DEVELOPMENT OF EVOLUTIONARY COMPUTATION ALGORITHMS FOR CLASSIFICATION OF CAVITATION SIGNAL

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ABSTRACT

This paper presents an Artificial Neural Network (ANN) approach that classifies a cavitation signal into 3 distinct classes viz., no cavitation, Incipient and developed cavitation signal. In this paper an Elman recurrent network have been used for the classification of cavitation signals in a pressure drop devices which are used for flow zoning in a Prototype Fast Breeder Reactor (PFBR). Classification process can be divided into stages, pre-processing, range fixing stage and classification stage. In pre-processing and range fixing stage, various types of cavitation signal from different zones are fed to recurrent network as input to get a simulated output. Initial processing of signal is carried out on neural network and through vigorous analysis of various cavitation signals, the classification range has been obtained from output of recurrent network based on the magnitude of RMS value of signal acquired from an accelerometers installed downstream of various flow zones. In classification stage, an Elman recurrent network have been used to evaluate the classification results and the optimum network architecture is evolved through an elaborate trial and error procedure. The classification results shows that recurrent network employing resilient back propagation algorithm was effective to distinct between the classes based on the good selection of both network and algorithm parameters. The proposed Elman recurrent model with resilient algorithm gives better performance, classification rate and only requires less computation time. The classification rate was 84.21% for the training sets and 92.89% for test data sets. It is concluded that the performance of the neural network is carried out zone wise and it is optimum, and the errors are very less. The paper also discusses the future research directions.

Key words: Classification of cavitation Signal, ANN model, Elman Recurrent Network, Resilient BPN Algorithm.

I. INTRODUCTION

Neural nets emerged from psychology as a learning paradigm, which mimics how the brain learns. There are many different types of neural networks, training algorithms, and different ways to interpret how and why a neural network operates. Over the past few years, an explosion of interest in ANN models and their applications has occurred. ANNs posses a number of properties which make them particularly suited complex classification problems. Unlike traditional classifiers, ANN models can examine numerous competing hypotheses simultaneously using massive interconnections among many simple processing elements. In addition, ANNs perform extremely well under noise and distortion [1]. In this work a multi layer recurrent network with resilient back propagation algorithm has been used, because 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 and if the derivative is zero, then the update value remains the same. The paper is organized as follows, Section II describes data acquisition, section III describes ANN modeling module for classification of 3 distinct classes of cavitation stages, section IV analyses the results and performance and section V concludes with future work.

II. DATA ACQUISITION

The data that was used to train and test the ANN were collected from prototype fast breeder reactor (PFBR) of Indira Gandhi Centre for Atomic Research (IGCAR) Chennai. To regulate flow in proportion to the heat generated in the subassembly of PFBR, the PFBR core has been divided into 15 flow zones by installing different diameters of orifices at the foot of the subassembly [2]. The cavitation data of all zones were recorded from accelerometers, which are installed at down stream side of the orifices for 2 different flow sets viz 110% (Channel 1) and 100% (Channel 2). Data set analyzed was provided in table 1.

Table 1. Data Set Analyzed

S. No	Flow Zones	Number of signals	
		Channel 1	Channel 2
1	ZONE II	58	–
2	ZONE IV	78	78
3	ZONE VI	28	15
4	ZONE VII	68	68

III. ANN MODELING MODULE

A. Elman Recurrent Network

A strict feed forward architecture does not maintain a short term memory. Any memory effects due to the way past inputs are represented to the network. A recurrent neural network (RNN) has activation feedback which embodies short term memory. A state layer is updated not only with the external input of the network but also with activation from the previous forward propagation. The feedback is modified by a set of weights as to enable automatic adaptation through learning [3].

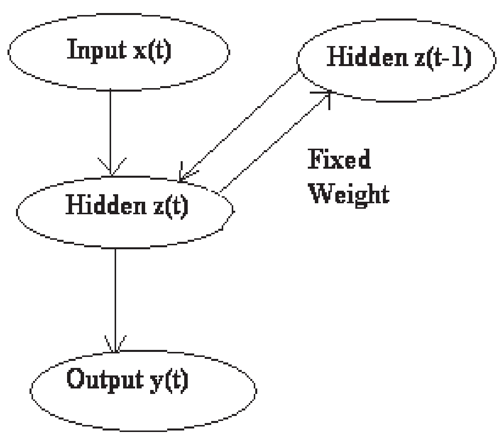


Fig 1. Architecture of Recurrent Network

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

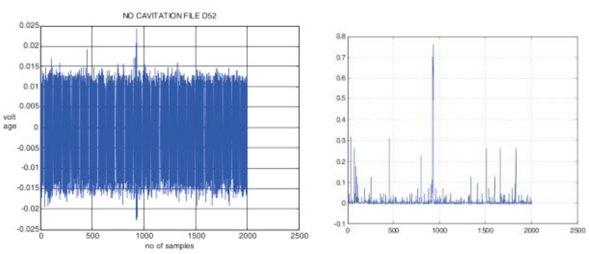
RPROP modifies the size of the weight step taken adaptively, and the mechanism for adaptation in RPROP does not take into account the magnitude of the gradient as seen by a particular weight, but only the sign of the gradient (positive or negative). This allows the step size to be adapted without having the size of the gradient interfere with the adaptation process [2] 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 [4].

IV. PERFORMANCE ANALYSIS

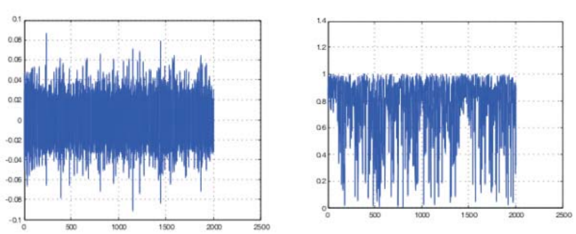
Classification of cavitation signal is important for incipient stage cavitation detection. This is achieved by implementing a neural network diagnosis algorithm. The scope of this research work was to classify a cavitation signal into 3 distinct classes, which are no cavitation, incipient and developed cavitation. Therefore the next step was to develop an ANN model to classify each of the signals. The network tested was an Elman recurrent network with resilient back propagation algorithm. MATLAB Neural Network Tool Box was chosen to be the platform in this work. It is convenient for training and testing the Elman recurrent network and also it provides many configuration choices for achieving better classification accuracy. Success with Elman recurrent network with resilient back propagation algorithms were achieved after proper selection of training data, network parameters, training algorithm parameters and fixing the classification range.

The major component of this analysis involved in fixing of classification range to classify the cavitation signal into 3 distinct classes. There is the difficulty to obtain the classification range for each classes based on the magnitude of the original rms value of accelerometer vibration signal because of the overlapping data which is shown in figure 2 (original Signal). So for fixing the classification range the magnitude of simulated output i.e after training network output has been used. Initial processing of signal is carried out on neural network and through vigorous analysis of various cavitation signals the classification range has been obtained from simulated output. The classification range has been fixed as, for No cavitation: - 0.009 to 0.09, incipient cavitation: 0.1 to 0.99 and Developed cavitation: 1 to 2.9. Following plots shows various stages of cavitation original signal and corresponding simulated (after training network output) signal.

A. No cavitation:



B. Incipient cavitation:



C. Developed cavitation:

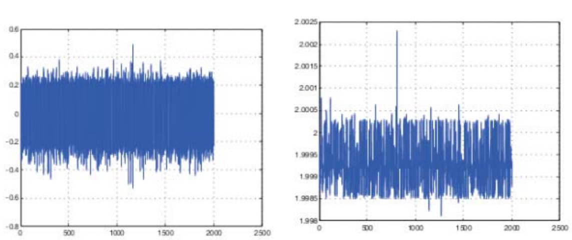


Fig. 2. Plot of original and simulated signal

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 [5,6]. The topology is trained with one input layer, six hidden layers and one output layer with tansig, logsig and purelin activation function respectively. For the proposed ANN model, Number of layers has been chosen as seven and 50, 40, 30, 20, 15, 10 as hidden neurons. Here, the learning function learngdm has been chosen for this application. trainrp was used with Learning rate = 0.01; Momentum constant = 0.9; Minimum performance gradient = 1e-10 as training algorithm.

Four data sets have been analyzed viz zone II, Zone IV, Zone VI and Zone VII. Zone II contains 58 files for channel 1, Zone IV contains 78 files of both channel 1 and channel 2, Zone VI has 28 files but 15 files has both channel 1 and channel 2 and 13 files has only channel 1 and Zone VII has 68 files containing both channel 1 and channel 2. For each zone separate goals were fixed as

$$\text{Goal for Zone II} = 0.214, \quad \text{Zone IV} = 0.446,$$

$$\text{Zone VI} = 0.0293 \text{ and } \text{Zone VII} = 0.472.$$

and network was trained with 15 files (each file containing 2002 samples) and the rest of the files were given for testing. A training input data has been selected from each zone. After analyzing the given input data, the network has been trained with respect to these input data.

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), [50,40,30,20,15,10,1], {'tansig',' logsig', '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 simulated output as input to 7 layered Elman recurrent network and trained using resilient back propagation algorithm. The efficiency of the network has been tested zone wise. The network performance has been calculated for zone wise trained and untrained input by MSE error function. The results are provided in table 2.

Table 2. Performance Analysis

Zone	Channel	Percentage of Detection	
		Train Data	Test Data
II	1	71.8	88.6
IV	1	90.5	86.9
	2	80.7	87.4
VI	1	87.8	100
	2	–	100
VII	1	96.1	93.28
	2	78.4	94.1

Total Percentage of Cavitation Detected

Overall %: Train Data Set = 84.21%,

Test Data Set = =92.89%

V. CONCLUSION AND FUTURE WORK

The above analysis concludes that the combination of seven layers with 50, 40, 30, 20, 15, 10 as number of hidden neurons and the combination of activation function Tansig (input), Logsig (hidden layers), Purelin (output) with Mean Squared Error (MSE) as Performance Function has been determined as the best Elman recurrent network parameters for classifying the cavitation signal into 3 distinct classes. The Percentage of Detection PoD can be improved by proper selection of network parameters. The Percentage of detection is analyzed zone wise based on Number of samples, Type of Cavitation and Data set (Train & Test) and the algorithm did not converge to a single set of parameters. The overall percentage of cavitation detection for train data set 84.21% and for test data set was found to be **92.89%.**

Future work can focus on extraction of features like signal frequency, power spectrum (power spectrum of a signal represents the contribution of every frequency of the spectrum to the power of the overall signal which is useful in many signal processing applications), mean value and average of the signals which can be the input to neural network. The possibility of designing generalized ANN model for cavitation classification irrespective of zones can be explored.

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