

DESIGN OF AN ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM FOR RECOGNITION PATTERN PROBLEM

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Abstract- Statistical Process Control (SPC) chart is one of the most crucial methods for surveilling a manufacturing flow and decide whether it is running under its normal pattern or unnatural one. Since, the recognition of control chart patterns (CCP) is gaining increasingly attention in last years as long as it greatly upgrades process quality. Artificial intelligence (AI) provides several tools for the recognition of all types of CCP; however, the accurate recognition of these patterns remains an important challenge. In the current work, an adaptive neuro-fuzzy inference system (ANFIS) network is applied as a recognizer because of its good performance shown in pattern recognition. Covering six typical patterns in CCP problems and improving the ANFIS suggested by validating its architecture using industrial data provided from the Tennessee Eastman Process (TEP), are the main contribution of this work. The theoretical results show that the proposed architecture of ANFIS-CCP gives good performance and the experimental results on TEP process demonstrate the potency of this architecture.

Keywords: Adaptive Neuro-Fuzzy Inference System, Control Chart Pattern, Recognition, Statistical Process Control.

1. INTRODUCTION

Statistical process control (SPC) is an approach that improves the quality and reliability of products through great control of variability. The objectives of the SPC are [1]: Give operators a machine control tool, formalize the production machine capability concept and sort out ordinary situations and extraordinary situations that require action. Essentially, the control chart applies statistical limitations to a series of points that reflect a monitored manufacturing flow [2]. Control charts are a relevant tool for monitoring a process performance. Interpretation of control chart pattern is a way to determine the manufacturing process behavior and make the appropriate decision based on this interpretation. The Western Electric Company (1958) listed 15 different types of CCPs: Normal, trend, shift, cyclic, systematic, stratification, mixture, freaks, and interaction, etc. Pattern that is operating under controlled conditions with assignable causes variations is called normal pattern.

All other unnatural patterns are indicating the presence of non-assignable cause's variation leading to an out-of-control process. In general, six basic patterns are widely exhibited by control chart as mentioned in Figure 1 [3, 4]:

- **Normal (NOR):** Over a sequence of sample points, the pattern shows no indication of being out of control. There is no trend, neither unexpected change. It remains steady.
- **Cyclic (CYC):** which are brief statistical trends, that appear repeatedly and have a succession of high sections or summits, separated by low portions. Common causes are seasonal effects such as temperature and humidity.
- **Increasing or decreasing trend (IT/DT):** is defined as steady flow up or down; a long series of points without a change of direction. Apparent reasons are tool wear, poor maintenance, increases or decreases in production schedules.
- **Upward Shift and Downward Shift (US/DS):** a sudden shift in level is shown by a positive change in one direction. Typical causes include new operator, new machine, and change in set-up or method.

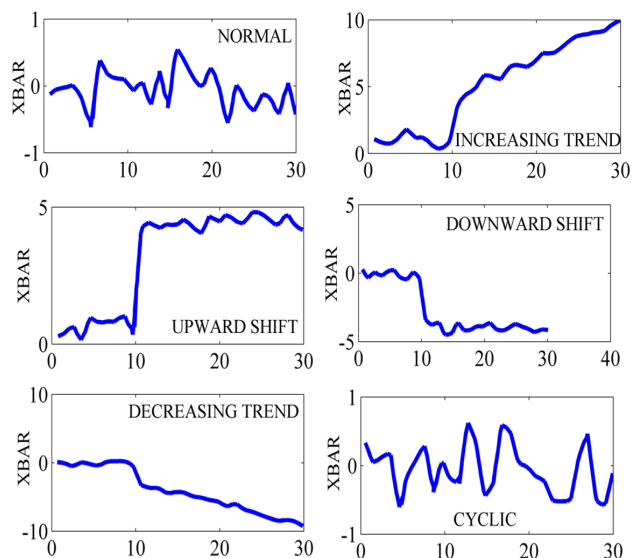


Figure 1. Six typical CCP [4]

Extensive researches have been carried out on the recognition of CCP's field using several machine learning algorithms particularly expert systems, supervised and unsupervised artificial neural network (ANN) [5], support vector machine (SVM) and fuzzy systems [6]. These techniques try to extract relevant knowledge through enormous datasets in order to identify process disturbances with lowest time and expense and maximum precision [7]. The performance to be achieved lies on ease of implementation, precision, system running speed, and datasets size. In this paper, we used an adaptive neuro-fuzzy inference system (ANFIS) for recognition of six patterns (NOR, CYC, IT/DT, US/DS). This approach combines ANNs with fuzzy-logic concept. The ANFIS has shown to be effective tool for pattern recognition, function approximation, prediction and system identification [6-8].

2. MATERIALS AND METHODS

2.1. Adaptive Neuro-Fuzzy Inference System

Fuzzy inference system alias fuzzy-rule-based system or Fuzzy model was first introduced by Takagi and Sugeno [9] and then used in many applications especially controlling, prediction and inference [10]. Inference system uses existing data to infer new knowledge. Jyh-Shing Roger Jang [11] have proposed his new architecture called ANFIS in 1993 as a fuzzy inference system applied within the context of adaptive networks.

ANFIS use the potential of neural networks to generate the fuzzy if \Rightarrow then rules with the fitting membership function to perform the inference. An adaptive network is a multilayer feedforward network where every node processes a specific function (Node function) on input signals as well as a group of values related to this node [12]. Based on Takagi and Sugeno's works, a basic structure of ANFIS with two inputs and one output is shown in Figure 2.

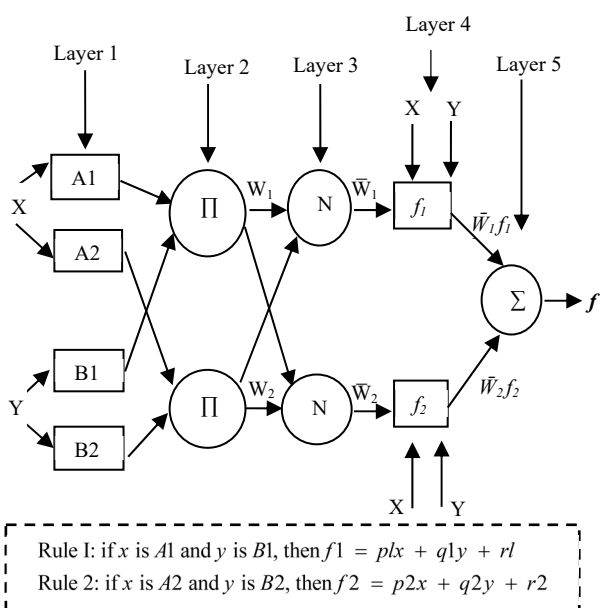


Figure 2. ANFIS basic structure [12]

The characteristics of a square node are different from those of a circular node. An adaptive network's parameter set is the concatenation of the parameter set off all adaptive nodes. These values are adjusted depending on the training data and a gradient-based learning technique to achieve the required input-output mapping [11].

2.2. Generating Data

Building and validating a CCP structure requires huge real manufacturing measurements. Since this amount of data is extremely hard to bring from real processes, simulated data is generally used for this purpose [13]. The following equations [6], shown in Table 1, are widely adopted in literature for simulating the six CCPs; We deployed MATLAB function $\text{randn}([p, n])$, which creates a p -by- n matrix of normally distributed random numbers.

Table 1. Parameters for simulating CCP [6]

CCP	parameters	Pattern Equation
NOR	Mean (μ) and Standard deviation (σ)	$\mu + \sigma \times \text{randn}([p, n])$ (1)
CYC	Amplitude (a) and Period (T)	$\mu + \sigma \times \text{randn}([p, n]) + a \sin((2\pi I) / T)$ where, $[I]: I_{ij} = 0$ for $i \leq p/3$, $p \times n$ and $I_{ij} = 1$ for $i > p/3$, and $a = 25; T = np$ (2)
IT	Gradient (g)	$\mu + \sigma \times \text{randn}([p, n]) + I \times g$ (3)
DT	Gradient (g)	$\mu + \sigma \times \text{randn}([p, n]) - I \times g$ where, $[I]: I_{ij} = 0$ for $i \leq p/3$, $p \times n$ and $I_{ij} = 1$ for $i > p/3$, and $g = 0.3$ (4)
US	Shift magnitude (s) and Shift position (P)	$\mu + \sigma \times \text{randn}([p, n]) + Ks$ where, $[K]: K_{ij} = 0$ for $i \leq p/3$, $p \times n$ and $K_{ij} = 1$ for $i > p/3$, and $s = 4$ (5)
DS	Shift magnitude (s) and Shift position (P)	$\mu + \sigma \times \text{randn}([p, n]) - Ks$ where, $[K]: K_{ij} = 0$ for $i \leq p/3$, $p \times n$ and $K_{ij} = 1$ for $i > p/3$, and $s = 4$ (6)

2.3. ANFIS Structure

Figure 3 below shows the ANFIS structure used as a classifier and adopted in our work. Inputs are Average \bar{X} and Standard deviation S of the n observations. The output corresponds to the normalized coding affected for each pattern. The training example was divided for training, and testing the network in to 70%, 30% respectively.

The training input is an (2)-by-(6xp) matrix as illustrated in the following Figure 4.

2.4. Setting Parameters of FIS Generation Methods

Parameters are set as mentioned in Table 2 and Table 3, for the three Sugeno-type FIS generation approaches used in this work.

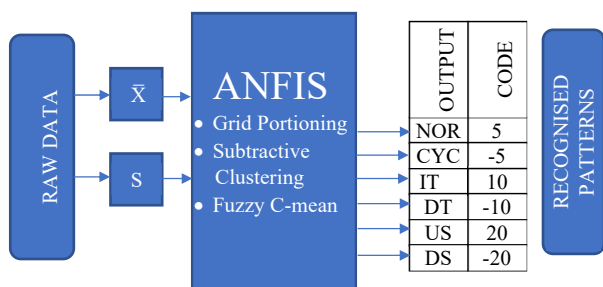


Figure 3. Basic ANFIS structure

Input data	\bar{X}	NORMAL	CYCLIC	INCREASING TREND	DECREASING TREND	SHIFT UP	SHIFT DOWN	Output data
	S							

Figure 4. Training input matrix

Table 2. Parameters for each Genfis

Genfis 1: Grid Partitioning	
Number of MFs	5
Input MF Type	Gaussmf
Output MF Type	Linear
Genfis 2: Subtractive Clustering	
Influence Radius	0.3
Genfis 3: Fuzzy C-mean	
Number of Clusters	15
Partition Matrix Exponent	2
Maximum Number of iterations	200
Minimum Improvement	1×10^{-5}

Table 3. Parameters for all Genfis

Genfis 1, 2 and 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

There are four techniques to tune the parameters in the training FIS procedure [14]:

Gradient Descent Only; Gradient Descent and One Pass of LSE; Gradient Descent and LSE; Sequential (Approximate) LSE Only. In this study, we used the hybrid-learning algorithm, which led to the best performance. It applies both least-squares method and the standard learning algorithm of ANFIS, which is backpropagation gradient descent.

3. TESTS AND RESULTS

3.1. Test Setup

The MATLAB scientific computing environment's fuzzy logic package is a useful tool for building fuzzy-logic-based systems. It includes several functions that enable practitioner to create and evaluate fuzzy inference systems, as well as adaptive inference systems and fuzzy classification [15]. Its frontend interface (GUI) enhances the phases of designing a neural FIS.

Simulink, on the other hand, gives fuzzy for simulating fuzzy systems inside a full model of the entire dynamic system [16]. The design and implementation of the proposed ANFIS-CCPR has been realized under MATLAB/SIMULINK environment 2014a, and we followed the step-by-step diagram below in the Figure 5.

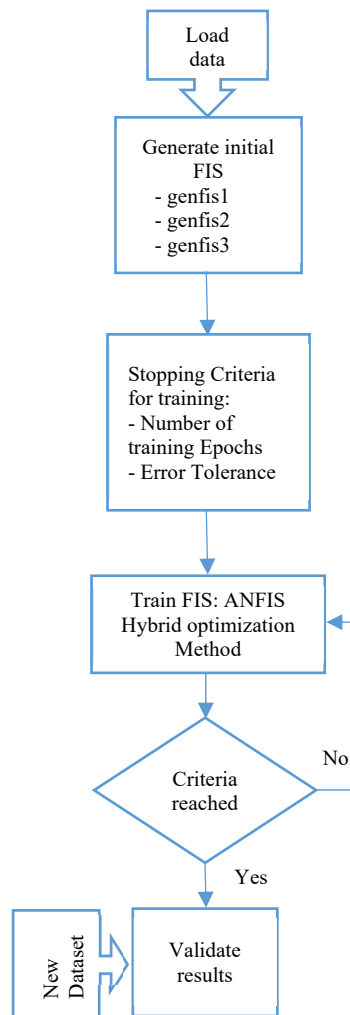


Figure 5. MATLAB coding diagram

3.2. Performance Metrics

Performance indicators (error measurements) are critical factors of several evaluation models. They are implemented in machine learning during the training and testing phases of the evaluation procedure [17]. To assess the performance of the suggested ANFIS recognizer [18], we have conducted comparison with the different FIS generation methods based on Pearson's correlation coefficient R (An R equal to 1 indicates a close link whereas 0 means an arbitrarily correlation) and two commonly used metrics as listed on Table 4 [19].

3.3. Results and Discussion

Table 5 compares accuracy between actual and expected outcomes for every training method.

Table 4. Performance metrics [19]

Metric Name	Equation	Notation
Mean Squared Error (MSE)	$MSE = \frac{1}{n} \sum_{i=1}^n e_i^2$ (7)	To simplify, we assume that we have n samples of model errors e calculated as ($e_i, i=1,2,\dots,n$)
Root Mean Squared Error (RMSE)	$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n e_i^2}$ (8)	

Table 5. Comparison of the performance indicators

FIS GENERATION APPROCH	Genfis1	Genfis2	Genfis3
R	7.7997 e-01	9.2325 e-01	0.99995
MSE	1.7136 e-01	4.3325 e-02	11.406 e-03
$RMSE$	4.1396 e-01	2.0815 e-01	1.831 e-01
Error Mean	1.6302 e-02	-2.7937 e-03	3.7088 e-03
Error St.D.	4.1387 e-01	2.0824 e-01	1.067 e-01

The results presented above shows that Genfis3 (FCM) gives the best values for the three criteria R , MSE and $RMSE$. Figure 6 describe that the coefficient R is close to one and Figure 7 shows that we achieved a good result considering the predicated target is close enough to the actual target.

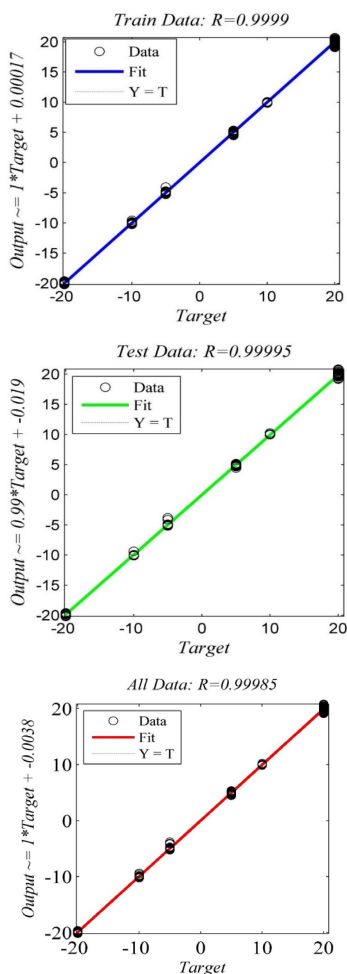


Figure 6. Coefficient of correlation R for the used model

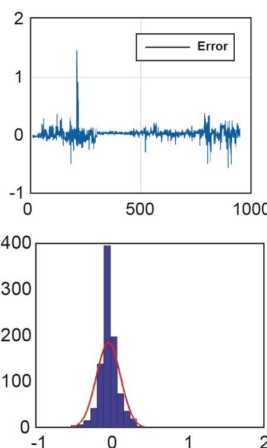
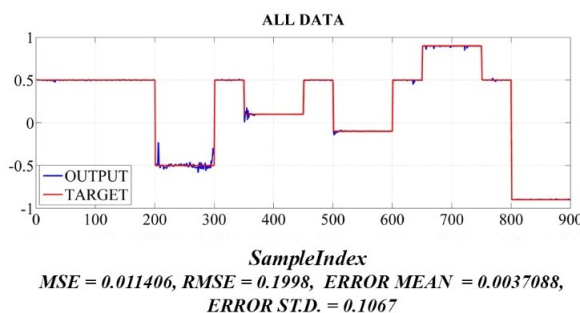


Figure 7. Comparison between actual targets and predicted targets

4. APPLICATION TO INDUSTRIAL DATA: TENNESSEE EASTMAN PROCESS

The corporate process control group for Tennessee Eastman Chemical Company has offered, many years ago, to the academic community there very challenging chemical process database. It aims to test and validate algorithms, models or patterns from any contrived process control problem with a realistic industrial dataset [20]. This process gives a large number of variables and data that can be used to validate our ANFIS-CCP model. We considered the Tennessee Eastman (TEP) reference process, shown in Figure 8.

The reactor, product condenser, vapor-liquid separator, recycled compressor and product stripper are the five primary activities in this chemical process. The TEP has 12 controllable variables and 41 measured ones. The return rate is mainly left out the variable as well as the other 52 variables are utilized to describe the complete manufacturing flow rate. Detailed data are given in [21] and [22].

In this study, we analyze the Defect (IDV4) (Table 8 [23]) which represents the reactor cooling water input temperature. The reactor cooling water flow variable (V51), as shown in Figure 9, can explain The IDV4 disruption. We can see that process disruptions have the greatest impact the behavior of the reactor coolant flow. It demonstrates that the flow dramatically rises and may be attributed to a step change in a process variable. To detect this drift, our model ANFIS-CCPr is applied. As can be seen in Figure 9, the change value is very large and our model easily detects this change in cooling water flow rate of the reactor (V51).

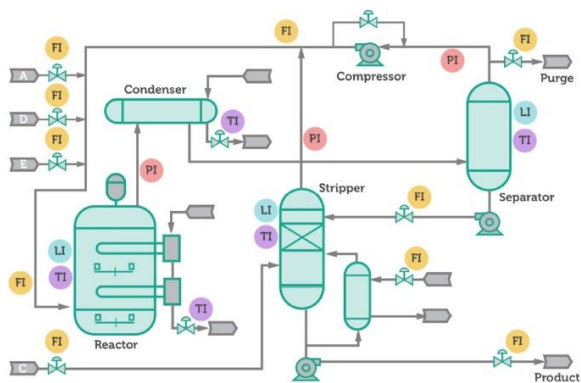


Figure 8. The process model of Tennessee Eastman Process [21]

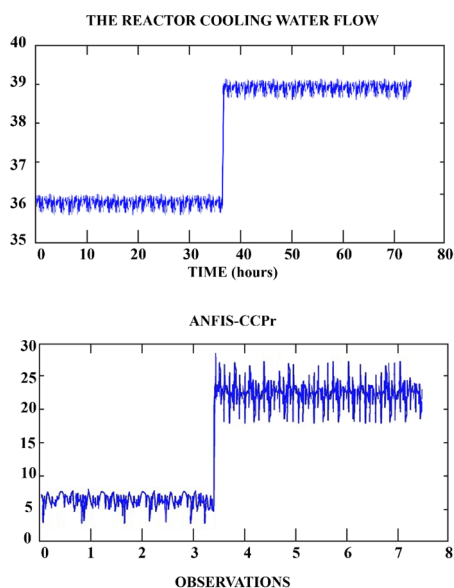


Figure 9. The reactor cooling water flow and ANFIS-CCPr

5. CONCLUSION

ANFIS is widely used in CCPR but still a challenging problem in implementation. This study represents an improved ANFIS-CCPR design in two aspects: extending the recognition of CCP to six patterns and confronting the proposed ANFIS design to real industrial data. We evaluated the proposed architecture using a simulated data set and compared it based on the three FIS generation methods. The simulation results indicate that our model classifies the patterns in an excellent way when adopting Fuzzy Cmean approach. Finally, we assessed our model as second evaluation by using TEP extracted Data. The technique used is capable of detecting easily the step change of the tracked variable.

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BIOGRAPHIES



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