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Application of Neuro-Fuzzy in the Recognition of Control Chart Patterns

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ABSTRACT
The control chart (CC) is an important tool in Statistical Process Control (SPC) to improve the quality of products and processes. An unnatural variation in control maps assumes that an assignable cause affects the process is present, and some actions need to be applied to solve the problem.

Thanks to their better recognition capability, NEURO-FUZZY is a powerful tool for process control and rapid detection of the drifts of their evolutions.

In this paper, a NEURO-FUZZY architecture is used to recognize control charts pattern (CCPR). Several forms and architectures have been tested and the results found show that the chosen architecture leads to the best recognition quality.

General Terms

SPC	=	Statistical Process Control;
CCPR	=	Control charts pattern recognition;
CCP	=	Control charts pattern;
CC	=	Control charts;
NOR	=	Normal;
IT	=	Increasing trend;
US	=	Upward shift;
ANFIS	=	Adaptive Neuro-Fuzzy Inference System;
MSE	=	Mean Square Error;

Keywords
Adaptive Neuro-Fuzzy Inference System (ANFIS), Statistical Process Control (SPC), Control Charts (CC), Control Charts Pattern (CCP).

1. INTRODUCTION
Statistical Process Control (SPC) has been widely used for monitoring the production process. Control chart pattern recognition is the most commonly SPC tools used for problem identification in processes due to special causes. Indeed, traditional Control charts use only the control limits to detect changes in the process according to the latest data sets. But the nature of the evolution of these data is not taking into account.

Otherwise the improvement of the detection quality by implementing control rules is limited by false alarms that arise by the simultaneous application of these rules.

There are three main types of patterns that commonly appear in CCP: normal (NOR), increasing trend (IT), and upward shift (US), as is shown in Figure 1.

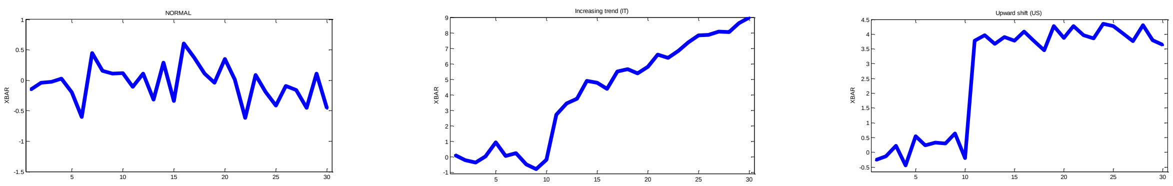
The NOR pattern indicates that the process is operating under control. All other types of patterns are unnatural and assume that an assignable cause affecting the process is present [1].

Some researchers have used expert systems for the recognition of unnatural models [2, 3]. The advantage of an expert system is that it contains information explicitly.

In the proposed method, an expert system was developed that has fuzzy rules obtained by an adaptive neural-fuzzy inference system (ANFIS). ANFIS represents the next generation of information processing systems. Fuzzy inference systems based on the adaptive network are good for tasks such as matching and classifying models, approximating functions, optimizing and grouping data [4-5].

This paper presents a contribution in CCP by using an Adaptive Neuro-Fuzzy Inference System (ANFIS) in order to improve the ability of pattern detection.The best configuration and the most accurate algorithm are retained.

The rest of the paper is organized as follow: The second section will review the literature in CCP and the use of Adaptive Neuro-Fuzzy Inference System (ANFIS) in this area. The third section will present the ANFIS design for pattern recognition. In the fourth section, the results obtained will be discussed. The last section will review the main results of the paper.



Normal (NOR) Increasing trend (IT) Upward shift (US)

Fig 1.Three types of basic CCPs

2. NEURO-FUZZY (ANFIS) FOR CONTROL CHARTS PATTERN RECOGNITION

ANFIS can be considered as a useful approach to the neural network for solving problems of approximation of the function. Data-based procedures for the synthesis of ANFIS networks are generally based on the grouping of a set of digital samples of the unknown function to be approximated. Since their first application, ANFIS networks have been successfully applied to classification tasks, rule-based process controls, model recognition problems and others. Here, a fuzzy inference system includes the fuzzy model [6, 7] proposed by Takagi, Sugeno and Kang to formalize a systematic approach to generating fuzzy rules from an input output data set. You can find more details about ANFIS in [8-9].

A basic structure of ANFIS is shown in figure 2.

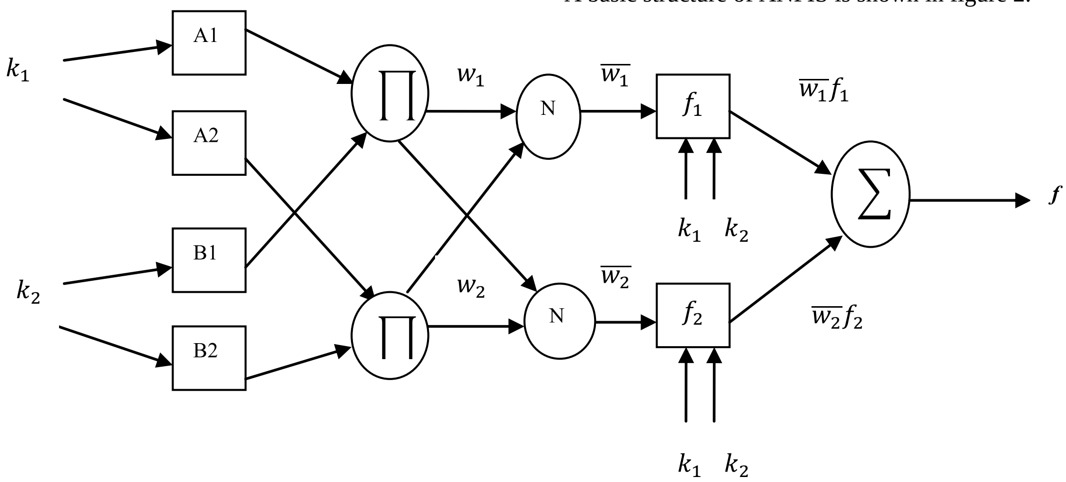


Fig 2. Basic structure of ANFIS

3. ANFIS DESIGN FOR PATTERN RECOGNITION

3.1 Sample patterns

Sample patterns to be classified are usually groups of measurements or observations coming from a real manufacturing process. Since real process containing all type of patterns is not available, simulated data are often used [10]-[11].The following equations, shown in Table (1), were used to generate the data points for the various patterns.

Table 1. Equations for generating various patterns

Patterns	Equations
Normal	$\mu + \sigma * \text{rand}([p, n])$ (3)
Trend increasin	$\mu + \sigma * \text{rand}([p, n]) + I * g$ (4)
Shift up	$\mu + \sigma * \text{rand}([p, n]) + K * s$ (5)

where *:*

- μ :is the nominal mean value of the process variable;
- σ :is the standard deviation of the process variable;
- g :is the gradient of an increasing trend pattern or a decreasing trend pattern;
- rand(p,n) is a Matlab Function that generates an p-by-n matrix of random normally distributed with mean μ =0,variance $\sigma^2 = 1$, and standard deviation $\sigma = 1$ (n is the size of the observation window and p is the number of observations);
- *s* :indicates the shift position in an upward shift pattern and a downward shift pattern(s =0 before the shift and s = 1 at the shift and thereafter)

In trend and shift patterns data generation the first p/3 samples have a normal distribution (K_{ij} and I_{ij} are set to 0),then after K_{ij} =1 and I_{ij}=1:

$$\underset{p\times n}{[K]}: \quad K_{ij} = 0 \quad \textit{for } i \le p/3, \textit{ and } K_{ij} = 1 \quad \textit{for } i > p/3$$

$$\underset{p\times n}{[I]}: \quad I_{ij} = 0 \quad \textit{for } i \le p/3, \textit{ and } I_{ij} = i \quad \textit{for } i > p/3.$$

For each type of the tree CCPs,(n*p) samples data were generated using the following values of parameters shown in table 2.

Table 2.Values Of Parameters Adopted To Generate Patterns

Patterns	Parameter’s values
Normal	$\mu = 0, \sigma = 1$
Increasing Trend	g =0.3
Shift Up	s =4

3.2 ANFIS design

In this study the ANFIS design consist of use two inputs and one output as shown in figure 3. The inputs represent the statistics of the n observations correspond to the sample size used for process control which are their average $\overline{X}$ and their standard deviation S [12].The output with the normalized coding shown in table 3.

Table 3.Values Of Output Targets Related To Each Pattern

Patterns	coded output = Target
Normal	0.5
Increasing Trend	0.1
Shift Up	0.9

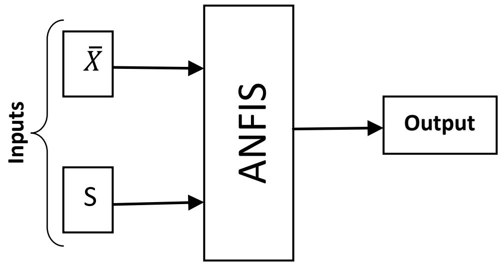


Fig 3.The structure of ANFIS used for CCPs

The training input is an (2)-by-(3xp) matrix illustrated as follow (Fig. 4).

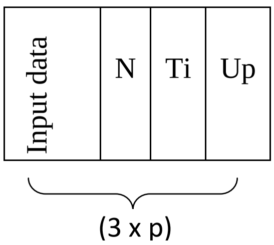


Fig 4. Training input data structure design

3.3 Setting the Parameters of FIS Generation Methods

We used three FIS generation approaches:

genfis1: Grid Partitioning.

genfis2: Subtractive Clustering.

genfis3: FCM.

In both the tables 4 and 5 we will found all parameters used in the execution

Table 4.Parameters for each Genfis

Genfis 3	Par	Genfis 2	Par	Genfis 1	Par
Number of Clusters	15	Influence Radius	0.3	Number of MFs	5
Partition Matrix Exponent	2			Input MF Type	gaussmf
Maximum Number of iterations	200			Output MF Type	linear
Minimum Improvement	1^{e}-5				

Table 5.Parameters for all Genfis

Genfis 1,2& 3	Parameters
Maximum Number of Epochs	200
Error Goal	0
Initial Step Size	0.01
Step Size Decrease Rate	0.9
Step Size Increase Rate	1.1

4. TESTS AND RESULTS

For the network of neuron used we chose the network already developed in our article [1].

Neuro-Fuzzy Matlab's Toolbox provides a complete environment to design, train, visualize, and simulate ANFIS networks.

To develop our code we have followed the flowchart shown in the figure 5.

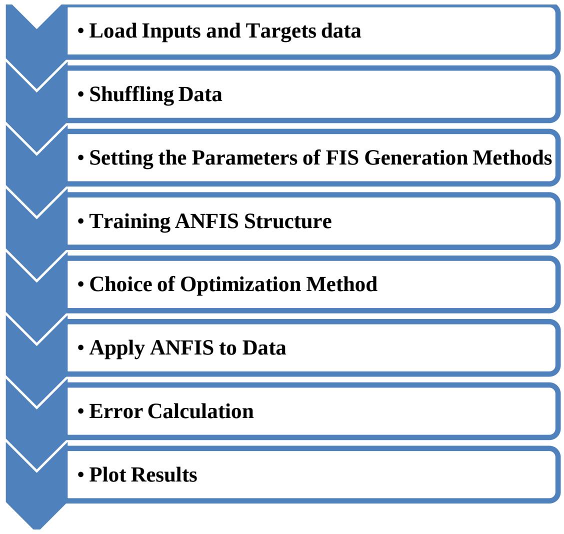


Fig 5. The flow chart of the developed code

This section presents results and comparisons of the performance between ANFIS recognizers trained and tested using three FIS generation approaches.

To determine the optimal Architecture, the coefficient of correlation (R) between actual targets and predicted targets and the mean sum of squares of the network errors (MSE) is used [13].

$$MSE = SSE/(n-p) \quad (1)$$

Where:

- SSE is the summed square of residuals
- n is the number of observations
- $p$is the number of terms currently included in the model.

Table 4 below present the comparison of *MSE* performance between actual targets and predicted targets for each training algorithm.

Table 4.Comparison Of The R, *MSE ,Error Mean and Error St.D* Performance

FIS GENERATION APPROCH	Genfis1	Genfis2	Genfis3
R	99.881^{e}-02	99.793 ^{e}-02	99.998 ^{e}-02
MSE	1.7235^{e}-04	2.9369^{e}-04	2.8933^{e-} 06
Error Mean	-1.5408^{e}-03	2.7661^{e}-04	8.5307^{e}-05
Error St.D	1.3068^{e}-02	1.7175^{e}-02	1.7028^{e}-03

Table 4 show the lowest MSE and the best R are obtained for Genfis3 (FCM).

In figure 6, the predicted target is practically identical with the actual target.

The implementation shows that the ANFIS architecture chosen gives the best performance sought (In figure 7:R close to 1

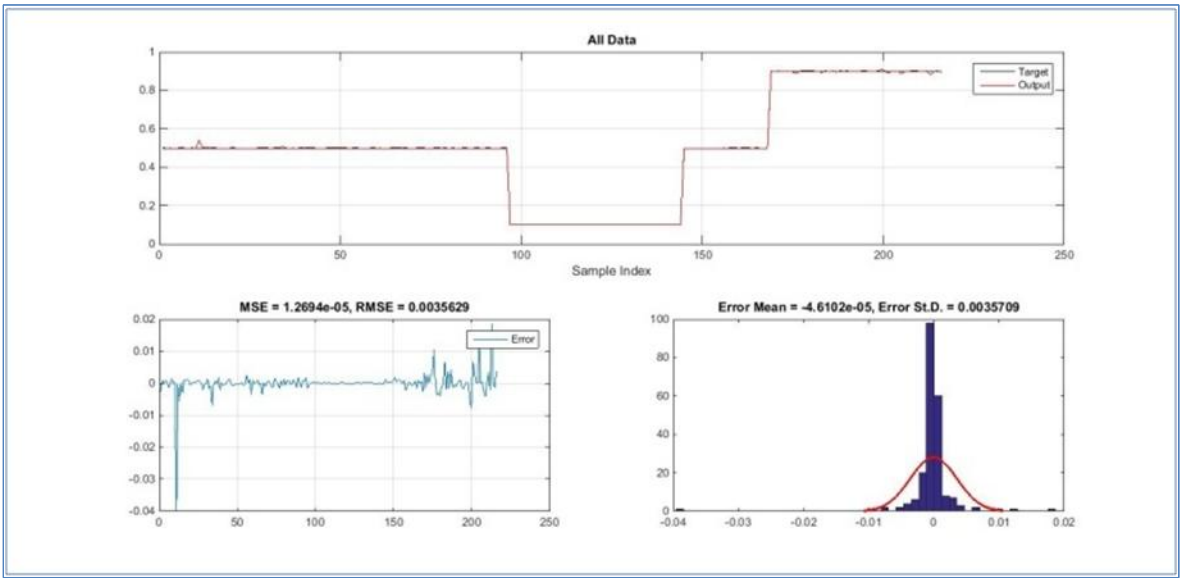


Fig 6. Comparison between actual targets and predicted targets

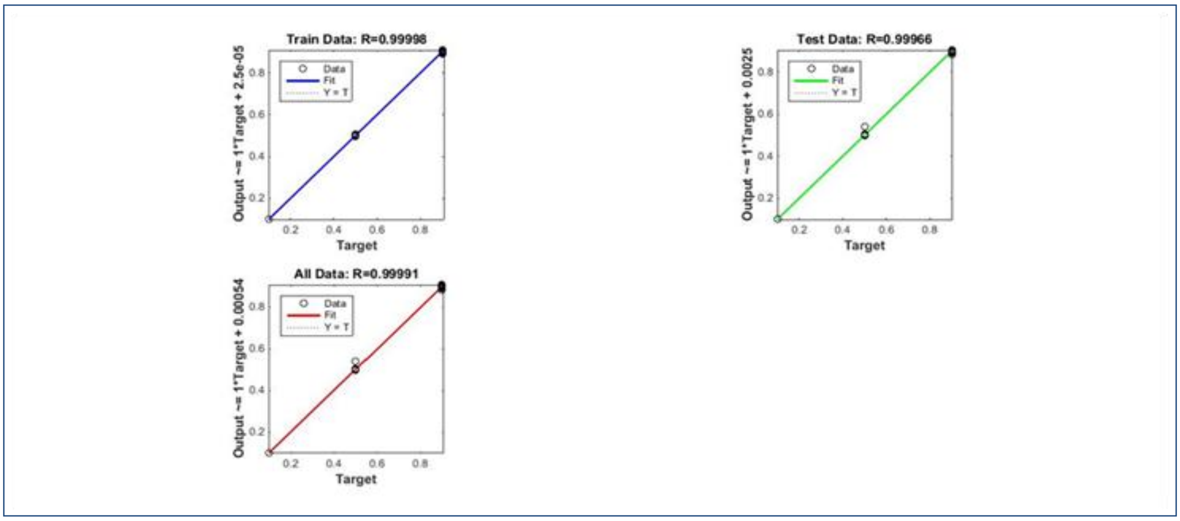


Fig 7. Comparison between actual targets and predicted targets

5. CONCLUSION

In this paper, the objective was to improve the quality of the Neuro-Fuzzy especially Adaptive Neuro-Fuzzy Inference System ANFIS in CCP recognition. To evaluate its relative performance. The results show that the ANFIS architecture chosen gives the best performance in patterns recognition problems.

The work will be extended to study other patterns namely: Decreasing trend (DT), Downward shift (DS) and cyclic (CYC) taking into account other criteria such as the number of iterations.

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7. AUTHOR PROFILE

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[2]**Pr Ali Moudden** was born in 1958 in Morocco. He obtained (1987) the " doctorat d'état" in physics at the University of Caen (France). He founded with other colleagues in 1991, the laboratory of instrumentation and measurements at the Faculty of Sciences of Agadir (Morocco), that became in 2005 the laboratory of metrology and information processing. Laboratory activities are focused mainly on the development of purely physical techniques for evaluation of materials and monitoring of processes. He was director of higher school of technology of Agadir during the period 2005 - 2011.