Implementation of Back-Propagation Neural Network for Leakage Estimation in Oil Pipelines

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Abstract:

There are various techniques in pipeline leakage detection using ANN. The computational detailed analysis handled by accurate neural network models can replace the human intervention in the duty of monitoring fliud flow and pressure waveforms which tend to warn the technical staff by the leakage occurrence and inform the magnitude and location of the leakage along the pipeline . This technique could be applied to track the distribution networks of natural oil and gas pipelines as well as industrial, commercial and residential gas pipelines in order to have safety operation and avoiding severe human health injuries or hazard environmental conditions caused by toxic gas leakages. Out of many recent methods for leakage detection, there exist a technique based on flow and pressure measurement but off course this need a nonlinear model simulation of fluid pipeline for processing the available data and simulate the flow of a used fluid with proposed leakage occurrence. The numerical solution is complex and out of this work's scope, however considering the availability for experimental test-bed that can simulate the actual pipeline used in the oil industrial field. Testing the proposed model is satisfied by using a back propagation neural network with the data-set for the normal and different leakage kinds in the oil pipeline to analyze the events and classify the leak existing and its magnitude by using classification performance measure such as error performance and confusion matrix.

Also different algorithms for training the proposed model is adopted with various transfer function characteristics in the hidden and output layer neurons to investigate for the suitable algorithm and to search for the optimal transfer function for the leak classification problem

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Keywords: pipeline leakage, back propagation neural network (BPNN), classification accuracy, learning algorithm

1- Introduction

More than 50% of energy in the world emerges from oil and gas resources. So, to safely and economically transport these resources, pipelines were adopted as a more suitable means of transportation. Pipelines nowadays transport a wide variety of materials such as oil, condensate refined products, natural gases, crude oil, process gases, as well as fresh, salt waters and sewage[1].

May be there are few million kilometers of transport pipelines around the world. In such cases, because of longer lengths and hard complex runs of remotely located pipelines, actual access may be restricted. In fact, pipelines can extend through desert, across hills, under bodies of oceans, or be located underground or subsea, even at depths exceeding few miles [2]. This scenario leads to an idea of potential risks and damage existing in gas pipelines which in turn impact on internal and environmental issues. The wave of pressure, fatigue cracks, tensile strength, material manufacturing errors, all of these potential damage risks can lead to pipeline leakage which may cause explosion in it. thus conducting a monitoring exercise on gas pipeline is necessary and vital[3]. Detection of fault in the gas pipeline transmission and specially the detection of leakage in it play an important role, not only to ensure safety and protection of the environment but also to protect the live projects from economical point of view [4]. Based on the above mentioned facts, leakage detection systems are subject to official regulations around the world for example API and TRFL. And leakage detection systems should be precise, sensitive, reliable, accurate, and stable [5]. Leakage detection systems can be classified into two major kinds; continuous and non-continuous systems. The non-continuous systems include: Inspection by helicopter, smart pigging, and even tracking dogs[6]. On the other hand continues system has at least three possible approaches to avoid leakage which can be summarized by[7]:

Firstly, internal on the basis of physical parameters such as mass flow rate or volume balanced method, statistical systems, pressure point analysis, Real Time Transient Model (RTTM) based systems and Extended RTTM.

Secondly, external implementation based on hardware such as wireless sensors changing impedance, the space periodic capacitor transducer, optical fiber based temperature profile, highly sensitive acoustic sensor, infrared camera for image and video processing.

Thirdly, Hybrid techniques which make a combination between first and second methods for example acoustic and pressure analysis by balancing mass and volume .

After reviewing for the recent ways to detect leakage, industrial efforts concentrated in establishing the combinational sensor technology for monitoring pressure, compressor conditions, flow, temperature, density and other important variables[8]. The problem starts from a tiny hole which can easily be detected by the means of instrumentation. For instance smart ball sends inside the pipeline to detect welding effect and early cracks of the wall sides using magnetic induction flux linkage features and ultrasonic waves. Recently optical fiber technology is used for monitoring of leakages based on some physical changes that occurred at the leak site, one of these physical changes is a noticeable change in temperature profile, so in order to detect such changes, a fiber optic cable is extended along the pipeline. But, using of this technique is only possible for a short length pipeline rather than a many reflections requirements to plot a useful temperature profile that will be used for detecting gas leaks, also infrared sensing method made possible through video cameras which contains a special featuring filter that is sensitive to a selected spectrum of infrared wavelengths. There exist some certain hydrocarbons that absorb infrared radiation from this spectrum, which makes it possible to detect the leaks as they will appear as a smoking image on the display server. On the other hand there are different mechanical methods adopted the measurement of diameter and the thickness of pipeline for corrosion detection and bulge diagnosis [9].

All above mentioned methods and techniques have complex mathematical models with detailed description rather than their analytical equations.

Oil and gas Pipelines modeling is a complex nonlinear system and the real pipeline system has many different conditions and environments. At present time, artificial intelligence techniques, such as artificial neural network and pattern recognition, which have rapid development along the world , are an excellent ways to solve this problem. According to challenges and critical issues, the precise rate of pipeline leakage detection is dramatically enhanced by adopting a neural network based method [10].

Although, the neural network has many preliminary problems such as the slow rate convergence speed, the need of training samples as a data-set and so on. However the Artificial Neural Network (ANN) shown in Fig(1) has powerful mathematical models and universal predictors that have been used to solve various real-world problems. Among different types of ANNs, multilayered perceptron (MLP) with well-known structure as in Fig(2) represent the best, and consists of three layers; the input layer, hidden layer and output layer, with every layer consisting of several neurons. The neurons are connected to each other's by a set of synaptic weights, which consists of values representing the strength of the connection. After applying the suitable dataset and during the training phase , the ANN continuously adjusts the values of these weights until it reaches a certain termination condition, usually measured by the performance of mean squared error value of the network , maximum allowable training time duration, the number of maximum iterations or epochs [11].

Among of various learning algorithms have been used for training of ANNs, the most well-known technique used to train the ANN is still the backpropagation (BP) algorithm The BP algorithm has a dramatic acceptance by the researchers due to its robustness and versatility while giving the most efficient learning algorithm for MLP networks. In addition, it is a gradient-descent based algorithm which upgraded the weights of ANN by using the gradients of their error in each iteration. so, the adjustments on every weight achieved by considering how much they affect the final output, and this offers a more refined local minimum searching capability while the process still keep looking for the global minimum. The BP algorithm using the same dataset by iterates and iterates again till the network converges to the searched minimum point. Generally, as the number of trained epochs and data-set samples increases, the accuracy and precision of the ANN to expect the output increases, but this will cause a longer training time, so there is a tradeoff between the time and accuracy in the training phase of the ANN [12].

From a technology point of view, *last years WSN* have attracted the interest of most researchers whereas many industrial branches with different applications are used *WSN* in different industrial fields. There are variety of methods in order to adopt abrupt development changes in technology for communication and wireless instrumentation industry on the basis of Electronics and Computers. Regarding remote control based on Zigbee and Wi-Fi protocols due to limitation of wide band frequency and low speed in data transmission that is appropriate for small plant and cannot be used for massive plants for oil pipelines. Therefore these problems have tendency to lead us towards *WSN* which *is based on zigbee protocol*. Structures of WSN are *three layers*. End device Sensor node, consists of voltage and current transducers which are placed in the first layer. Microcontroller which is needed for the processing and wireless communication along with the servers also locates in this layer. The Second one is router which is the responsible for retransmission the data from the end device to the coordinator . The third is the core for the WSN including the intelligent algorithms installed in an intelligent controller to lead the whole data coming from sensor and give a final decision for the actuators or make any advanced or speed processing [13].

It seems there is a global agreement that a major problem for most ANN researchers are facing is in selecting the suitable ANN topology. However according to literatures , the influence of the network topology on the final output is tremendous despite not having a direct interaction with the external environment. And hence the influence of this network topology on the output will be consequently reflected in the form of other new problems, such as the slow convergence rate, and getting trapped in local minima. In this instant , there have been no officially established methods to determine the optimal topology of an ANN for any given problem, and this will e extended to the other layers especially in the number of neurons for the hidden layer. If the number of neurons is inadequate, it may result in under-fitting, which means that the neural network will be unable to learn all the information contained in the applied dataset. Conversely, an overabundance of neurons in the hidden layer will lead to over-fitting, a situation in which the neural network hold the noise of the training data-set, negatively impacting its ability to predict new data in future[14].

Some literature and papers may offer rules of thumb methods or guidelines for selecting the number of adequate hidden neurons by using any value between the number of input and output neurons for the ANN, but a good topology cannot be decided solely based on the number of inputs and outputs neurons alone [15].

2- Theoretical background

The multilayer feedforward neural network is the core of the artificial Neural Network. It can be used for both data fitting and pattern recognition assignments. With the addition of a new proposed tapped delay line, it can also be used for system model prediction. The training functions described in this paper are not limited to multilayer networks. They can be used to train arbitrary network architectures (even hybrid networks), as long as their components are differentiable [16].

The procedure for the artificial neural network design summarized by about seven primary steps described hereunder:

- **a)** Collect input / output data-set
- **b)** Create the network structure
- **c)** Configure the network topology
- **d)** Initialize the weights and biases for all neurons
- **e)** Train the neural network
- **f)** Validate the network results (post-training analysis).
- **g)** Use the network for the new real input.

Noting that first Step should be happened outside the framework of artificial Neural Network programming, but this step is critical to the success of the whole design process, such that the ANN will simulate the real system response for the new test input, as it was already trained by an actual data-set [17].

When the network weights and biases are initialized, the network is ready for training.

The multilayer feed forward neural network can be trained for function fitting (as a nonlinear regression) or pattern recognition problem. The training process requires a set of samples from a proper network behavior, it means network input vector P and target output vector T [18].

The training process of a neural network try to tune the values of the weights and biases of the network neurons in each of hidden and output layers, to optimize network performance, as defined by the network performance function which is (for most MLP neural network) mean square error MSE, that represent the average squared error between the network outputs Y and the target outputs T [19].

Training of BPNN can be achieved via two methods; either incremental method or batch method. In incremental method, the gradient of error is computed and the weights are updated after each applied input. Unlikely, In batch method, the weights are updated after all the inputs in the training set are applied to the network. Based on results in table (2) Batch training algorithm is noticeably fast and produces smaller errors than other incremental training algorithms[20].

Any standard numerical optimization algorithm can be used For training multilayer feedforward networks, however, to optimize the performance function, there are a some optimization methods that have shown excellent minimization error performance for neural network training. These optimization methods use either the performance gradient of the network with referred to the weights, or the Jacobian of the network errors with respect to the weights. The gradient and the Jacobian are calculated using a procedure known as backpropagation algorithm, within which computations are performed backward through the network [21].

The term "backpropagation" in some literatures, ambiguously used to point to the gradient descent algorithm specifically, when applied to neural network principles. But in this work terminology is used precisely, since the process of the gradient and Jacobian calculations backward through the network is applied in all the used training functions in this work. It is clearer to use the name of the specific optimization algorithm that is being used, rather than to use the term backpropagation alone [22].

Another millstone terminology is, sometimes the multilayer network is referred to as a backpropagation network. But, the backpropagation way that is used to calculate Jacobians and gradients in a multilayer network can also be used for many different neural network architectures [23].

3- Block diagram proposed model

The block diagram for the proposed experimental system is shown in Figure (3).The details of different operating parameters and material parts of the system are given in table (4).

Each leak size is given a certain output class which in turn after combination with other classes compromise a classification code for the output layer as per table (1) to control the classification problem with BP ANN.

Experimental set up is consists of a pipeline having length of 7m & diameter of 2 inch ,The pipeline has four sections 1, 2, 3 & 4 having length of 1.5m each.

Pipeline sections are connected using a flange assembly. while every flange has an orifice plate & rubber gasket that are placed between them. Also 4 nut-bolts each has diameter 0.5 inch are used for each section of the assembly. Two tapings are provided for manometer connection at suitable positions across the flanges.

In order to measure the pressure drop four inverted manometers are connected in each section, a sump with capacity 500 liters is used. While oil is flowing into the pipeline using 1 hp motor oil pump.

Dropped oil is returned to the sump using other 3 inch pipeline, pressure drop across the orifice in each section can be recorded by varying the oil flow-rates at normal conditions. Leak positions are artificially generated by creating a hole in the pipeline at different positions from the flanges as explained in table (4).

4- Experimental results and discussion

Referring to the simulation results at Fig(4) to Fig(17), the fastest training function is generally Levenberg-Marquardt .However, The quasi-Newton method, is also quite fast. Although both of these methods tend to be inefficient for large networks (with thousands of neurons weights), because they need more memory and more computation time for these weights upgraded. In fact, Levenberg-Marquardt algorithm performs better on curve fitting (as a nonlinear regression) assignments than on pattern recognition assignments see Fig (10) through Fig (17).

On the other hand, when large networks are training, or pattern recognition problems to be solved, Resilient Backpropagation and Scaled Conjugate Gradient are better choices due to their minimum memory requirements, and yet they are much faster than other classical gradient descent algorithms.

Referring to Fig (4) through Fig (9), sometimes the network is not sufficiently accurate, and in order to improve the performance some points are followed:

a) The process is re-initialized and the network is trained again. In order to get new solutions.

b) The number of hidden neurons are increased .keeping that, larger numbers of hidden layer neurons of course give the network more flexibility because the network will have more candidate optimization parameters.

c) A different training algorithms, such as Bayesian regularization training can sometimes produce better generalization capability than using early stopping.

d) Finally, by using additional training data-set (if possible). Off course additional data delivery for the network is more likely to produce a network that will perform excellence to new data.

5- Conclusions and recommendations

The main objective of the present paper was to emphases the possibility of using an ANN in leak detection system in oil pipelines. For this reason, experimental data was generated for normal and leaked conditions for flow of oil in a pipeline. Tiny holes were created artificially for generating leak conditions at different locations on the pipeline. Pressure drop across the orifice are placed at four positions in the pipeline to be used for recording these normal & leak conditions. ANN models with different scenario were developed that detect the existing of leak or not as a binary classification problem. Also, pressure drop was simulated at four different locations with different leak size ranged from 0.25" up to 1" in step of 0.25. The accuracy of prediction of these classification models is calculated and seen to be 100% via confusion matrix form and validated for 240 samples of the pressure data set for training the ANN divided as 168 samples for training and 36 samples for each of validation and testing phases of the training process. Based on the results and discussions, it can be said that all the ANN models developed in the present work are accurate in classification for leak existing and its size estimation . It can be thus generally concluded that, ANN can be efficiently deployed in developing a mathematical model that can be used as a classifier for the data which may be available for industrial field at normal or faulty conditions from oil and gas pipeline.

Fig (2): Model of Multilayer Perceptron

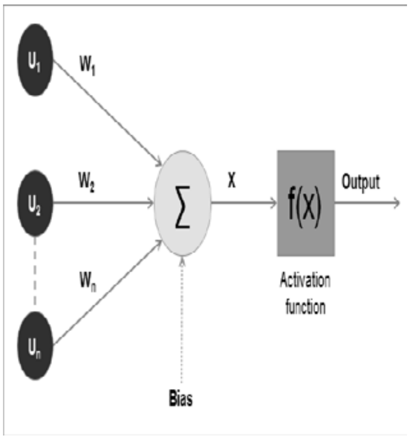
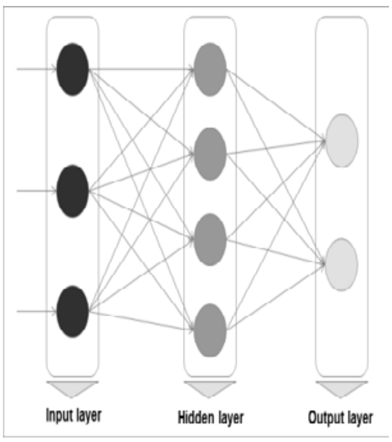
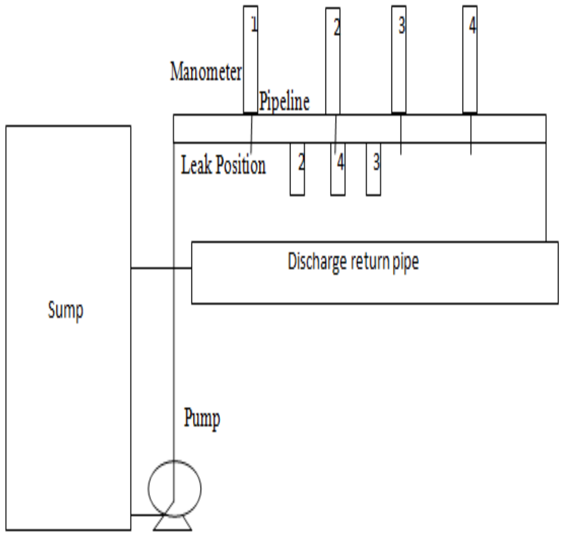


Fig (1): Mathematical model of artificial neuron





Fig(3) block diagram for the proposed experimental leak detection system

Table (1) States for classifying the simulated proposed system

State	Leak position	F1	F2	F3	F4
1	*No leak*	*0*	*0*	*0*	*0*
2	1	1	0	0	0
3	2	0	1	0	0
4	3	0	0	1	0
5	4	0	0	0	1
6	1 & 2	1	1	0	0
7	1 & 3	1	0	1	0
8	1 & 4	1	0	0	1
9	2 & 3	0	1	1	0
10	2 & 4	0	1	0	1
11	3 & 4	0	0	1	1
12	1 & 2 & 3	1	1	1	0
13	1 & 2 & 4	1	1	0	1
14	1 & 3 & 4	1	0	1	1

15	2 & 3 & 4	0	1	1	1
16	1 & 2 & 3 & 4	1	1	1	1

Table (2) classification accuracy comparison between different learning algorithms

Transfer function: Hidden layer/ purelin , Output layer/ purelin hidden neurons =10			
Learning algorithm	Classification accuracy %	Learning algorithm	Classification accuracy %
Batch weight/bias (B)	46.7	Polak-Ribiére Conjugate Gradient (CGP)	43.3
Gradient Descent (GD)	46.3	Levenberg-Marquardt (LM)	43.3
Gradient Descent with Momentum (GDM)	45.8	One Step Secant (OSS)	43.3
Variable Learning Rate Gradient Descent (GDX)	45	Conjugate Gradient with Powell/Beale Restarts (CGB)	42.9
Scaled Conjugate Gradient(SCG)	44.6	Quasi-Newton (BFG)	42.9
Bayesian Regularization (BR)	44.2	Resilient Backpropagation (RB)	42.5
Fletcher-Powell Conjugate Gradient (CGF)	43.3		

Table (3) performance evaluation comparison for different transfer function for Batch learning algorithm with 10 hidden neurons

Transfer function		Learning algorithm	Classification accuracy %	Perf. %	num_epoch	best_ train perf	best_test perf
Hidden layer	Output layer						
Compet	compet	Batch weight/bias	100	45.31	0	0.4663	0.3785
Poslin	Poslin	Batch weight/bias	100	19.58	1000	0.0825	0.0677
radbas	radbas	Batch weight/bias	100	20.19	1000	0.0803	0.0754
tribas	tribas	Batch weight/bias	100	19.96	86	0.0813	0.0764
hardlim	hardlim	Batch weight/bias	100	20.62	0	0.2987	0.3490
logsig	logsig	Batch weight/bias	100	20.53	1000	0.0805	0.0766
softmax	softmax	Batch weight/bias	100	19.72	100	0.0816	0.0676
Elliot2sig	Elliot2sig	Batch weight/bias	100	26.77	1000	0.0010	4.1918e-04

Table (4) details for experimental tools and operating parameters

Part of the experimental set up	Details
Sump	500 liter
Pump	Centrifugal oil Pump, 0.75 Hp
Suction & Discharge Sections	Flexi pipe
Total Length of Pipe	7 m
Pipe Diameter (Inside)	2 ”
Material of construction for pipe	PVC
Number of Pipe sections	4
Number of Orifice Plates used	4
Orifice diameter	0.5" , 0.25" , 1"
Number of flanges	8
Flange to flange assembly	4 nut(0.5”)-bolts for each assembly

Flange Material	Acrylic Sheet 6 mm thick
Flange diameter (outer)	4”
Gasket material	Rubber
Manometers	4 Inverted U-Tube Manometers
Experimental Fluid	oil
Manometer Fluid	oil
Flow Rate	0.3- 0.35 liters per sec
Temperature	30-35 degree centigrade
Leak position 1	1 m from 1st flange
Leak magnitude 1	1 -1.25 ml per sec
Leak position 2	1 m from 2nd flange
Leak magnitude 2	0.5-0.75 ml per sec
Leak position 3	1m from 3rd flange assembly
Leak magnitude 3	0.75 - 1 ml per sec
Leak position 4	1m from 4th flange assembly
Leak magnitude 4	1.2 -1.45 ml per sec

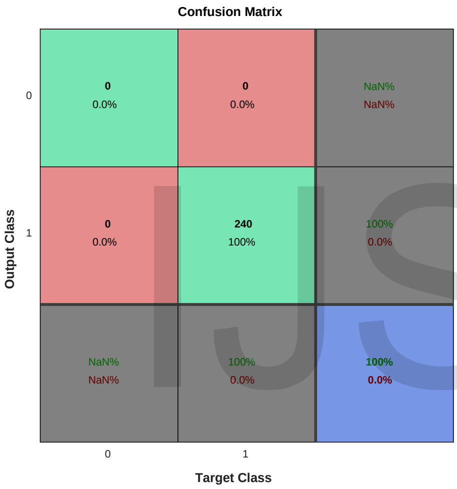


Fig (4) Confusion matrix for Batch learning algorithm

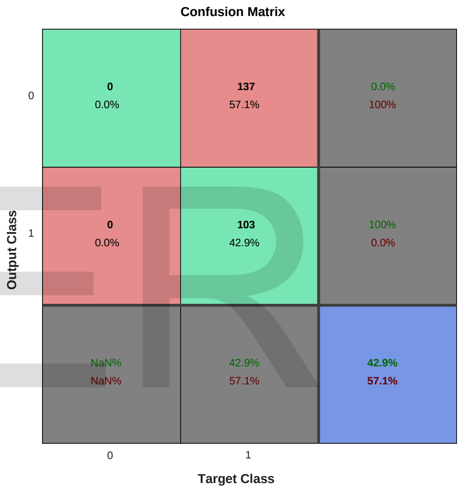


Fig (5) Confusion matrix for CGB and BFG learning algorithms

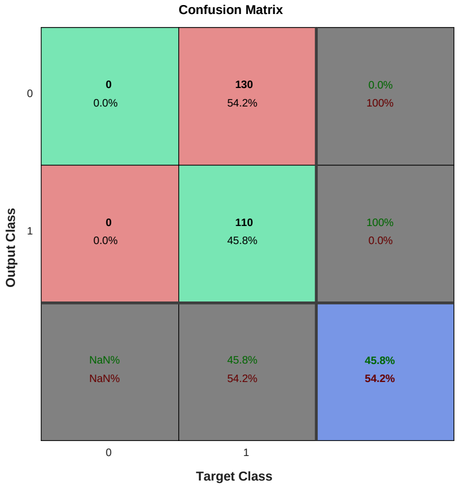


Fig (6) Confusion matrix for GDM learning algorithm

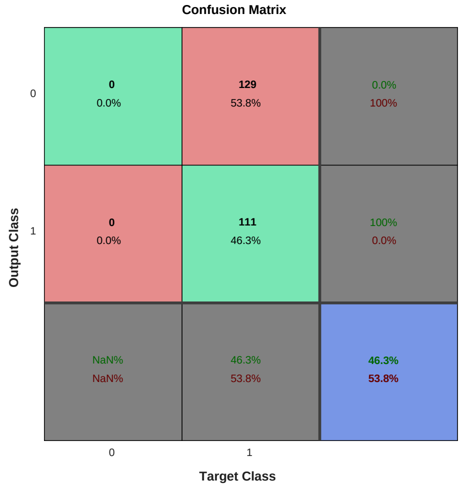


Fig (7) Confusion matrix for GD learning algorithm

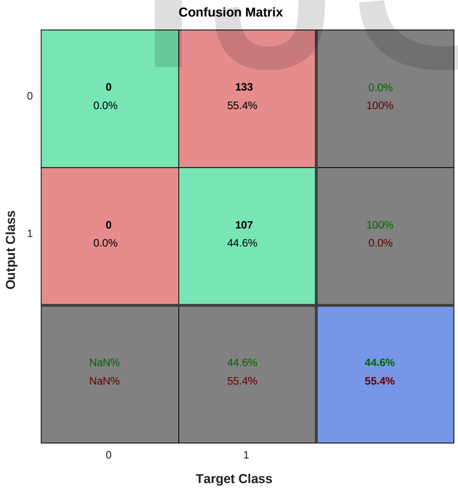


Fig (8) Confusion matrix for SCG LM,CGF,CGP learning algorithm algorithm

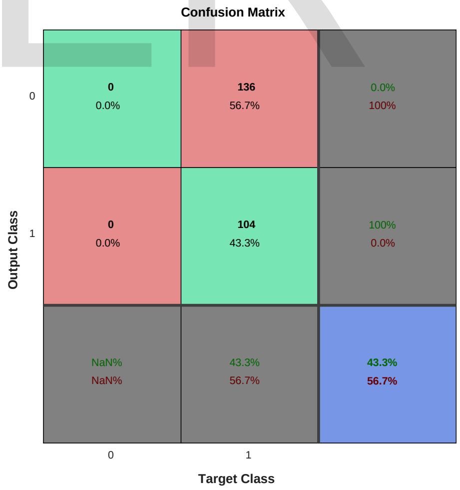
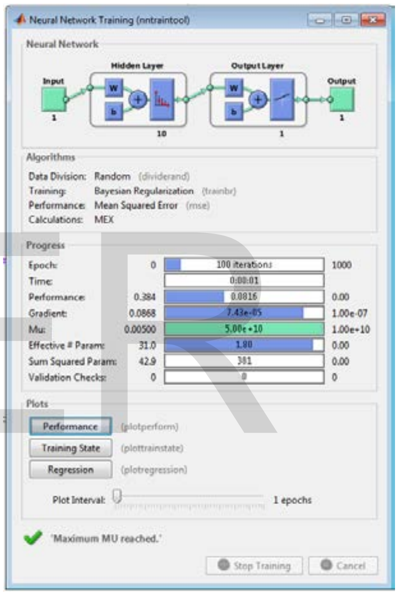


Fig (9) Confusion matrix for

and OSS learning

Fig(10) Training with Elliot2sig transfer function for hidden and output layers



Fig(11) Training with Softmax transfer function for hidden and output layers

Fig (12) Training with Logsig transfer function for hidden and output layers

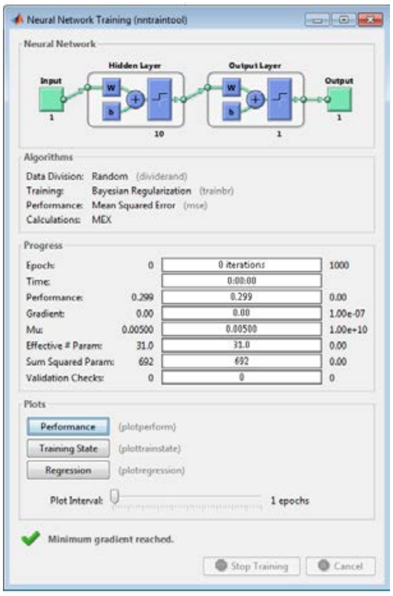


Fig (13)Training with Hardlim transfer function for hidden and output layers

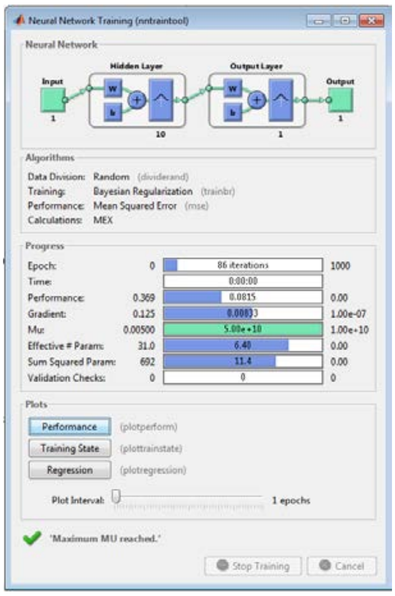


Fig (14) Training with Tribas transfer function for hidden and output layers

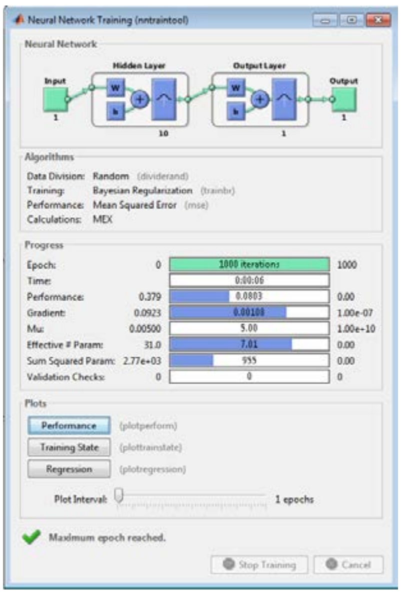


Fig (15) Training with Radbas transfer function for hidden and output layers

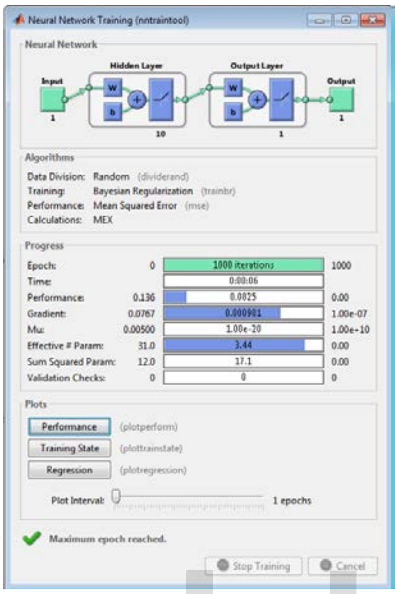


Fig (16) Training with Poslin transfer

transfer

function for hidden and output layers

Fig(17) Training with Competition

function for hidden and output layers

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