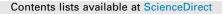
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## Feasibility of ANFIS towards multiclass event classification in PFBR considering dimensionality reduction using PCA

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#### ABSTRACT

Nuclear power plant (NPP) such as Prototype Fast Breeder Reactor (PFBR), is a paradigm of complex engineering which is safety critical in nature. It sends copious plant signals to the main control room. An amalgamation of plenty of such plant signals escorts an operator to make appropriate decision during catastrophic circumstances. This decision must be quick and unambiguous in order to overcome any adverse situation. The concept of dimensionality reduction aids the purpose as it reduces the number of inputs to any system or model or classifier which ultimately makes the decision process faster. The fundamental aspect which should be taken paramount care is that there should not be any loss of information due to dimensionality reduction, as in a NPP, safety is the foremost goal. One of the most prevalently used dimensionality reduction algorithms is principal component analysis (PCA). This is achieved by dumping the principal components which has less variability.

In this paper, the feasibility of dimensionality reduction is studied for classification of some of the events in PFBR. Two cases are considered in this paper out of which in first one, the event is divided into two sub events such as primary and secondary part of the event based on the importance of classification. The event data is fed to two separate classifiers which classify both the parts of the event separately. Finally, the event is classified as the concatenation of the outputs of both the classifiers. Unlike the first case, where two classifiers identify the event, here, in second case, a single classifier does the event classification. The classifier used is the adaptive neuro fuzzy inference system (ANFIS). This classifier has the advantage of both neural networks and fuzzy system where the neural network concept is used to tune the fuzzy membership function. PCA is used for dimensionality reduction and scree test for factor analysis. The performance of the PCA-ANFIS classifier is measured by calculating the area under the receiver operating characteristics curve (AUC) which is one of the most popularly used performance measures for any classifier. A comparative study is done on the AUC of all the PCA-k-ANFIS classifiers for both the cases mentioned above. Here, k represents the number of principal components considered as input data to the ANFIS classifier without using PCA.

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#### 1. Introduction

A nuclear power plant (NPP) is a multifaceted engineering which is composed of many critical yet imperative components. The usage of these components is obligatory. But at times, due to some circumstantial effect, these components are prone to malfunction or may lead to complete failure. These events should be identified well in advance before they lead to any catastrophic results in the plant. In a NPP, during any abnormal incident, the

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http://dx.doi.org/10.1016/j.anucene.2016.09.015 0306-4549/© 2016 Elsevier Ltd. All rights reserved. operator stationed in the control room must have the appropriate decision making ability. In order to make such decisions quick, unambiguous and accurate, the overloading of information must be reduced from the operator. Hence, for smooth operation of the NPP, event identification is considered extremely important and a support to the operator (Jeong et al., 1996).

Many soft computing techniques facilitate event identification. The occurrence of a transient is designated as an event in NPP. Transient identification in NPP using fuzzy rule based classification system is an example of a soft computing technique being used for event identification (Prusty et al., 2015, 2014). The neural model is also used for such identification in dynamic processes (Mol et al., 2003). Evolutionary computation technique such as particle swarm

Please cite this article in press as: Prusty, M.R., et al. Feasibility of ANFIS towards multiclass event classification in PFBR considering dimensionality reduction using PCA. Ann. Nucl. Energy (2016), http://dx.doi.org/10.1016/j.anucene.2016.09.015 optimization algorithm which is also a soft computing technique is used for transient identification in NPP (Carlos Canedo Medeiros and Schirru, 2008). There are many other soft computing techniques which are used for various transient identification in NPP (Moshkbar-Bakhshayesh and Ghofrani, 2013).

An excellent adaptive approach to tune the human-like reasoning capability of a model is well constructed and collated in the adaptive network fuzzy inference system (ANFIS) technique. This technique is used to tune the shape of the membership functions in order to achieve a better result. This is an iterative process where the characteristic features of the membership functions are modified. ANFIS is used in quite a number of diversified fields for classification problems. ANFIS is used for fault classification in power distribution system (Zhang et al., 2013). Automatic RNA virus classification using the Entropy-ANFIS method is a novel application of ANFIS (Dogantekin et al., 2013). It can be also used for fault location in underground cables (Barakat et al., 2014). Multi-ANFIS or MANFIS is an improvement of ANFIS for multiple outputs (Huang and Chang, 2011; Osman et al., 2009; Son et al., 2014)

In PFBR, there are almost ten thousand signal data which are being sent from the sensors in the plant site to the local control centers. Out of these sensor data, four thousand essential signal data are sent to the main control room which helps to scrutinize the status of the plant. The plant is said to be in normal state or full power when all the sensor signals are within their corresponding threshold limits. During an abnormal state, there is a heavy pandemonium with the alteration in so many sensor signals. During this state, the operators need to have agile notice on many critical signals for taking the best decision to avoid catastrophe. In order to combat this quandary, it is recommended to highlight only the significant and impactful signals. With a large set of sensor data being fed every cycle, an algorithm which discards non critical signals automatically for a particular event could reduce the information overloading on the operator. Hence, principal component analysis (PCA) can help in processing the sensor data and arrange them in descending order of their significance (Jolliffe, 2002). Instead of monitoring huge data. PCA helps in discarding the inconsequential data resulting in dimensionality reduction (Jolliffe, 2002; Wang, 2012). In dimension reduction process, normalization and standardization are methods used to ensure that the variables receive equal attention (Maier and Dandy, 2000). PCA is the basic theory and is widely used to reduce the dimensionality of time series (Bankó and Abonyi, 2012; Karamitopoulos et al., 2010). A novel method was developed for time series data mining known as asynchronous- based PCA (Li, 2014). There are instances where PCA have been used for feature extraction using neural network pattern recognition (Segreto et al., 2014).

This paper details on different aspect of the usage of PCA based ANFIS classifier for event identification or classification in PFBR. Section 2 explains the concept of ANFIS algorithm and its advantages over traditional FIS. This section also explains about all the layers that a general ANFIS algorithm follows during the training phase. Section 3 explains briefly the PCA algorithm and its approach towards dimensionality reduction. In Section 4, a brief introduction to PFBR and the components which are considered as events are illustrated, along with the experimental procedure. This procedure explains the usage of PCA along with ANFIS for event classification in PFBR using two different approaches. Section 5 explains the performance of ANFIS classifier with and without using PCA for classifying the considered events in PFBR. Finally, Section 6 explains the final inference and comparison among both the approaches mentioned above. Section 7 concludes the paper suggesting the feasibility result of the PCA based ANFIS classifier and the best result which is observed using this combination for event classification in PFBR.

#### 2. Adaptive network based fuzzy inference system

ANFIS is a fuzzy inference system (FIS) using Takagi-Sugeno model which exercises back propagation technique in artificial neural network (ANN). ANFIS is also termed as adaptive neurofuzzy inference system. Using this technique, the shapes of the input membership functions are varied in order to reduce the error between the desired output and the actual output of the system. This technique was introduced by Jang (Jang, 1993). It coalesce the best features of ANN and FIS. In FIS, there is neither a proper procedure to develop the membership function nor the rule base. Hence, it is always a herculean task to modify these two sections if the result is not satisfactory from the FIS. Back propagation algorithm used in ANN comes as a rescuer to this problem. The modification in the shape of the membership functions is done by changing its characteristic parameters. These characteristic parameters are denoted as the weights of the ANN and using back propagation algorithm these weights are modified. Finally, a comparatively reduced error is achieved using ANFIS technique.

Fig. 1 shows the ANFIS architecture which commonly consists of 5 layers. For simplicity, only two input variables  $x_1$  and  $x_2$  along with the output variable y have been shown in the network. Each input variable has only two linguistic values (say less and high). According to Sugeno FIS (Takagi and Sugeno, 1985), for a two dimensional input variable containing two membership functions each, there can be four fuzzy rules in the rule set. These fuzzy rules are simple if-then statements which covers the necessary domain of the input variables and can be expressed as

Rule 1:	If $x_1$ is $A_1$ and $x_2$ is $B_1$ ,
	then $f_1 = p_1 x_1 + q_1 x_2 + r_1$ .
Rule 2:	If $x_1$ is $A_1$ and $x_2$ is $B_2$ ,
	then $f_2 = p_2 x_1 + q_2 x_2 + r_2$ .
Rule 3:	If $x_1$ is $A_2$ and $x_2$ is $B_1$ ,
	then $f_3 = p_3 x_1 + q_3 x_2 + r_3$ .
Rule 4:	If $x_1$ is $A_2$ and $x_2$ is $B_2$ ,
	then $f_4 = p_4 x_1 + q_4 x_2 + r_4$ .

The consequence functions  $(f_i)$  in the rules mentioned above are function of the antecedence variables  $(x_1, x_2)$ . The coefficients of the consequence function in Sugeno-type FIS  $(p_i, q_i, r_i)$  which are otherwise called as consequence parameters are chosen in such a way that it describes the output of the model within the fuzzy region. In ANFIS, the consequence parameters are adaptive in nature so initialization of these parameters at the beginning is done randomly and later on it is modified using least square method during every forward pass of the ANFIS until the final output is achieved.

#### 2.1. Layer 1

Every node in this layer *l* is adaptive in nature. There are two portions as shown in Fig. 1. The input variable  $x_1$  along with the linguistic variables,  $A_1$  and  $A_2$  constitute one portion. The other portion  $x_2$  along with  $B_1$  and  $B_2$  is similar to that of the previous portion. The input variables are fuzzified and a membership value  $O_i^{1}$  from each node *i* is obtained.

$$O_i^{1} = \mu_{A_i}(x_1) \quad i = 1, 2 \tag{1}$$

 $O_i^1 = \mu_{B_{i-2}}(x_2)$  i = 3, 4 (2)

Here,  $x_i$  denotes the input variable to node i and  $(A_i, B_i)$  denotes the linguistic variables used to categorize the input variable to node i.

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