Manufacturing process quality control by means of a Fuzzy ART neural network algorithm

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Abstract. Neural networks are potential tools that can be used to improve process quality control. In fact, various neural algorithms have been applied successfully for detecting groups of well-defined unnatural patterns in the output measurements of manufacturing processes. This paper discusses the use of a neural network as a means for recognising changes in the state of the monitored process, rather than for identifying a restricted set of unnatural patterns on the output data. In particular, a control algorithm, which is based on the Fuzzy ART neural network, is first presented, and then studied in a specific reference case by means of Monte Carlo simulation. Comparisons between the performances of the proposed neural approach, and those of the CUSUM control chart, are also presented in the paper. The results indicate that the proposed neural network is a practical alternative to the existing control schemes.

1 Introduction

The main goal of quality control in manufacturing is to maintain a constant and acceptable level of some process characteristics. Usually, a certain amount of variability affects measurements of the quality parameters of interest. Two sources of variability may influence the outcomes of a process; commonly they are referred to as *unassignable* and *assignable* causes [1]. The variations due to unassignable causes are the result of numerous unremarkable changes that may occur in a process. Often, this kind of variation is inevitable without a profound revision of the whole production procedure. When only unassignable causes are in effect, a process is considered to be in a natural state (i.e. in control). On the other hand, the variations due to assignable causes are generated by factors that lie outside the process. New methods and different machines, or changes in the measurement instruments, are common examples of assignable causes. In such cases, the process is said to be in an unnatural state (i.e. out of control), and quality improvement is possible by detection and removal of the assignable causes.

Among the Statistical Process Control (SPC) methods, the control charts are the most common tools to reveal unnatural variations in the monitored measurements [1]. However, with the growing exploitation of automatic on-line data-collection methods, nowadays a demand exists to automate the analysis of process data.

In the last decade, the artificial neural networks have been widely used for data analysis in quality control applications [2]. The neural networks appear suitable for quality control because of their ability to elaborate large amounts of data in real-time, and their capacity for handling noisy, uncertain or fuzzy data. Many different neural networks and learning algorithms have been proposed in the literature [2]. Hwarng and Hubele [3] proposed a multilayer perceptron (MLP) trained with back-propagation algorithm (BP) to detect six unnatural patterns. Smith [4] described a similar algorithm in order to analyse both mean and variance shifts. Guh and Tannock [5] developed a MLP BP neural network for concurrent unnatural pattern recognition. Cook *et al.* [6] discussed the development of a MLP BP neural network to identify changes in the variance of serially correlated process parameters.

The neural network for quality control, which has been proposed by researchers in almost all the published works, is the MLP BP [2]. The MLP BP has been studied thoroughly, and has been exploited successfully in various applications. However, the use of a supervised neural network means that both a set of well-defined patterns and an adequate number of examples are available for neural network training. Frequently, in various industrial cases, training patterns are not available because unnatural process behaviours cannot be manifested by the appearance of predictable patterns and thus, the mathematical models are not readily available or they cannot be formulated.

With the exception of two published works [7,8], little attention has been devoted by researchers to the development of quality control systems based on the Adaptive Resonance Theory (ART). ART neural networks are competitive learning pattern classifiers. Competitive learning is an unsupervised training strategy that accomplishes a clustering task, which is based on a function optimisation (e.g. a distance between vectors of an *n*-dimensional space). The ART neural network can be used to monitor process under the assumption that no knowledge on the unnatural state is available in advance for network training.

Recently, we have investigated on the use of ART for quality control applications [9]. A neural network approach, based on a simplified Fuzzy ART that is capable of fast and cumulative learning, has been proposed for quality control. In this paper, the Fuzzy ART control system is firstly presented, and then it is applied to identify a special pattern of process data: the upward trend. The purpose of this paper is to analyse the

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performance of the proposed system in recognising trend of process data when network training is limited on the natural target and on a specific unnatural off-target value.

The Fuzzy ART algorithm is based on the fuzzy set theory operations, thus the values of the input nodes, as well as of the weights of the network, can range between zero and one. The reader is referenced to the papers 10 and 11 for further details on Fuzzy ART.

The rest of the paper is organised as follows. Section 2 gives an overview of the neural network algorithm for process monitoring. Section 3 explains the training phase of the proposed neural network while in section 4 the testing phase is discussed. Section 5 discusses the performance of the artificial neural network for the reference test case. Finally, conclusions are given.

2 Outline of the neural algorithm

The use of a control chart as well as of a neural network algorithm for process monitoring resembles hypothesis testing. Usually, the process is analysed to verify a constant mean with some natural inherent variation. The null hypothesis H_0 and the alternative hypothesis H_1 of the test can be formulated as follows.

$$\begin{aligned} &H_0 : \text{the process is under control.} \\ &H_1 : \text{the process is out of control.} \end{aligned} \qquad (1$$

In order to investigate the Fuzzy ART performances for quality control applications, in the present work the output of a generic manufacturing process has been synthetically reproduced by means of Monte Carlo simulation. In the reference test case, the measurements of the quality parameter are collected at regular interval of time. Let $\{Y_t\}$ be the random time series of the mono-dimensional process output. Generally, the outcomes of a manufacturing process in a natural state may be realistically modelled by a random time series, which values are distributed normally, independently, and identically (NID). Without loss of generality, it is assumed that the mean and the variance of such a distribution are equal to zero and one respectively, i.e. NID(0,1). Moreover, it is assumed that when the process starts drifting from the natural state, a form of a special disturbance signal overlaps the series of output measurements.

Let $\{Z_t\}$ be the time series of the natural process data and let $\{S_t\}$ be the time series of the special disturbance signal. At each instant of index t, the statistical test can be re-formulated as reported by the following equation 2.

$$\begin{aligned} &H_0 : Y_t = Z_t \\ &H_1 : Y_t = Z_t + S_t \end{aligned} \qquad (2$$

The proposed neural system for quality control and the simulation model of the reference manufacturing process are both depicted by figure 1. At the time of index t, the control system accepts as input the process output Y_t, and produces the binary signal $b_{nn,t}$ that is the result of the test performed by Fuzzy ART on the state of the process. In particular, the algorithm produces $b_{nn,t} = 1$ if the process is considered in a natural state, $b_{nn,t} = 0$ otherwise.

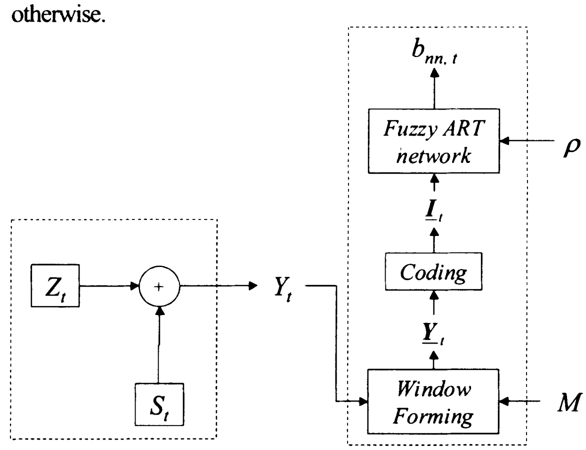

Fig. 1. The proposed neural system for quality control

As depicted by figure 1, some pre-processing of the input data takes place before they are presented to the Fuzzy ART neural network. The first stage (*Window Forming*) depends on the integer parameter $M \geq 1$ (called the *Window Size*). It transforms the time series $\{Y_t\}$ of process output data into *M*-dimensional vectors. In particular, the most recent *M* observations are collected to form the vector $\underline{Y}_t$ that is equal to:

$$\underline{Y}_t = [Y_{t-M+1}, Y_{t-M+2}, \ldots, Y_{t-1}, Y_t] \qquad t \geq M \qquad (3$$

The second pre-processing stage (called *Coding*) takes as input an *M*-dimensional input pattern $\underline{Y}_t$ and transforms it into the corresponding *M*-dimensional output vector (say $\underline{I}_t$) whose components fall into the interval $[0,1]$. The implemented *Coding* stage is a linear re-scaling of the process data. Specifically, let $\underline{I}_t$ be:

$$\underline{I}_t = [I_{t-M+1}, I_{t-M+2}, \ldots, I_{t-1}, I_t] \qquad t \geq M \qquad (4$$

then we have for $t - M + 1 \leq \tau \leq t$ that

$$\begin{cases} I_\tau = 0 & Y_\tau < -l; \\ I_\tau = \dfrac{1}{2}\left(1 + \dfrac{Y_\tau}{l}\right) & -l \leq Y_\tau \leq l; \\ I_\tau = 1 & l < Y_\tau; \end{cases} \qquad (5$$

In the reference test case, the parameter l has been fixed to $l = 3$. This is motivated by the assumption that, when the process is a natural state, the output time series values are modelled as NID(0,1). We expect that about 99.74% of the natural observations fall into the interval $[-3,3]$.

The Fuzzy ART neural network accepts as input the vector $\underline{I}_t$. The neural network consists of two major subsystems, the attentional and the orienting subsystem. Three fields of nodes denoted as *F0*, *F1* and *F2* compose the attentional subsystem. On the other hand, the orienting subsystem consists of a single node called the reset node.

In the most simplified terms, the layer *F1* acts as a feature detector that receives external input patterns. The layer *F2* acts as a category classifier that receives internal patterns. The application of an input vector leads to a neural activity that results in the formation of a pattern in both the layers *F1* and *F2*. The orienting subsystem is responsible for generating a reset signal to *F2* when the bottom-up input pattern and the top-down template mismatch according to a vigilance criterion. The vigilance criterion depends on the vigilance parameter ($\rho \in [0,1]$). The choice of high values for the vigilance parameter implies that only a slight mismatch will be tolerated before a reset signal is emitted. On the other hand, a small value implies that large mismatches will be tolerated.

In the *F0* field, an additional pre-processing stage on the incoming input vectors $\underline{I}_t$ is implemented. This pre-processing stage accepts an *M*-dimensional vector, and it produces the following *2M*-dimensional output vector.

$$\underline{I}_t^c = (\underline{I}_t, \underline{1} - \underline{I}_t)$$
$$\underline{I}_t^c = [I_{t-M+1}, \ldots I_t, 1 - I_{t-M+1}, \ldots, 1 - I_t] \qquad (6$$

The above transformation is called the *Complement Coding*.

3 Training phase

In the present work, it is assumed that a predetermined list of natural and/or unnatural input patterns is not available for network training. Instead, it is assumed to know the *target* of the process, and a specific *off-target* value that we want to detect quickly. The target is the nominal mean of the process, i.e. the output that the process should have if both assignable and unassignable causes of variation are not present. The off-target is a specific deviation from the natural target that we want to reveal promptly. If both the natural target and the shifted target can be considered constant over time (steady-state response), then the Fuzzy ART training list consists of two *M*-dimensional vectors only: the steady-state natural process mean (the target), and the unnatural shifted mean (the off-target).

During training, we want that Fuzzy ART stores both the vectors and thus the vigilance parameter is set to its maximum value ($\rho = 1$). In such way, the network learns two different categories that reproduce the specific training patterns: the first one represents the natural target and the second one the shift (Perfectly Learned Patterns – PLP training approach). The number of list presentations for the Fuzzy ART training can be reduced to one because once a cluster has been formed the weights of this category cannot change during the subsequent list presentations if the vigilance parameter is set to $\rho = 1$ [10,11].

4 Testing phase

Let us assume that at time of index $t \geq M$ an *M*-dimensional input pattern $\underline{I}_t$ is presented at the *F0* field of the Fuzzy ART. The appearance of the *2M*-dimensional pattern $\underline{I}_t^c$ across the *F1* field produces bottom-up inputs that affect the nodes in the *F2* layer. The bottom-up inputs activate a competition process among the *F2* nodes, which eventually leads to the activation of a single node in the *F2*, namely the node that receives the maximum bottom-up input from *F1*. In particular, let $\underline{w}_\mu^c$ ($\underline{w}_s^c$) be the top-down weight vector of the committed node in the *F2* layer that stores the natural (unnatural) cluster. The natural cluster wins the competition on the unnatural one if the following condition is satisfied.

$$\frac{\left|\underline{I}_t^c \wedge \underline{w}_\mu^c\right|}{\alpha + \left|\underline{w}_\mu^c\right|} \geq \frac{\left|\underline{I}_t^c \wedge \underline{w}_s^c\right|}{\alpha + \left|\underline{w}_s^c\right|} \qquad (7$$

Where α is a constant called the *choice parameter*; $|\underline{x}|$ is the size of a vector $\underline{x}$, (i.e. the sum of the absolute value of its components $|\underline{x}| = \sum_i |x_i|$); $\underline{x} \wedge \underline{y}$ is the vector whose i^{th} component is the minimum between the i^{th} component of the vector $\underline{x}$ and the i^{th} component of the vector $\underline{y}$, thus: $\underline{x} \wedge \underline{y} = [\ldots, \min(x_i, y_i), \ldots]$. The operation $\wedge$ is called the fuzzy min operator.

Then, the neural network classifies the input pattern $\underline{I}_t^c$ natural (i.e. as a member of the natural cluster) if the following check is passed [10,11].

$$\frac{\left|\underline{I}_t^c \wedge \underline{w}_\mu^c\right|}{\left|\underline{I}_t^c\right|} \geq \rho \qquad (8$$

The vigilance parameter ρ, which is used in this phase, can be different from that used in the training phase.

The size of each input vector $\underline{I}_t^c$ is equal to *M* since it results that:

$$\left|\underline{I}_t^c\right| = \left|(\underline{I}_t, \underline{1} - \underline{I}_t)\right| = \left|\underline{I}_t\right| + M - \left|\underline{I}_t\right| = M \qquad (9$$

Moreover, since the PLP training approach has been used, it results also that $\left|\underline{w}_\mu^c\right| = \left|\underline{w}_s^c\right| = M$. Therefore, both the equations 6 and 7 can be rewritten as follows.

$$\begin{cases} \left|\underline{I}_t^c \wedge \underline{w}_\mu^c\right| \geq \left|\underline{I}_t^c \wedge \underline{w}_s^c\right| \\ \left|\underline{I}_t^c \wedge \underline{w}_\mu^c\right| \geq M\rho \end{cases} \qquad (10$$

In other words, the input pattern $\underline{I}_t^c$ is recognised by the neural network as a natural pattern (i.e. the output is set to $b_{nn,t}=1$) if the following check is passed:

$$\left|\underline{I}_t^c \wedge \underline{w}_\mu^c\right| \geq \max\left\{M\rho, \left|\underline{I}_t^c \wedge \underline{w}_s^c\right|\right\} \qquad (11$$

Otherwise, the input patter is classified as unnatural and the output result is set to $b_{nn,t}=0$.

As underlined by the above equation 11 the performance of the neural network for quality control depends on two parameters, namely the window size M and the vigilance parameter ρ.

5 Testing results

In order to evaluate the performances of the proposed neural algorithm for quality control, two characteristics are calculated by means of computer simulation. The first is the ability to model unassignable causes of variation without creating Type I errors (i.e. false alarms), which indicate that the process is out of control when it is in fact not. This property is measured by reporting the mean of the false alarm occurring in process data having only unassignable sources of variation (say $\hat{\alpha}$). The second performance measures the control system ability to detect unnatural patterns in the process output data. This property is calculated experimentally by reporting the mean of the Type II errors (say $\hat{\beta}$, i.e. the non-alarm signals) occurring in the process data when a special disturbance, with a controlled magnitude, is introduced. In particular in this work, an upward linear trend has been used to simulate a special disturbance of the process mean that we want to detect by using the Fuzzy ART neural network. In figure 2 the effect of such a pattern on a control chart is depicted.

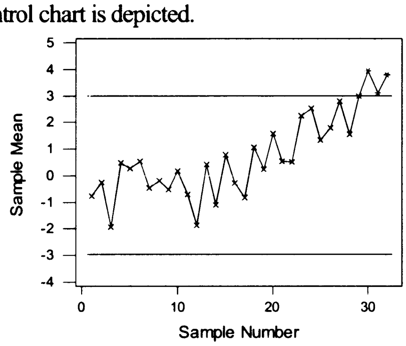

Fig. 2. The linear trend pattern depicted on a control chart

In order to evaluate the performance of the neural network, in table 1 the simulation results are compared to those of a SPC benchmark: the CUSUM control chart [1]. The CUSUM parameters have been chosen in order to both detect changes in the process mean of one unit of standard deviation, and to obtain a Type I error of about 0.27%. For the comparison to be unbiased, the CUSUM alarms, which occur during the first $M-1$ observations, have been neglected, and the performances have been measured for time indexes $t \geq M$. Furthermore, the Fuzzy ART neural network has been firstly tuned to give comparable performance in terms of Type I error to that of the reference CUSUM chart. In particular, the window size has been set to $M=75$ and the vigilance parameter ρ has been adjusted to give a Type I error level comparable to that of the CUSUM control chart (that results in $\rho=0.8375$). The comparison is based on the Type II error estimators for the linear upward trend pattern. Twenty levels of magnitude (ranging in $[0.001, 0.020]$ with steps of 0.001 unit of standard deviation) have been considered in the simulations.

Table 1 presents both the Type I and Type II error estimator points of the neural network ($\hat{\alpha}_{nn}, \hat{\beta}_{nn}$ respectively) and of the CUSUM chart ($\hat{\alpha}_{cc}, \hat{\beta}_{cc}$ respectively), as well as the confidence intervals (coverage 95%) of the difference between them. Specifically, the column labelled as $\hat{\alpha}_{nn}-\hat{\alpha}_{cc}$ reports the difference between the Type I error point estimator of the neural network ($\hat{\alpha}_{nn}$) and that of the control chart ($\hat{\alpha}_{cc}$). The column marked as $\hat{\beta}_{nn}-\hat{\beta}_{cc}$ reports the difference between the Type II error estimator points.

	CUSUM k=0.5 h=4.7749	*Fuzzy ART M=75 ρ=0.8375*		*Fuzzy ART - CUSUM*	
	$\hat{\alpha}_{cc}$%	$\hat{\alpha}_{nn}$%	$(\hat{\alpha}_{nn}-\hat{\alpha}_{cc})_-$	$\hat{\alpha}_{nn}-\hat{\alpha}_{cc}$	$(\hat{\alpha}_{nn}-\hat{\alpha}_{cc})_+$
	0.269	**0.268**	-0.047%	-0.001%	0.045%
	$\hat{\beta}_{cc}$	$\hat{\beta}_{nn}$	$(\hat{\beta}_{nn}-\hat{\beta}_{cc})_-$	$\hat{\beta}_{nn}-\hat{\beta}_{cc}$	$(\hat{\beta}_{nn}-\hat{\beta}_{cc})_+$
0.001	**99.358**	**98.991**	-0.425%	-0.367%	-0.309%
0.002	**98.860**	**98.196**	-0.735%	-0.664%	-0.593%
0.003	**98.255**	**97.054**	-1.305%	-1.201%	-1.097%
0.004	**97.459**	**95.560**	-2.041%	-1.899%	-1.757%
0.005	**96.269**	**93.261**	-3.207%	-3.008%	-2.809%
0.006	**94.635**	**90.030**	-4.877%	-4.605%	-4.333%
0.007	**92.002**	**84.931**	-7.452%	-7.071%	-6.690%
0.008	**87.831**	**77.471**	-10.835%	-10.360%	-9.885%
0.009	**81.436**	**66.932**	-15.231%	-14.504%	-13.777%
0.010	**71.347**	**53.706**	-18.457%	-17.641%	-16.825%
0.011	**57.216**	**38.954**	-19.207%	-18.262%	-17.317%
0.012	**39.172**	**24.756**	-15.453%	-14.416%	-13.379%
0.013	**21.739**	**13.946**	-8.690%	-7.793%	-6.896%
0.014	**10.106**	**7.153**	-3.529%	-2.953%	-2.377%
0.015	**3.835**	**3.419**	-0.823%	-0.416%	-0.009%
0.016	**1.294**	**1.416**	-0.080%	0.122%	0.324%
0.017	**0.336**	**0.623**	0.162%	0.287%	0.412%
0.018	**0.095**	**0.219**	0.058%	0.124%	0.190%
0.019	**0.023**	**0.068**	0.011%	0.045%	0.079%
0.020	**0.000**	**0.030**	0.009%	0.030%	0.051%

Table 1. Comparison between Fuzzy ART (*M*=75, *ρ*=0.8375) and CUSUM (*k*=0.5, *h*=4.7749) chart (simulation results).

The results of table 1 show that the neural network performance is comparable to the CUSUM chart in terms of Type I errors since the confidence interval includes the zero value. This implies that there is no statistical evidence to reject the hypothesis $\alpha_{nn} = \alpha_{cc}$. The neural network has better performances than those of the CUSUM to recognise upward trend of small and medium slope, i.e. 0.001 - 0.015 units of standard deviation. In fact, the confidence intervals on the difference between the point estimators include only negative values and thus we can statistically conclude that $\beta_{nn} < \beta_{cc}$. On the other hand, the performances of the neural network are either approximately similar to those of the control chart for nigher magnitude (0.016-0.020 units of standard deviation) or slightly worse.

In figure 3, the simulation results are graphically depicted. In addition, figures 4 and 5 show in more detail the simulation results in the case of high errors of Type II (i.e. higher than 95%) and low errors of Type II (i.e. lower than 5%) respectively. In particular, in figure 4 the case of low slopes of the trend pattern (less than 0.005 units of standard deviation) is considered, while in figure 5 only slopes of higher magnitudes (i.e. higher than 0.01 units of standard deviation) are taken into account.

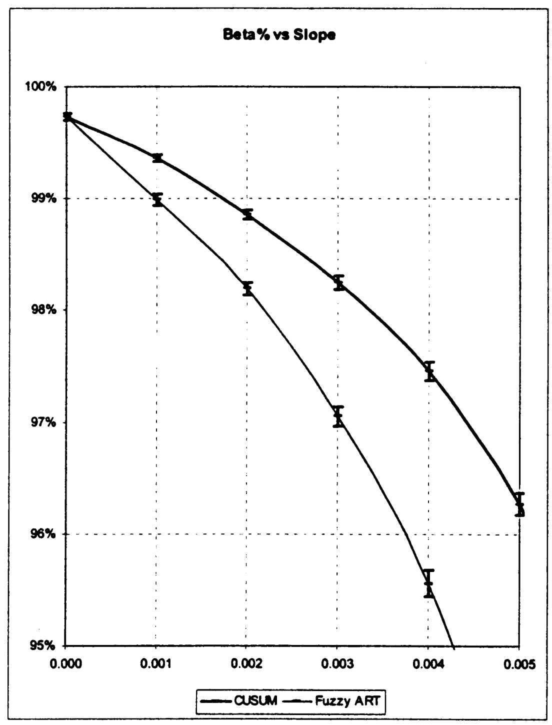

Fig. 4. Detail. Neural network (thin line) and CUSUM (bold line) type II point estimators (>95%, ordinate) vs. trend slope (abscissa) and interval estimators at coverage 95% (simulation results).

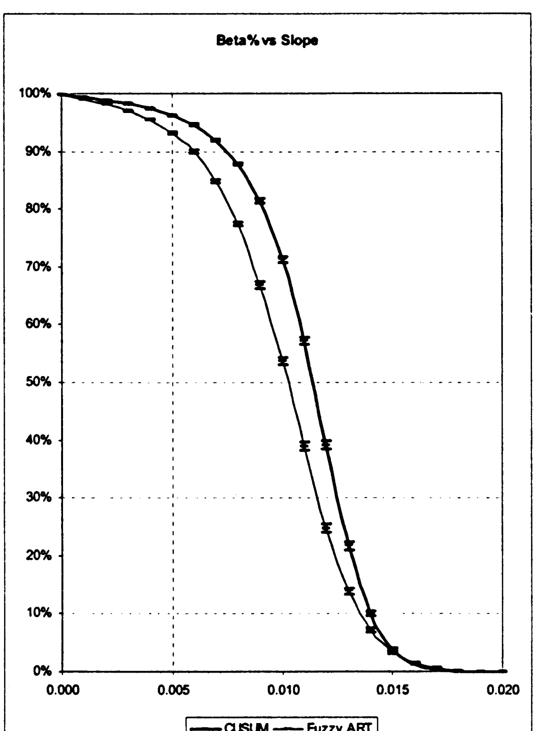

Fig. 3. Neural network (thin line) and CUSUM (bold line) type II point estimators (ordinate) vs. trend slope (abscissa) and interval estimators at coverage 95% (simulation results).

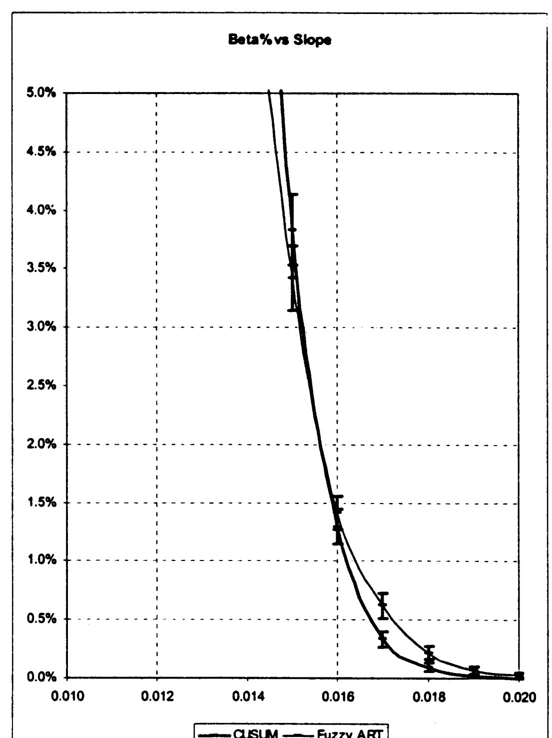

Fig. 5. Detail. Neural network (thin line) and CUSUM (bold line) type II point estimators (<5%, ordinate) vs. trend slope (abscissa) and interval estimators at coverage 95% (simulation results).

6 Concluding remarks

In this paper, the application of Adaptive Resonance Theory for quality control tasks has been briefly analysed. Several proprieties of ART-based neural network make it a practical tool for quality control applications over supervised ones. Since ART networks are self-organising, the number of training iterations needed to mach the performances of supervised neural networks is lower. Thus, training times in the development of a neural-based control system are significantly reduced.

The main advantage of this approach is that it requires no previous information about unnatural pattern appearances, related mathematical models, or probability distribution functions. This neural network can be potentially adopted to signal any types of unnatural pattern, so it provides a powerful diagnostic tool for detecting assignable causes in real processes.

We recommend the proposed Fuzzy ART neural algorithm when probabilistic/mathematical models of either the natural or unnatural process output are not available. Especially when a new process is starting up for which earlier data are not sufficient to obtain an adequate number of training examples for a supervised neural network control system.

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