameters and range values. The terms so-called *short-range interval* and *long-range interval* are introduced in this article to refer the ANN parameters used during ANN training/testing stages.

The organisation of the paper is as follows. After the Introduction is given in this section, related work is reviewed in section 2 as well as the original contribution is highlighted. In section 3, the main characteristics of the FuzzyARTMAP network is provided. Section 4 introduces formally the proposed methodology for pattern recognition and describes the data for validation through simulation. Results from main experiments are presented in section 5 and conclusions are given in section 6.

2. Related Work and Original Contribution

Considering the disadvantages of the CC, diverse investigations suggest the use of ANN as an alternative (Cook et al., 2006; Guh, 2005). The advantages of using ANN's in comparison with CC are:

a) It is possible to work in real-time (Zobel et al., 2004)
b) The assumption of data normality is not necessary (Cheng, 1997); and
c) Great amounts of complex data can be processed in a short time (E.S. Ho and S. I. Chang, 1999).

Hindi, used the Fuzzy ARTMAP to determine the type of change presented in the process parameters (Hindi, 2004). He compared the results with the obtained from the application of the $\bar{X}$ and R-chart[1]. He used values 0 and 3 for μ and 1 and 3 for σ, considering the combination $\mu = 0$ and $\sigma = 1$ to represent a state of statistical control. The FAM parameter values were fixed. Guh R. S. proposed the use of ANN Back-Propagation (BPN) in combination with a decision tree for pattern recognition. In his work (Guh, 2005); Guh makes reference to three modules. Module A is in charge of data pre-processing, module B works like a CC detecting abnormal cases of variation whereas the module C determines the type of pattern based on a pre-defined decision tree. Our method compares favourably to this previous work having the following advantages: Normality assumption is not required since network parameters are determined through experimental design using either *short-range interval* and *long-range interval* for maximum efficiency avoiding the trial and error procedure; high sampling size to guarantee data normality is not required since ANN testing parameters are selected automatically according to the type of probability distribution.

Moreover, a similar study was introduced by Tao et al., (2010). In this article they use the artificial neural network FuzzyARTMAP to recognize patterns special variation, using the method of Monte Carlo to generate the numerical series. They test the effect on the selectivity of the net changes in training conditions, considering different large databases of training vectors, but they do not modify or experiment with the operating parameters of the network.

This article demonstrates that the use of design of experiments is useful for establishing processes to optimize the selectivity of the fuzzyARTMAP. This allows to know the behavior of these parameters and their effect on the selectivity of the network.

3. Neural Network

3.1 Adaptive Resonance Theory

The Adaptive Resonance Theory (ART) (Carpenter and Grossberg, 1995) was developed by Stephen Grossberg and Gail Carpenter at Boston University. The network solved the so-called stability-plasticity dilemma. That is, the network is sensitive to novelty capable of distinguishing between familiar and unfamiliar events (plastic) and still remains stable. Different model variations have been developed to date based on the original ART-1 algorithm for binary input patterns (Carpenter and Grossberg, 1987), ART 2-A for analogue and binary input patterns (Carpenter et al., 1991), and ART 3 based on chemical transmitters. Supervised learning is possible through ARTMAP (Carpenter et al., 1991) that uses two ART modules and its

[1] $\bar{X}$ and R-chart is a typical chart for manufacturing process control.

variants, Fuzzy ARTMAP (Carpenter et al., 1992), Gaussian ARTMAP (Williamson, 1996) and ART-EMAP even though there are many other variants adapted for specific applications (Carpenter and Grossberg, 1995). In the next section a brief explanation of the mechanics of ART-1 and Fuzzy ARTMAP is given. The ART-1 architecture consists of two parts: attentional subsystem and orienting subsystem as illustrated in figure 1.

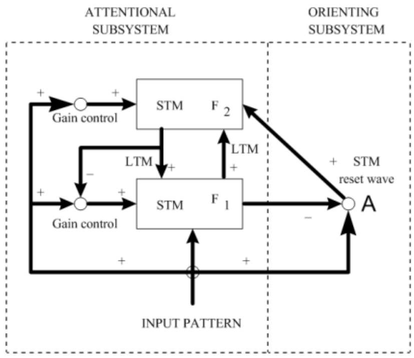


Figure 1: Basic ART Architecture

The attentional subsystem is made up of two layers of nodes F_1 and F_2. In an ART network, information in the form of processing-element output reverberates back and forth between layers. If a stable resonance takes place, then learning or adaptation can occur. On the other hand, the orienting subsystem is in charge of resetting the attentional subsystem when an unfamiliar event occurs. A resonant state can be attained in one of two ways. If the network has learned previously to recognise an input vector, then a resonant state will be achieved quickly when that input vector is presented. During resonance, the adaptation process will reinforce the memory of the stored pattern. If the input vector is not immediately recognised, the network will rapidly search through its stored patterns looking for a match. If no match is found, the network will enter a resonant state whereupon the new pattern will be stored for the first time. Thus, the network responds quickly to previously learned data, yet remains able to learn when novel data is presented, hence solving the so-called stability-plasticity dilemma. The activity of a node in the F_1 or F_2 layer is called short-term memory (STM) whereas the adaptive weights are called long-term memory (LTM). Gain controls handle the discrete presentation of the input signals. A vigilance parameter measures how much mismatch is tolerated between the input data and the stored patterns, which can be used to control the category coarseness control of the classifier.

3.2 Fuzzy ARTMAP (FAM)

In the *F*uzzy ARTMAP (FAM) network there are two modules ART_a and ART_b and an inter-ART module Map−field that controls the learning of an associative map from ART_a recognition categories to ART_b categories. This is illustrated in figure 2.

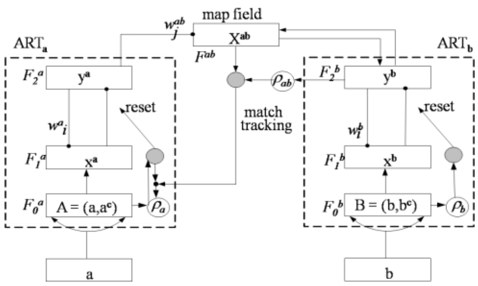


Figure 2: FuzzyARTMAP Architecture

The Map field module also controls the match tracking of ART_a vigilance parameter. A mismatch between Map field and ART_a category activated by input I^a and ART_b category activated by input I^b increases ART_a vigilance by the minimum amount needed for the system to search for, and if necessary, learn a new ART_a category whose prediction matches the ART_b category. The search initiated by the inter-ART reset can shift attention to a novel cluster of features that can be incorporated through learning into a new ART_a recognition category, which can then be linked to a new ART prediction via associative learning at the Map−field. A vigilance parameter measures the difference allowed between the input data and the stored pattern. Therefore this parameter is determinant to affect the selectivity or granularity of the network prediction. For learning, the FuzzyARTMAP has 4 important factors: Vigilance in the input module (ρ_a), vigilance in the output module (ρ_b), vigilance in the Map field (ρ_{ab}) and learning rate (β). These were the considered factors in this research.

4. Proposed Method for Pattern Recognition

In this paper a time series [x_1, x_2, x_t] in time *t* will be referred as vector **X** or simply **X**. The algorithm to maintain the process under statistical control is composed mainly by the pattern recognition module which is shown in Figure 3.

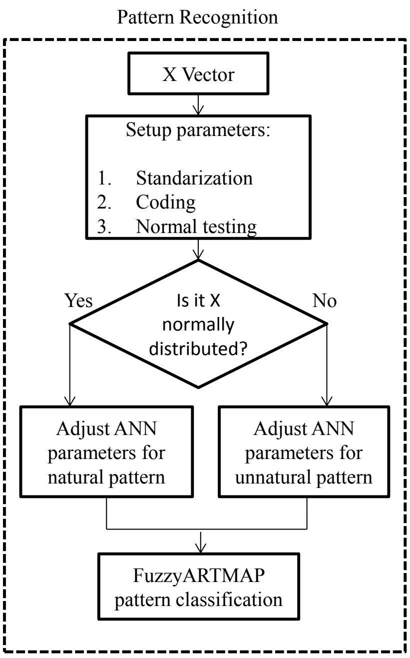


Figure 3: Pattern Recognition Module

During pattern recognition the **X** vector is pre-processed using two important mathematical considerations, which are the *standardization* and the *codification* of the input data. Training and testing data needs to be pre-processed in these two stages before entering a test on normal distribution. Based on the normal distribution test, the network parameters have to be adjusted so that the ANN reaches maximum efficiency regardless the type of data entered into the pattern recognition module.

4.1 Standardization and Codification

The standardization means that the data have to be linearly transformed from data with mean (μ) and standard deviation (σ) into data with μ = 0 and σ = 1 using equation 1.

$$Y_t = (x_t - \mu)/\sigma \qquad (1)$$

where:
Y_t = standardized value from x_t.
x_t = sample value at sampling time t.
μ = process mean.
σ = process standard deviation.

The x_t data are generated by a process simulator of Monte Carlo (Guh, 2005), according to equation 2

$$x_t = \mu + n_t + d_t \qquad (2)$$

where
μ = process mean.

n_t = common cause variation at sampling time t.
d_t = special disturbance at time t ($d_t = 0$ when the pattern is natural).

The effect of d_t in eq. (2) is very important. It affects **X** central tendency as well as its dispersion and distribution shape. Small values mean little affectation while high values generate **X** vector data with non-normal distribution, which is a fundamental aspect of the algorithm to keep the process under statistical control. This paper shows experimental results for the robustness of the algorithm when $d_t = 0$ and normality is present within the set of input data. On the other hand, with the codification of Y_t the variation interval of [0, 1] is obtained, which is a requirement for the neural network operation that reduces the effects of common causes of variation (noise).

4.2 Pattern data generation for validation

A specific value x_t of **X** vector data is obtained from the sum of three mathematical considerations:

(i) Global and historical effect (μ).
(ii) Natural variation effect (n_t).
(iii) Disturbance variation effect (d_t).

Mathematically, equation 2 expresses this situation. In terms of industrial quality, these effects can be thought of as the global and historical mean obtained from experience (i), thought of as data variation which is unavoidable and it is always present (ii); and finally, the data variation due to disturbances which is associated to special causes that may cause the process to be out of statistical control (iii).When a sample data has only influence on natural causes of variation, then $n_t > 0$ and $d_t = 0$, and the data pattern will be natural and its probability distribution will be normal. On the other hand, if $d_t > 0$, then the pattern data will be unnatural, and meaning that a cause of special variation has occurred in time t and non-normality can occur. It must be noticed that for any type of special pattern data $0 < n_t < d_t$. If the d_t value is very similar to n_t then neural network output can be misleading between a special pattern and a natural one. Two typical process patterns under consideration are described as follows:

Natural Pattern

The data used for this pattern was generated using the Monte Carlo simulator using equation 2. An example of this type of pattern is shown in figure 4. The graph data comes from a time-series of **X** that did not consider any trend or shift in the global mean and with data distribution randomly assigned. According eq. 2, this type of pattern is obtained when $d_t = 0$, $\mu = 0$ and n_t considers the random variation effect in **X** with $\sigma = 1$.

Shift Pattern

Data used for either *downward shift* or *upward shift* shows two data set separated by an abrupt change as shown in figure 5. This occurs because the reference mean also changes. This can be positive or negative and its magnitude depends on the cause of special variation in the manufacturing process.

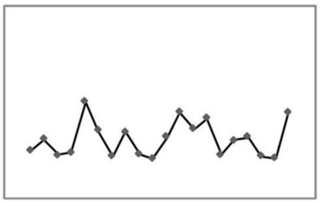


Fig. 4: Natural Pattern

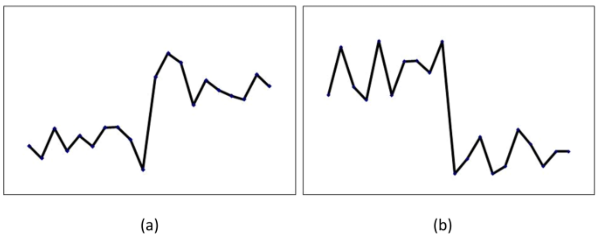


Fig. 5: Shift Patterns. (a)Upwards.(b)Downwards

In this type of pattern, the term d_t is the change magnitude with respect to the mean value. This research generated time series datasets adapting equation 2 and using the MATLAB® statistical toolbox. The generic equation is given by eq. 3. In this equation N is comprised by the standard deviation from **X** and the random number p as $N_t = \sigma p_t$. The number p_t is uniformly distributed within the [0, 1] interval.

$$x_t = \mu + N_t \qquad (3)$$

To generate a normal matrix data of c × d dimensions, with mean μ and standard deviation σ, we used the following random generator[2] from MATLAB®

$$X = \text{normrnd}(\mu, \sigma, c, d) \qquad (4)$$

5. Experimental Results

The ANN parameters considered in this paper are showed in table 1. Two experiments were carried out. Experiment I had two purposes: Firstly, to determine significant factors, considering the null hypothesis, that establish that their effect is not important to the ANN output. Secondly, the determination of the feasibility interval range (a_i, b_i) for the i factor, where i ∈ [A, G] with range $R_i = b_i - a_i$, obtained from the interval (0.0, 1.0) and where [A, G] = {A, B, C, D, E, F, G} represents the Control Factors related to the FuzzyARTMAP parameters as indicated in Table 2. The range value R = 1.0 defines all possible values for each parameter of the ANN. Experiment II was a complete factorial design tested in the range (a_i, b_i) with ranges R_i obtained from experiment I. In both designs, central points were considered to test the null hypothesis of curvature absence effect.

Table 1. FuzzyARTMAP parameters (experimental factors).

Control factor	Parameter	Mode	Module
A	Base vigilance $\rho_{(a)1}$	Train	ART A
B	Rho map $\rho_{(ab)1}$	Train	Map field
C	Learn rate β_1	Train	Map field
D	Vigilance $\rho_{(b1,2)1}$	Train	ART B
E	Rho map $\rho_{(ab)2}$	Test	Map field
F	Base vigilance $\rho_{(a)2}$	Test	ART A
G	Learn rate β_2	Test	Map field

According to equation 4, the **X** vectors were generated for experiments I and II using $\mu = 0, 1.5$ and 3; $\sigma = 1, 2$ and 3 and finally $c = 1$and $d = 20$. Input and output data for training was coded as showed in table 2. In this way the **X** vector will be standardized and its variation range will be $\mu \pm 3\sigma$ with a probability value of 99.7%. A linear transformation was used for the transformation of the **X** vector to the range [0, 1] and the prediction efficiency of the ANN (η) was evaluated in experiments I and II.

Table 2. InputsI^a and I^b for the FuzzyARTMAP

I^a	I^b				
normrnd(0,1,1,20)	1	0	0	0	0
normrnd(0,2,1,20)	0	1	0	0	0
normrnd(3,3,1,20)	0	0	1	0	0
normrnd(1.5,1,1,20)	0	0	0	1	0
normrnd(1.5,2,1,20)	0	0	0	0	1

5.1 Experiment I

An experimental design2_{IV}^{k-p}, with k = 7 and p = 2 and two replicates with 4 central points, hence, $2(2^5) + 4 =$ 68 runs were used. The alias generators were F=ABCD and G=ABDE (according with letters using for FuzzyARTMAP-parameters showing in table 1). The factors level were 0.1 (low or -1) and 0.9 (high or +1), that implies a range interval $R=0.8$ for any factor. Through experimental analysis of the standardized factors using a Pareto chart resulted in significance levels of 10% as showed in figure 6.

In figure 6, according with the Pareto chart from standardized effects, the control factor with significant effects are denoted with letters as in table 1. These are: F, CD, C, AB, D, ACE, E, BD, BCE, DG and AD.

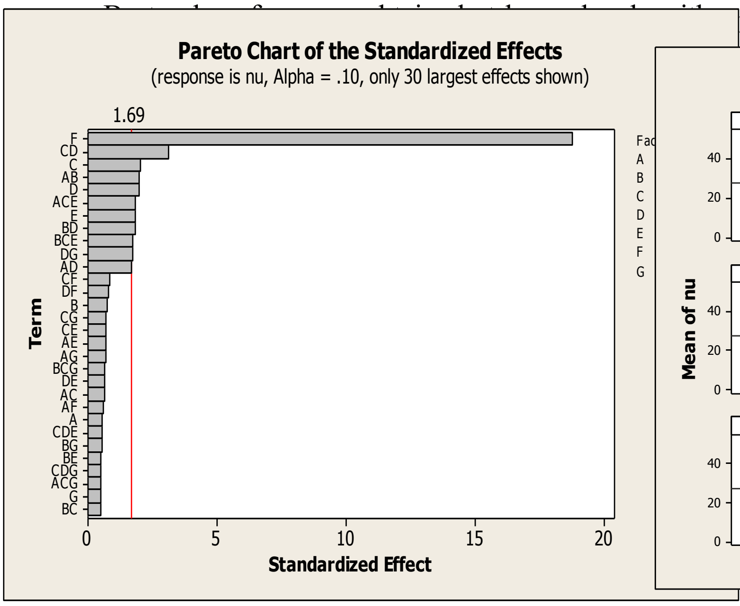
[2] Equation 4 is linked to equation 3 to generate the random numbers. In eq. 3, the N value is obtained with p = rand and this number generator can produce floating point numbers in the range $[2^{-53}, 1-2^{-53}]$. Theoretically, it is possible to obtain 2^{1492} values before the same value can be repeated again.

Considering the significant effects and the ANN parameters, we have:

- Principal effects are $\rho_{(a)2}$ (F), β_1 (C), $\rho_{(b1,2)1}$ (D) and $\rho_{(ab)2}$ (E).
- Double interaction effects are: $\beta_1$with $\rho_{(b1,2)1}$ (CD), $\rho_{(a)1}$with $\rho_{(ab)1}$ (AB), $\rho_{(ab)1}$with $\rho_{(b1,2)1}$ (BD), $\rho_{(b1,2)1}$with β_2 (DG) and $\rho_{(a)1}$with $\rho_{(b1,2)1}$ (AD).
- Triple interactions effects are: $\rho_{(a)1}$with $\beta_1$and $\rho_{(ab)2}$ (ACE), and $\rho_{(ab)1}$with $\beta_1$and $\rho_{(ab)2}$ (BCE)

The above results verify the importance of the ART$_a$, Map-field and ART$_b$ modules in the operation of the ANN. There was a combination of control factors that produced unfeasibility zones for the calculation of η since the ANN produced no prediction results; for all these cases, it was assumed that $\eta = 0$. A graphic illustration of this and related to the control factors can be observed in figure 7 where the slopes of the factor effects are showed with level in the range -1 to 1. In the figure, the horizontal axis in the graph represents the factor levels and the vertical axis the predicted efficiencies. It is demonstrated in this figure that the F control factor has a principal effect since its slope is higher than in the other cases. For F, $\eta = 0$ (or unfeasible) if its value is in high level (+1 or 0.9). This factor corresponds to the base vigilance ($\rho_{(a)2}$) from ART$_a$ during testing phase. A careful analysis from figure 7 resulted in the following conclusions:

- Maximum values for η are located around central points.
- The best values for η are obtained at higher levels with $\rho_{(a)1}$, $\rho_{(ab)1}$, β_1 and $\rho_{(b1,2)1}$ parameters in contrast to lower levels (the slope of the effects line is positive).
- … ab)2, $\rho_{(a)2}$ and β_2 parameters in contrast to higher



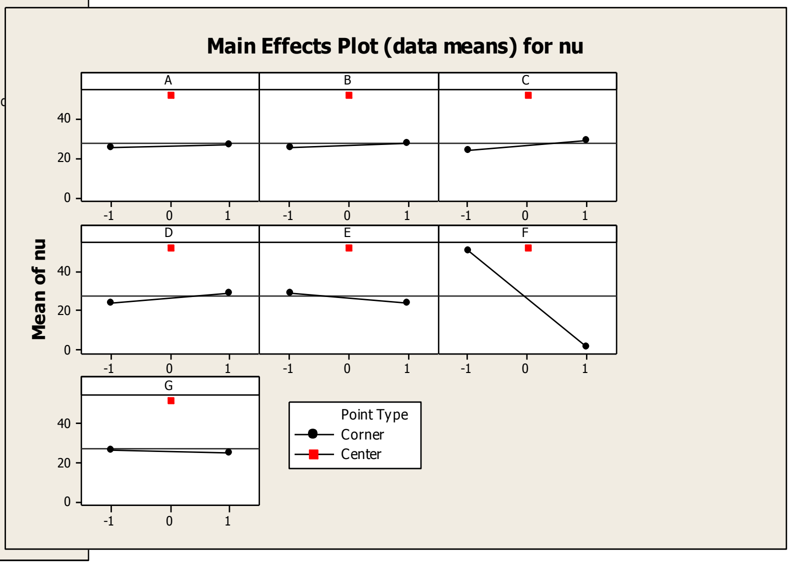


Figure 6: Standardized Effects Experiment I[3] **Figure 7: Principal effects for the mean of η**

From the above observations we can conclude that with a *long-range interval* ($R = 0.8$ for experiment I), the ANN parameters generate experimental unfeasibility.

5.2 Experiment II

For experiment II, the values from a *short-range interval* are showed in table 3 and were considered with $R = 0.4$ for all factors.

From the analysis of experiment II, it can be observed that the ANN efficiency is affected by principal effects and interactions up to third order with significance level of 0.05 according to the analysis of variance showed in table 4. It was also determined that the curvature is significant and not the adjustment. Then the adjustment model (eq. 5) is adequate for data representation with $R^2=87.14\%$ and $R^2_{adjusted}=82.95\%$.

[3] Considering that these results come from a fractional design, confounded effects can occur.

Table 3.Values within the short-range interval

Control factor	Para-meter	Mode	Module	Level	
				Low	High
A	Base vigilance $\rho_{(a)1}$	Train	ART A	0.5, (-1)	0.9, (+1)
B	Rho map $\rho_{(ab)1}$	Train	Map field	0.5, (-1)	0.9, (+1)
C	Learn rate β_1	Train	Map field	0.5, (-1)	0.9, (+1)
D	Vigilance $\rho_{(b1,2)1}$	Train	ART B	0.5, (-1)	0.9, (+1)
E	Rho map $\rho_{(ab)2}$	Test	Map field	0.1, (-1)	0.5, (+1)
F	Base vigilance $\rho_{(a)2}$	Test	ART A	0.1, (-1)	0.5, (+1)
G	Learn rate β_2	Test	Map field	0.1, (-1)	0.5, (+1)

Table 4. ANOVA[4] for experiment II

Source	DF	Seq SS	Adj MS	F	p
Main Effects	7	6748.0	963.9	92.91	0.0
2-Way Interactions	21	3551.5	169.1	16.30	0.0
3-Way Interactions	35	740.4	21.1	2.04	0.0
4-Way Interactions	35	265.0	7.57	0.73	0.86
5-Way Interactions	21	10.0	0.47	0.05	1.0
6-Way Interactions	7	4.2	0.59	0.06	1.0
Curvature	1	207.9	207.8	20.03	0.0
Residual Error	133	1380.0	10.3	----	---
Lack of Fit	1	0.3	0.31	0.03	0.86
Pure Error	132	1379.7	10.4		
Total	260	12907.0			

$$\eta = 137.079 - 95.8643A - 112.036B - 111.567C - 148.95D + 104.443AD + 57.5684BC + 186.084CD + 189.6BD + 122.803AC + 132.178AB - 129.395ABD - 114.746BCD - 111.816ACD - 45.4102ABC \quad (5)$$

Figure 8 shows standardised effects corresponding to ANN training with a significance level of 10%. In this graph, significative effects are clearly separated from non-significative effects. It can be observed that η is affected by $\rho_{(a)1}$ (A), $\rho_{(b1,2)1}$ (D), β_1 (C), $\rho_{(ab)1}$ (B), and as well as the interactions $\rho_{(a)1}$ with $\rho_{(b1,2)1}$ (AD), $\rho_{(ab)1}$ with β_1 (BC), $\beta_1$with $\rho_{(b1,2)1}$ (CD), $\rho_{(ab)1}$with $\rho_{(b1,2)1}$ (BD), $\rho_{(a)1}$ with β_1 (AC), $\rho_{(a)1}$with $\rho_{(ab)1}$ (AB), $\rho_{(a)1}$with $\rho_{(ab)1}$and $\rho_{(b1,2)1}$ (ABD), $\rho_{(ab)1}$with $\beta_1$and $\rho_{(b1,2)1}$ (BCD), $\rho_{(a)1}$ with β_1 and $\rho_{(b1,2)1}$ (ACD) and finally $\rho_{(a)1}$with $\rho_{(ab)1}$and β_1 (ABC).

In terms of ANN parameters, significative effects are due to:

a) 4 principal effects: $\rho_{(a)1}$, $\rho_{(ab)1}$, β_1 and $\rho_{(b12)1}$
b) 6 double interaction effects: $\rho_{(a)1}$with $\rho_{(b1,2)1}$, $\rho_{(ab)1}$with β_1, $\beta_1$with $\rho_{(b1,2)1}$, $\rho_{(ab)1}$with $\rho_{(b1,2)1}$, $\rho_{(a)1}$with $\beta_1$and $\rho_{(a)1}$with $\rho_{(ab)1}$
c) 4 triple interaction effects: $\rho_{(a)1}$ with $\rho_{(ab)1}$ and $\rho_{(b1,2)1}$;$\rho_{(ab)1}$ with β_1 and $\rho_{(b1,2)1}$; $\rho_{(a)1}$with β_1 and $\rho_{(b1,2)1}$ and finally, $\rho_{(a)1}$ with $\rho_{(ab)1}$ and β_1

In *short-range interval*, in comparison with *long-range interval*, none of the testing parameters are significative, so that statistical significance is due to only the training parameters. Figure 9 shows lines about principal effects regarding the network efficiency. It can be observed positive slope lines for all cases. This means that the network efficiency improves when crossing from low factor values to higher factor values.

[4] Table obtained by MINITAB® statistical software. Where DF: Degrees of freedom; Seq SS: sequential sums of squares; Adj MS: adjusted mean square; F: A test to determine whether the interaction and main effects are significant; p: is the probability of obtaining a statistic test that is at least as extreme as the actual calculated value, if the null hypothesis holds true.

However, a central point indicates a better ANN performance.

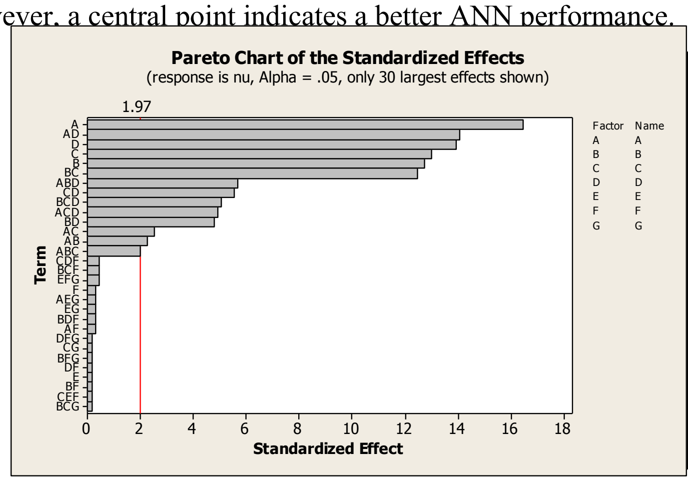


Figure 8: Standardised Effects Experiment II

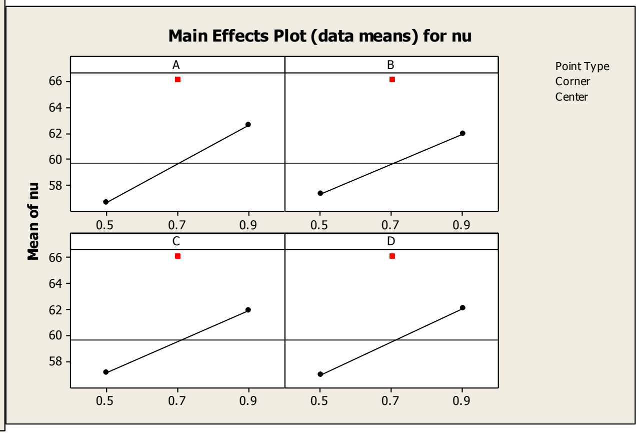


Figure 9: Principal effects for the mean of η

6. Conclusions

The pattern recognition scheme involves standardisation and coding before data normality is determined. According to the type of statistical distribution, the ANN parameters are selected. A detailed analysis was carried out in this paper regarding the range interval for the FuzzyARTMAP parameters which, in this investigation, can take any value from the interval (0.0, 1.0). From the obtained results the following conclusions are drawn:

A selection of *long-range interval* values from 0.1 to 0.9 (R = 0.8) for all the network parameters is not possible since it may result in efficiencies η = 0 resulting in experimental unfeasibility. An important parameter that defines this situation is the base vigilance during the testing stage ($\rho_{(a)2}$) since the experimental unfeasibility was detected when $\rho_{(a)2}$ was closer to 0.9. On the contrary, if a *short-range interval* (R=0.4) was chosen then the unfeasibility can be avoided.

It was observed that training parameters produced higher efficiencies if their values were selected from the second half of the *long-range interval* and the testing parameters were located in the first half.

With *short-range* values it was found that the training stage was more important in terms of efficiency than the testing stage while with *long-range* values the opposite was the case.

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