Intelligent Fault Diagnosis of Distillation Column System based on PCA and Multiple ANFIS

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***Abstract*— this paper proposes a novel method based on multiple adaptive neuro-fuzzy in combination of statistic method to detect and diagnose the faults occurring in complex dynamical systems. The basic idea is to use PCA to extract the features for reducing the complexity of the data achieved from a process. The most superior features are fed into multiple ANFIS to identify different faulty conditions in order to prevent the system from serious system failure and possible shutdowns. Each ANFIS has employed to diagnose one of the faults in order to make a decision about the abnormal cases. Ability, and at the same time simplicity and rapidity has significantly enhanced. Moreover, there's no need to have information about the model or the structure, which is the best advantage of using this approach. Using multiple ANFIS units significantly reduces the scale and complexity of the system, speeds up the diagnosis, and simplifies the training of the network. As an example, the proposed algorithm has applied to fault diagnosis of a simulated nonlinear MIMO distillation column. Results confirm the effectiveness of this method comparing to single ANFIS. The presented procedure is applicable to a variety of industrial applications in which continuous on-line monitoring and diagnosis is needed.**

***Keywords*— fault detection, fault diagnosis, multiple ANFIS, principal components analysis, PCA, distillation columns**

I. Introduction

Increasing complexity of modern industrial systems and the high process quality, reliability and safety requirements, arise the vital need to automation of diagnostics in order to make it possible to determine the place, reason and time of the possible faults accurately [1]. Different methods of fault diagnosis have been developed and used effectively to detect the complex chemical process faults at an early stage [2]. Early detection of faults can be achieved by model-based fault detection, in which a prompt fault detection requires an accurate model of the process which itself leads directly to system identification problem. Real processes are usually dynamic, non-linear and stochastic, meaning that analytical approaches of identification are rarely suitable.

In the presented method, statistical characteristics of different domains are extracted to acquire rich faulty information and enhance the competence of the diagnosis systems, but this large number of feature-sets contains irrelevant or redundant features as well as superior ones. Classification using all of the features in the feature-set would result in a slower and less accurate process. Thus, to increase the accuracy and reduce the computational burden of the classifier, some of the features with obvious characterizing ability to the machine conditions, need to be selected from the original feature-set. There are many feature selection methods such as Conditional Entropy, Genetic Algorithms and Distance Evaluation Technique [1]. This article enhances a Principle Component Analysis Technique for feature selection. Typical applications of PCA in chemical and process engineering can be found in multivariate statistical process monitoring, fault diagnostics, gross error identification, instrument validation and etc [4]. The number of principal components (PC) is the essential parameter of PCA and ultimately determines the performance of this useful statistical method [8].

In this PCA-based study, four salient feature-sets are obtained and fed to classifier to diagnose the faults. Our classifier is based on Adaptive Neuro-Fuzzy Inference System (ANFIS) for training and testing fault diagnosis system. ANFIS architecture is an integration of fuzzy logic and neural network algorithm [9] which utilizes the learning abilities of neural networks and human knowledge representation abilities of fuzzy systems. In other words, ANFIS is a hybrid model which combines the ANNs adaptive capability and the fuzzy logic qualitative approach, and overcomes their own shortcomings simultaneously. ANFIS is in fuzzy rule-based systems that approximate the way human process information. Successful implementations of ANFIS have been reported in the medical [10], chemical [11] and fault diagnosis fields [12].

The proposed method is applied to fault diagnosis of theoretical distillation column. The fault signals were measured through the distillation top and bottom product feed rate, feed composition rate, boil up flow and flux flow, under various operating input, output, fault, and different immeasurable disturbances including different fault categories and severities. The results show the effectiveness of the approach. The targeted distillation column used in this study, has 20 theoretical stages plus a reboiler at stage one and a total condenser. Moreover, assume binary component separation (with constant relative volatility and negligible vapor hold up) and also perfect level control (using distillation top and bottom product flow rate in LV configuration). One feed and two products have been considered. The proposed technique uses Statistical Method for feature extraction and ANFIS for classifying features, which lead to fault diagnosis process. This is a computationally simple, fast and accurate expert system for fault diagnosis of distillation column. This approach may contribute to minimizing process shutdowns and production losses due to unexpected faults, in any process control system component or sub-system.

II. THE FAULT DIAGNOSIS ALGORITHM

The fault detection system provides the ability to detect symptoms of faults occurring in transient conditions. The fault detection system includes a feature extractor that measures sensors data during transient conditions and extracts salient features from this data. The extracted salient features are fed to a classifier that analyzes these features to determine if a fault has been occurred during the transient conditions. Detected faults can then be passed to a supervisory diagnostic system where they can be used by maintenance personnel. This fault diagnosis system is designed to monitor the various states of the distillation column system to detect potential faults. This system aimed to detect and diagnose the potential faults so that these potential faults can be addressed before leading to serious system failure.

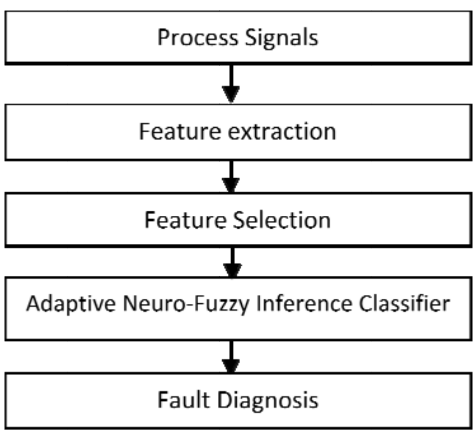

Figure 1. Proposed System for Fault Diagnosis

III. PRINCIPAL COMPONENT ANALYSIS

PCA methods have been recently extended to perform fault detection and diagnosis. They can be excessively suitable for fault diagnosis of complex plants because of low computation load [16] and ability to be applied without a need to model of the process. It performs a dimensionality reduction of the process variables by generating new non-correlated variables called Principal Components (PCs). PCs and some related statistics can be used online as part of a classification algorithm or an expert system to perform fault diagnosis.

A chemical process under normal operating condition has a correlation among variables due to mass balance, energy balance, operational restrictions and etc. This correlation can be described in a data-driven manner because of its simplicity and practicability, e.g., PCA statistical model. Generally, PCA can be considered as a subspace decomposition technique by which the process measurement space is divided into two orthogonal subspaces, that is, the principal component (PC) subspace and residual subspace. Consider a process data matrix $X_{n\times m}$ composed of m sample instants with n measurements collected when the process is in control, and assuming the data matrix X, without loss of generality, has been normalized before PCA modeling. Its corresponding correlation matrix is denoted as ($R = X^T X \,/\, m -$). Performing singular value decomposition (SVD) to the matrix R would lead to

$$R = UD_\lambda U^T \qquad (1)$$

Where $U_{n\times n}$ is a unitary matrix and $D = diag(\lambda_i)$, $i=1,...,n$ is a diagonal one.

The column vectors in the matrix $U = [u_1, u_2, \cdots u_n]$ form a new orthonormal base of space $R^n$by which the data matrix X is optimally described in a sense that its variances under the new coordinate directions is in descending order: $\lambda_1 > \lambda_2 > \cdots > \lambda_n$, (where $\{\lambda_i\}_{i=1,\cdots n}$ is corresponding diagonal elements of the matrix D_λ). The first k (< n) linear independence vectors $P = [u_{k+1}, u_{k+2}, \cdots u_n]$ of U span the principal component subspace $\hat{S}$, and the retained n-k vectors $\tilde{P} = [u_{k+1}, u_{k+2}, \cdots u_n]$ of U span the residual subspace $\hat{S}$. The number of principal components (PCs) can be selected as its corresponding Cumulative Percent Variance (CPV) larger than a prescribed threshold (here 98.93%) by convention .The data vector $x \in pn$ at every sampling instant can be decomposed as

$$\bar{x} = \hat{x} + \tilde{x} = \hat{C}_k x + \tilde{C}_k x \qquad (2)$$

where $\hat{x} \in \hat{S}$, and $\tilde{x} \in \tilde{S}$are projections of x on the principal component subspace $\hat{S}$ and residue subspace $\tilde{S}$, respectively. The matrix $\hat{C}_k = P_k P_k^T$ and $\tilde{C}_k = \tilde{P}_k \tilde{P}_k^T = I - \hat{C}_k$ are the corresponding projection operators. Here, the subscript 'k' means the corresponding quantity is a mathematical function of the number of PCs.

Thus, the original n dimensional data matrix X can be Analyzed in the two lower dimensional subspaces, i.e., $\hat{S}$ and $\tilde{S}$, meanwhile linear dependant variables in X are Decorrelated. Then the PCA statistical monitoring model is built as two hypothesis tests in subspaces $\hat{S}$ and $\tilde{S}$.

According to large size of measured data acquired from distillation column, we have lots of features from different aspects, which have different importance degrees in identifying different faults. For instance, some features are salient and closely related to the fault. Moreover, PCA can improve the capability and reliability of fault detection and diagnosis as well as the accuracy of the sensor fault estimation.

Though PCA-based monitoring is very effective in detecting abnormal process situations, it has been found inefficient when it comes to pinpointing the root cause of the problem (fault isolation and diagnosis). Contribution Chart, Multi-Block Approach, Sensor Validity Index and Pattern Recognition Technology [13] have been discussed to solve this problem, but none of them could provide a complete solution. Analytical Redundancy (AR) methods based on the fundamental model could develop fault isolation utilizing a structured or directional residual set, but such a model is not easily obtained due to nonlinearity, complexity, and high dimensionality of the process [14].

IV. ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM

Training of multi-layer perception neural network is a time-consuming task, and the performance of the neural network depends on both quality and quantity of the training samples. For the particular application proposed in this paper, such drawbacks may become even more pronounced when multiple faults are to be diagnosed. To remedy and improve the performance of the neural network-based algorithm, use of Adaptive Neuro-Fuzzy Inference is considered in this section.

A Fuzzy Logic System (FLS) can be viewed as a non-linear mapping from the input space to the output space. The mapping mechanism is based on the conversion of inputs from crisp numerical domain to fuzzy domain with the use of fuzzy sets and fuzzifiers, and then applying fuzzy rules and fuzzy inference engine to perform the necessary operations in the fuzzy domain. At the end, the result is converted back to the numerical domain using defuzzifiers. As such any FLS can contain five main components: fuzzy sets, fuzzifiers, fuzzy rules, an inference engine and defuzzifiers [10]. Adaptive neuro-fuzzy networks are enhanced FLSs with learning, generalization and adaptively capabilities. These networks encode the fuzzy if-then rules into a neural network-like structure and then use appropriate learning algorithms to minimize the output error based on the training/validation data sets. In this paper, we use the Adaptive Neuro-fuzzy Inference System (ANFIS) structure and optimization processes because of their accuracy. The ANFIS is a fuzzy Sugeno model of integration where the final fuzzy inference system is optimized via the ANNs training. It maps inputs through input membership functions and associated parameters, and then through output membership functions to outputs To present the ANFIS architecture, two fuzzy if-then rules based on a first order Sugeno model are considered:

Rule 1: If (x is A_1) and (y is B_1) then ($z_1 = p_1x + q_1y + r_1$),
Rule 2: If (x is A_2) and (y is B_2) then ($z2 = p_2x + q_2y + r_2$),

where x and y are the inputs, A_i and B_i are the fuzzy sets, z_i(i = 1,2) are the outputs within the fuzzy region specified by the fuzzy rules, p_i, q_i and r_i are the design parameters ANFIS architecture to implement these two rules is shown in Fig. 2, in which a circle stands for a fixed node, whereas a square indicates an adaptive node.

The ANFIS learning algorithm is then used to obtain these parameters. This learning algorithm is a hybrid algorithm consisting of the gradient descent and the least-squares estimate. Using this hybrid algorithm, the rule parameters are recursively updated until acceptable error is reached. In the defuzzification layer, crisp output is produced from the output of the inference layer. Maximum defuzzification and centroid defuzzification were used as defuzzifiers. The centroid defuzzifier determines the center of the gravity of the final fuzzy space and uses this value as the output of the fuzzy inference system. Therefore, the resulting output is related to all the rules executed in the preceding layer. This is then compared with a threshold to determine whether or not a fault

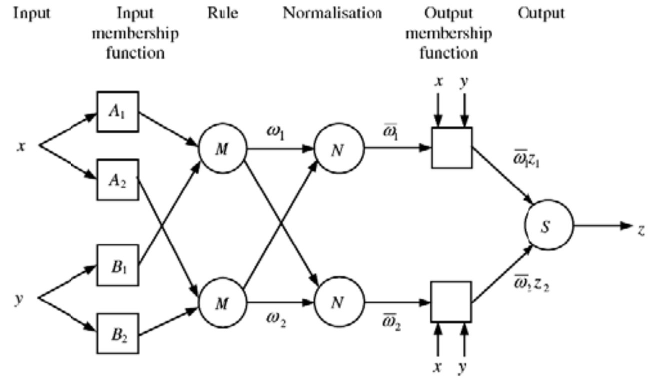

Figure 2. ANFIS structure used in proposed method

mode should be reported. The ANFIS used in this approach used Gaussian functions for fuzzy sets, constant functions for the outputs rules and Sugeno's inference mechanism. The parameters of the network are the mean and standard deviation of the membership functions (antecedent parameters).

The features of the signals received from process must be extracted to feed into multiple ANFIS to identify different abnormal cases. Here feature extraction for input ANFIS is achieved through statistical characteristics method in time-domain. In the present work, each of the signals used by ANFIS has processed to extract selected time-domain features by PCA method in normal operation mode.

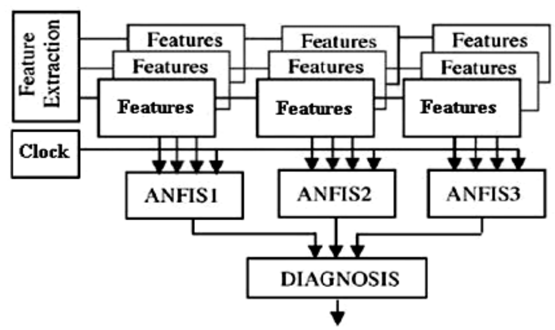

Figure 3. Multiple ANFIS units for multiple fault diagnostics

Using multiple ANFIS prepare expandable platform for further fault modes; moreover, based on specialized classifiers it can perform more accurate and generalizable classification.

V. SIMULATION

To demonstrate the performance of ANFIS-based classifier which fed in with PCA as salient feature, the detailed nonlinear multivariable distillation column system developed by Skogestad [5] in Simulink MATLAB® controlling in LV-configuration shown in figure 4 used. The scheme was developed as simulation. ANFIS based fault identifier were developed using Matlab fuzzy logic toolbox.

In order to evaluate the proposed method, we conducted our experiment over eight different operating conditions (normal condition, increased and decreased in feed rate, feed composition, reflux flow and boil up flow as fault scenarios) with the fault defect size of 20% upper and under from steady state in normal operation. The detailed description of the eight faults is shown in Table 1. 900 samples for training and 450 for

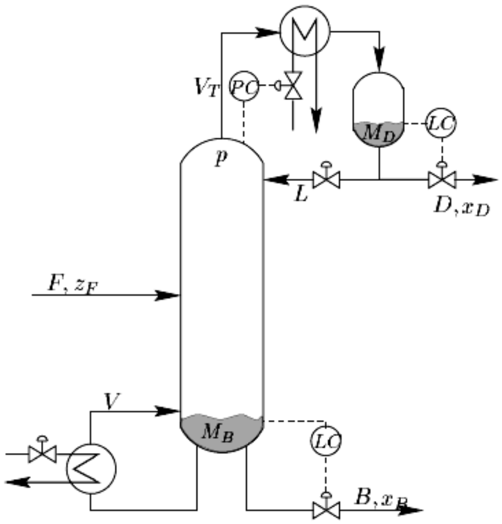

Figure 4. Simple typical distillation column controlled with LV-configuration

testing data were used during the experiment. The sample training data consists of 100 samples for training each fault. Each sample consists of a 42 vector output signal achieved from 42 measurement sensors in 20 stages of the distillation column.

These sensors report the mole fractions of light component, x_i, and the liquid holdup in each tray called M_i , as well as reboiler and condenser holdup calling M_B and M_D respectively, as process variables.

TABLE I. FAULT SCENARIOS

Fault No.	Fault Name	Description	Unit	ANFIS Output
0	N	Normal Operation		0
1	F	Increased Feed rate 20%	Kmol/min	4
2	F	Decreased Feed rate 20%	Kmol/min	-4
3	z_F	Increased Feed Composition 20%	Mole fraction	3
4	z_F	Decreased Feed Composition 20%	Mole fraction	-3
5	V	Increased Boil up Flow 20%	Kmol/min	2
6	V	Decreased Boil up Flow 20%	Kmol/min	-2
7	L	Increased Reflux Flow 20%	Kmol/min	1
8	L	Decreased Reflux Flow 20%	Kmol/min	-1

Figure 5 shows the output vector after occurring the startup fault based on fault scenario at time 5. It is a nine-class classification task corresponding to the eight different faulty operating conditions plus the normal operation. For each fault occurring during startup we extracted 4 salient features to feed the related ANFIS. After training eight different types of faults the resulting ANFIS set works as a classifier and diagnoses the fault type. Because of burden of data including in signals acquired from process it is very critical to select the best features of sensor signals to detect and diagnose fault without any ambiguity. If all of the features in each feature-set fed into classifiers directly, they will make the classification process slower and the classification accuracy lower.

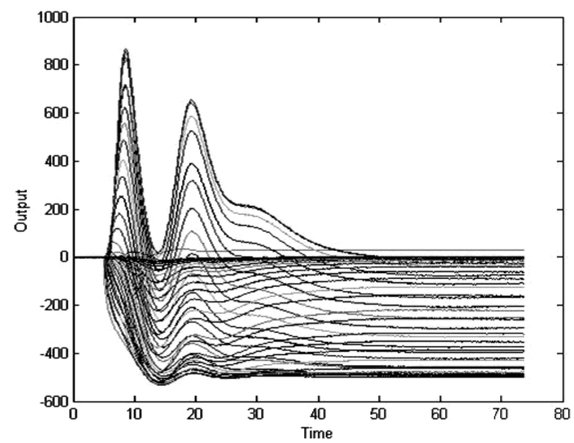

Figure 5. Output vector signal cause by fault no. 1

The feature extractor performs a principal component analysis on every output signal to extract salient feature. In this case after using PCA we 4 selected to satisfy the Cumulative Percent Variance (CPV) criterion on 89%, as it shown in figure 6 selected principle components for each fault from superior ones out of 42 possible components are shown.

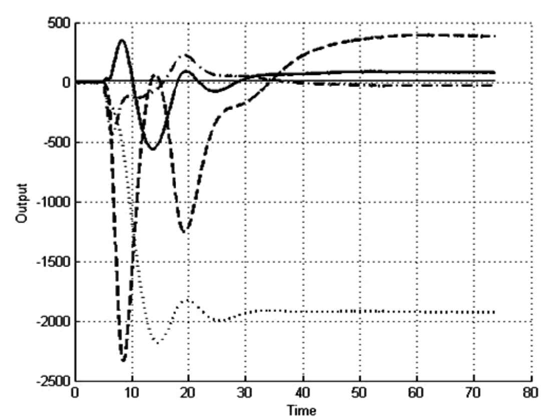

Figure 6. Salient extracted features from fault no. 1

Figure 7 shows the classification results of diagnosing different predefined faults using ANFIS (fed with these extracted features). The trained ANFIS diagnosed the entire sample fault based on the training data for each type of fault during its transient time (until reaching steady state), and tested with 50 testing data, training error and testing error. Results are included in table II. In order to improve the training efficiency and eliminate the possible trapping due to local minima, a hybrid learning algorithm is employed to tune the parameters of the membership functions [10].

Here we used 8 different ANFIS to diagnose 8 different faults and every ANFIS trained in normal condition as well as

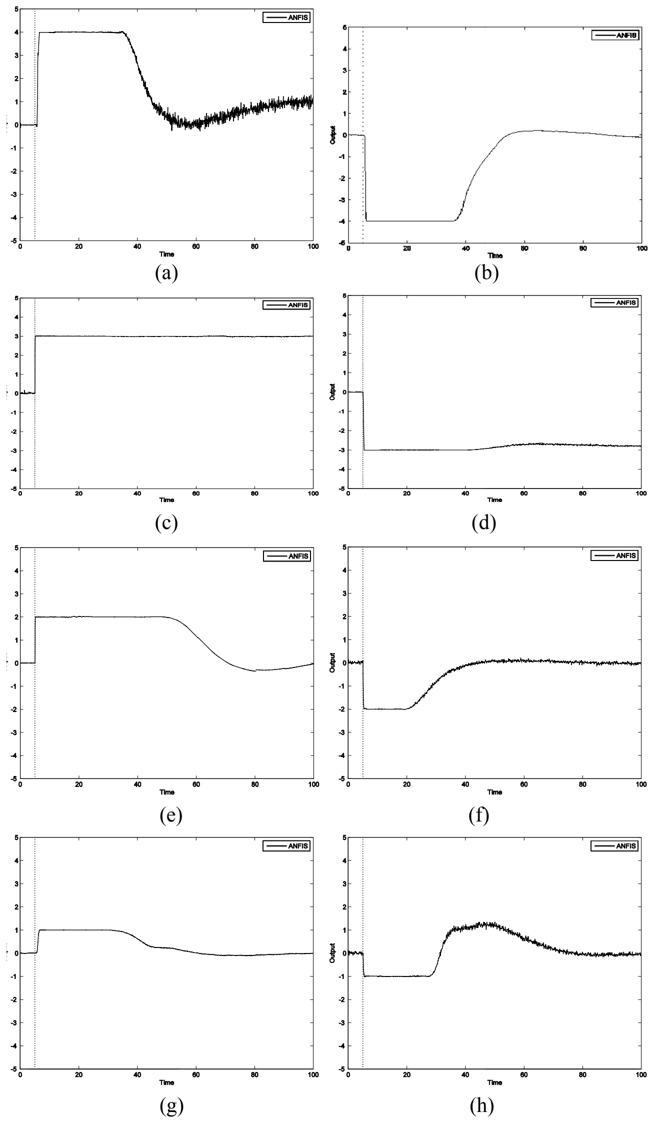

Figure 7. The Fault Diagnosis Function when a fault occurs at feed rate (a),(b) feed composition (c),(d) boil up flow (e),(f)and reflux flow (g),(h)

its corresponding fault. As the training and testing data are shown in fig. 8, the result of diagnosing was satisfying. In the process of evaluating the proposed method, we also tested the way which relating 2 faults to one ANFIS; the accuracy of this architecture was lower than previous structure. As it is clearly shown in figure 7, the ANFIS output follows the fault for a long period, until the variables reach their steady state which demonstrates that this method can diagnose the transient fault and follows the effects of every fault till system goes to its steady state. This result can be achieved because of each ANFIS trained by the faults data from all abnormal condition all over its transient time.

In this setup we use 4 membership function and constant output. Note that accuracy increased by using Gaussian membership function. Adding a new ANFIS block to existing network has been also tested. The structure could easily diagnose the new fault mode. Consequently, more ANFIS blocks can be added to the system for diagnosing more fault modes.

Unlike Artificial Neural Networks, the addition of extra ANFIS units will neither affect the coefficient of the rest of the network nor increase the complexity of it. By using multiple ANFIS accuracy of the diagnosis system increases and the process of training and testing is accelerated.

TABLE II. EFFICIENCY OF THE MULTIPLE ANFIS CLASSIFIER DIAGNOSING DIFFERENT FAULTS

Fault No.	**Table Column Head**					
	Triangular		**Gaussian**		**Bell-shape**	
	Training Error	***Testing Error***	***Training Error***	***Testing Error***	***Training Error***	***Testing Error***
1	.0075	.0077	.0040	.0044	.0068	.0070
2	.0093	.0098	.0040	.0048	.0047	.0049
3	.0032	.0035	.0026	.0028	.0028	.0031
4	.0030	.0033	.0020	.0023	.0024	.0028
5	.0023	.0026	.0021	.0023	.0024	.0026
6	.0026	.0028	.0023	.0025	.0025	.0026
7	.0051	.0053	.0043	.0045	.0045	.0046
8	.0074	.0077	.0039	.0041	.0040	.0042

VI. CONCLUSION

Modern chemical processes are getting increasingly complex. The complexities of these plants have led to an increasing need for automated fault diagnosis systems. In this paper we presented a computationally simple, fast and accurate expert system for fault diagnosis of Distillation Column. The proposed method is based on Principal Component Analysis (PCA) that is much more suitable than model-based

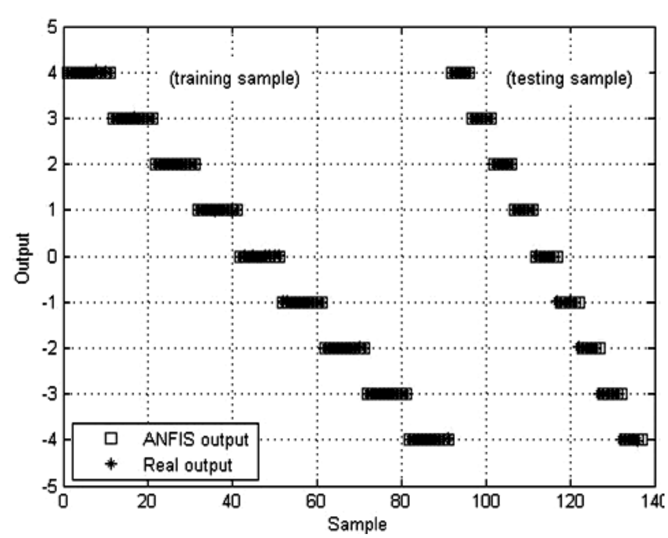

Figure 8. Classification result using multiple ANFIS

approaches, because it is often difficult to develop detailed physical models for large scale chemical processes. Adaptive Neuro-Fuzzy Inference System (ANFIS) is applied and discussed in detail. Instead of using single fault identifier for all fault, separate fault identifiers were developed which is more effective during the transient and also the period of monitoring. Note that the developed fault diagnosis system is able to provide discrete and unambiguous indication of faults such as transient feed rate failure and composition boil up flow within the distillation column that lead to simplicity in monitoring and maintenance. ANFIS based control can be easily combined with the ANFIS based fault identifier to form integrated fault tolerant system, which can improve dynamic response of the distillation column system. This approach may contribute to minimizing process shut-down and production losses due to unexpected faults on any process control system component or sub-system. This method may contribute to achieving incipient fault detection and appropriate fault identification to support and improve troubleshooting, decision making and maintenance tasks (preventive maintenance).

Further works and studies such as using Particle Optimization method to minimizing the number of rules generated by ANFIS is suggested. Currently, we are designing a multiple ANFIS fault diagnosis model using cause and effect tree of process to predict upcoming fault in abnormal condition of operation.

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