ZONE WISE ANALYSIS OF CAVITATION IN PRESSURE DROP DEVICES OF PROTOTYPE FAST BREEDER REACTOR BY KURTOSIS BASED RECURRENT NETWORK

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Abstract:

This paper aims to analyze the quality of pressure drop devices (orifices), which is used for flow zoning in proto type fast breeder reactor (PFBR) by analyzing the occurrence of cavitation. The magnitude of root mean square (RMS) of the acoustic time signal acquired from an accelerometer installed downstream of the cavitation test section. In this paper, the statistical feature based on the first-order distribution measure kurtosis (dimensionless parameter) is selected as input feature. Depends on mean and standard deviation values kurtosis varied i.e. peakness of the distribution varied. Nevertheless, the presence of background noise can have an influence on the values of these cavitation indicators. An adequately trained neural network is used for classification of a pressure drop devices as cavitating or non cavitating, under given operating conditions. Neural network used here is Elman Recurrent Networks which propagate data from later processing stage to earlier stage. A copy of the previous values of the hidden units is maintained which allows the network to perform sequence-prediction. The training algorithm used is the resilient back propagation algorithm. It is a systematic method to train the neural network. The purpose of it is to eliminate the harmful effects of the magnitudes of the partial derivatives. Only the sign of the derivative is used to determine the direction of the weight update and the magnitude of the derivative has no effect on the weight update. The proposed recurrent network contains 5 layers. The extracted feature (kurtosis) is normalized between –1 to +1 and fed as input to ANN model. The classification range has been fixed, from kurtosis values of varies cavitation signals such as no cavitation, incipient cavitation and developed cavitation signals. It is concluded that the performance error of the recurrent network is – 0.0093.

Key words: Kurtosis, ANN model, Recurrent Network, Resilient BPN Algorithm.

I. Introduction

To regulate flow in proportion to the heat generated in the subassembly of PFBR the reactor core has been divided into 15 flow zones. This is achieved by installing pressure drop devices like orifice at the foot of the subassembly [1]. These devices should meet the pressure drop requirements without any cavitation. The cavitation free performance of the device must be ensured by detection of the various cavitation stages such as no cavitation, incipient and developed cavitation.

In order to detect various stages of cavitation, a 5 layer recurrent network with resilient algorithm has been developed. In this paper, kurtosis based recurrent network for zone wise classification of cavitation data has been implemented. A good method for training is an important problem with ANN model. Here, Rprop algorithm has been selected because it is generally much faster than the standard steepest descent algorithm and the size of the weight change is determined by a separate update value. The paper is organized as follows, Section II describes data acquisition module, section III describes ANN modelling module for detection of various cavitation stages, the results and performance are explored in section IV and section V presents conclusion with future work. The network uses is recurrent network. Recurrent networks are neural networks that have feed back. By imposing constraints on the feedback connections, the convergence can be guaranteed. The recurrent networks are used for classification in time series cavitation signal.

II. Data Acquisition

Prototype Fast Breeder Reactor core consists of 15 flow zones (Zone I – Zone XV) to regulate flow in proportion to the heat generated in the subassembly. This is achieved by installing pressure drop devices like orifices of different diameters (for each zone diameter of the orifice differs) at the foot of the subassembly [1]. Accelerometer has been installed and cavitation data has been collected from various accelerometers which are placed down stream side of orifices of all zones for two different flow rates viz 110% and 100% [2]. Four data sets have been analyzed viz zone II, Zone IV, Zone VI and Zone VII. Zone II contains 58 signals for channel 1, Zone IV contains 78 signals of both channel 1 and channel 2, Zone VI has 28 signals but 15 signals has both channel 1 and channel 2 and 13 signals has only channel 1 and Zone VII has 68 signals containing both channel 1 and channel 2. Each signals containing 2002 data samples. Where Channel 1 means 110% flow rate and channel 2 means 100% flow rate.

III. ANN Modeling Module

A. Elman Recurrent Network

A recurrent neural network (RNN) is a class of neural network where connections between units form a directed cycle. This creates an internal state of the network. While a feed forward network propagates data linearly from input to output, recurrent networks propagate data from later processing stages to earlier stages.

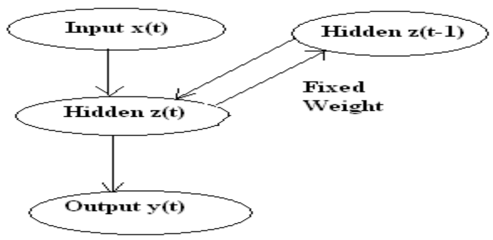

Fig 1. Architecture of Recurrent Network

Fig 1 shows architecture of an Elman recurrent network, with the addition of a set of context units in the input layer. There are connections from the hidden layer to these context units fixed with a weight. At each time step, the input is propagated in a standard feed-forward fashion, and then a learning rule is applied. The fixed back connections result in the context units always maintaining a copy of the previous values of the hidden units (since they propagate over the connections before the learning rule is applied). Thus the network can maintain a sort of state, allowing it to perform the tasks as sequence-prediction.

B. Resilient BPN Algorithm

Resilient back propagation algorithm is generally much faster than the standard steepest descent algorithm and the size of the weight change is determined by a separate update value. The update value for each weight and bias is increased or decreased by a factor del_inc or del_dec and if the derivative is zero, then the update value remains the same.

It is a systematic method to train the neural network. The purpose of it is to eliminate the harmful effects of the magnitudes of the partial derivatives. Only the sign of the derivative is used to determine the direction of the weight update and the magnitude of the derivative has no effect on the weight update. It also has a very good feature that it requires only a modest increase in memory requirements [7].

C. Kurtosis

The probability function Kurtosis is taken into consideration. In probability theory and statistics, kurtosis is a measure of the "peaked ness" of the probability distribution of a real-valued random variable. Higher kurtosis means more of the variance is due to infrequent extreme deviations, as opposed to frequent modestly-sized deviations. Kurtosis is more commonly defined as the fourth cumulant divided by the square of the second cumulant, which is equal to the fourth moment around the mean divided by the square of the variance of the probability distribution minus 3,

$$\gamma_2 = \frac{\kappa_4}{\kappa_2^2} = \frac{\mu_4}{\sigma^4} - 3,$$

which is also known as excess kurtosis. The "minus 3" at the end of this formula is often explained as a correction to make the kurtosis of the normal distribution equal to zero. The kurtosis of a random variable is the ratio of its fourth central moment μ_4 to the fourth power of its standard deviation σ. Kurtosis is denoted as γ_2.

$$\gamma_2 = \mu_4/\sigma^4.$$

Where **σ** - standard deviation and **μ** – mean.
The Syntax used for kurtosis function in Mat lab is

Y = kurtosis (X)

which returns the sample kurtosis of X.
An ANN model for zone wise classification of cavitation signal is assimilated with kurtosis as the classification feature. Because it is found that the incidence of cavitation could be characterized by the change of kurtosis values as follows i.e. from maximum to minimum.

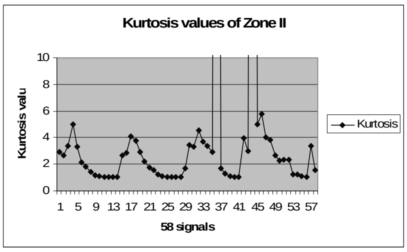

Fig 2. Kurtosis values of various signals in Zone II (Before normalized)

IV. Performance Analysis

The first major component of this analysis involved evaluating the dependence of the cavitation signal on the kurtosis value. Incidence of cavitation could be characterized by the kurtosis values (from max. to min.). That is kurtosis is maximum for cavitation signal and minimum for non-cavitation signal. So, kurtosis has been chosen as a feature input to neural network. Kurtosis values of all signals from different zones are extracted and analyzed to obtain the classification range with respect to various types of cavitation signals. The classification range has been fixed from the dependence of cavitation signal with kurtosis values. Initially the extracted kurtosis values (normalized) of various zones are fed to network then from the network output (unnormalized) the classification range has been obtained. The classification range for No Cavitation is 0.1 to 0.79, for Incipient Cavitation 0.8 to 0.9 and for Developed Cavitation is 1 to 2.9. i.e. initial processing of signal is carried out on neural network and through vigorous analysis of various cavitation signals such as no cavitation, incipient cavitation, incipient towards no cavitation, incipient towards developed cavitation and developed cavitation signal; the above classification range has been obtained.

To develop ANN model, the following network specifications such as, Network structures, number of layers, number of neurons in each layer, activation function of layers, learning function and performance evaluation has been defined [3,4]. The topology is trained with one input layer, four hidden layers and one output layer with tansig, logsig and purelin activation function respectively [5,6]. For the proposed ANN model, Number of layers has been chosen as five and 50, 40, 30, 20 as hidden neurons. Here, the learning function learngdm has been chosen for this application. In the present work the network architecture are evolved out through randomly choosing the number of layers and neurons for each layer. trainrp was used with Learning rate = 0.01; Momentum constant = 0.9; Minimum performance gradient = 1e-10 as training algorithm. A zone wise goal has been fixed as follows.

Goal for Zone II = 0.214, Zone IV= 0.446,

Zone VI= 0.0293 and Zone VII = 0.472.

Both zone wise trained and untrained inputs have been tested by proposed network and their efficiency was determined for various error functions. A training input data has been selected from zone wise. After analyzing the given input data, the network has been trained with respect to these input data. Four data sets have been analyzed viz zone II, Zone IV, Zone VI and Zone VII. The proposed neural network suggested for zone wise detection of various cavitation stages of cavitation signals from pressure drop devices of PFBR is,

Net = newelm (minmax(p), [50,40,30,20,1],{‘tansig’, ‘logsig’, ‘logsig’, ‘logsig’, ‘logsig’, ‘purelin’}, ‘trainrp’, ‘learngdm’, ‘mse’);

The network was trained and tested zone wise and the following results were obtained. Table 1 shows performance analysis with kurtosis as input to 5 layered Elman recurrent network and trained using resilient back propagation algorithm. The efficiency of the network has been tested on zone wise. The results are provided in the table 1.

Table1. Performance Analysis

ZONE	CHANNEL	PERCENTAGE OF DETECTION	
		Train Data	Test Data
II	1	51.84	56.16
IV	1	59.49	56.49
	2	60.02	62.24
VI	1	64.67	80.2
	2	-	88.04
VII	1	60.45	63.22
	2	62.18	54.69

TOTAL PERCENTAGE OF CAVITATION DETECTED **Overall %:** Train Data = **59.78%,**

Test Data = **65.86%.**

The network performance has been calculated for zone wise trained and untrained input by different error function such as SSE, MSE, MAE and MSEREG. From the result, MSE error function gives the (less error -0.0093%) best performance. Table 2 shows the percentage error of various error functions.

Table 2 Analysis based on error function

S.No	ERROR FUNCTION	EPOCHS	ERROR %
1	MSE –Mean Square Error	321	- 0.0093
2	MAE – Mean Absolute Error	368	- 0.0562
3	MSEREG – MSE with Regression	420	51.45%
4	SSE – Sum Square Error	489	< 100

V. CONCLUSION AND FUTURE WORK

The relationship between the kurtosis values and cavitation types is ambiguous due to the effect of noise in the time signals, the recurrent neural network (RNN) was applied to solve the ambiguous problem of classification problem. Non-dimensional parameter (NSP) kurtosis in time domain was defined, which can reflect the characteristics of time signal measured for the classification of cavitation signals.

This paper proposes a kurtosis based recurrent network for zone wise classification of cavitation signals from pressure drop devices of proto type fast breeder reactor. This model examines the performance of various cavitation signals, which are collected from different flow zones (totally 15) of PFBR. We test our proposed model zone wise i.e. train and test data has been selected from each zone and also the goal has been fixed zone wise with four data sets (from 4 different zones). The results indicate that the proposed model is an efficient way of classifying the various cavitation signals. The proposed kurtosis based zone wise recurrent model has the combination of five layers with 50, 40, 30, 20 as number of hidden neurons and the combination of transfer function Tansig (input layer), Logsig (all hidden layers), Purelin (output layer) with Mean Squared Error (MSE) as Performance Function for detecting various cavitation stages of pressure drop devices of PFBR. The Percentage of Detection PoD can be improved by proper selection of network parameters. The Percentage of detection is analyzed based on Type of Cavitation and Data set (Train & Test). The overall percentage of cavitation detection for train data is **59.78%** and for test data was found to be **65.86%.** Future work can focus on integrating the feature extraction efficiency of the wavelet transform with the classification capabilities of neural network for signal classification in the context of detecting the cavitation.

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