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Application of Artificial Neural Network to Fault Detection in Telephone Switching System

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Abstract: One of the major problems in the telecommunication industry is the intermittent behaviors of the telephone switch. The application of IT technologies that make use of telephone network is dramatically increasing. There is a growing demand to rapidly detect and repair fault telecommunication lines, thus calls for proper monitoring. This paper discussed a means of detecting fault on a telephone line by the use of Artificial Neural Networks, current anticipation and localization procedures and suggest means of identifying potential faults within the network. It also discusses at the results that were obtained when using an Artificial Neural network to create voice sensitive music software. As a result of the data intensity of a TSS, an ANN architecture called feed forward back propagation is adopted and trained using MATLAB neural network toolbox. The results btained provides a better way of detecting fault in a telephone network.

Keywords: Telecommunications, Artificial Neural Network

I. INTRODUCTION

Over the years, so much research activities have gone into artificial intelligence to explore the promising approaches to machine intelligence. These brought about computers modeled after the human brain called neural networks. Neural networks are best distinguished from other intelligent techniques because they are non-rule based and stochastic. Stochastic behaviour allows a neural network to explore its environment more fully and potentially to arrive at a better solution than linear methods might allow [1].

Artificial neuron network whose architecture is modeled after the brain consists of many hundreds of simple processing units wired together in a complex communication network. Each unit is a simplified model of a real neuron, which fires a new signal based on the strength of the signal received. The computational power of the network depends on the working together of these rather feeble processing units on any task, termed parallel processing, which is closer to the physical workings of the brain.

A. Artificial neuron network:

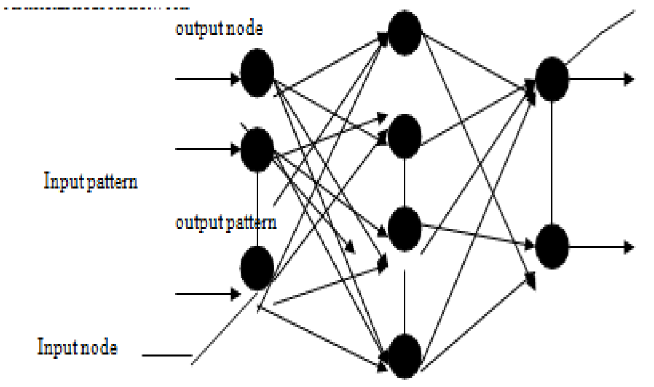


Figure.1. A Simple Neuron network (MS Encarta 2002).

Telecommunications, which deals with the transmission of voice, data, and pictures in form of electronic signals, requires thorough monitoring for optimum efficiency[2]. The adoption of neural networks is therefore very important to handle the complexity and data intensity of the switching system, which handles the transmission path. In the telephone switching system, manual connection of wires together, which may involve hundreds of telephone cables are managed through a central telephone switching hub.

Figure 2Telephone switching hub

The current Telephone network based on the development of Almon Stronger in 1889 is comprised of a few basic network components [2] These are the user equipment, access network, main network, transmission equipment and switching equipment. Telephone switching system is based on circuit-switching concept [3]. It provides an end-to-end connection on demand, which is maintained without any interference, until the call is complete. This concept also preserves the quality of communication. It is assumed that it takes about 10 seconds for the connection to come through.

B. How ANN Works:

Simulation of a neural network is a drastically simplification of the human brain, using special properties for each problem domain. Each neural net consists of neurons and connections between them. The neurons are transporting incoming information on their outgoing connection to other neurons. These connections are called weights and the electrical information is simulated with specific values stored in them.

Information called input is sent to the neuron on its incoming weights. This input is processed by propagation function that adds up the values of all incoming weights, the resulting value is compared with a certain Threshold value by the neuron's activation function. If the input exceeds the threshold value, the neuron will be activated, and otherwise it will be inhibited. If activated, the neuron sends an output on its outgoing weights to all connected neurons.

In a neuron network, the neurons are grouped in layers called Neuron Layers[4]. Usually, each neuron of one layer is connected to all neurons of the following layer. Only the input and output layers are no connected to preceding or succeeding layers respectively. The information given to a neural network is propagated layer-by-layers from input layer to output layer through none, one or more hidden layers. Depending on the learning algorithm, it is also possible that information is propagated backwards through the network.

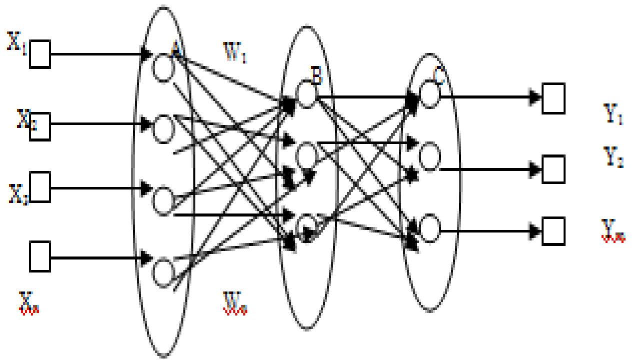


Figure.3.0A neural network with three neuron layers

X=input values
Y=output values
W=weights
A=input neuron layer
B=hidden neuron layer
C=output neuron layer.

C. Feed Forward Back Propagation Network:

The in and out layer in the flow of information during recall. Recall is the process of putting input data into a trained network and receiving the answer. Back-propagation is not used during recall, but only when the network is learning a training set. The number of layers and the number of the processing element per layer are important decisions. These parameters to a feedback, back- propagation topologies are also the most ethereal. They are the art of the network designer. There is no quantifiable, best answer to the network for any particular application. There are only general rules picked up over time and followed by most researchers and engineers applying this architecture of their problem.

- ***a.*** ***Rule one:*** As the complexity in the relationship between the input data and the desired output increases, then the number of the processing elements in the hidden layer should also increase
- ***b.*** ***Rule two:*** If the process being modeled is separated into multiple stages, then additional hidden layer(s) may be required. If the process is not separable into stages, then additional layers may simply enable memorization and not a true general solution
- ***c.*** ***Rule three:*** The amount of training data available sets an upper bound for the number of processing element in the hidden layers. To calculate this upper bound, use the number of input output pair examples in the training set and divide that number by the total number of input and output processing elements in the network. Then divide that result again by a scaling factor between five and ten. Larger scaling factors are used for relatively noisy data. Extremely noisy data may require a factor of twenty or even fifty, while very clean input data with an exact relationship to the output might drop the factor to around two. It is important that the hidden layers have few processing elements. Too, many artificial neurons and the training set will be memorized. When this happens, then no generalization of the data trends will occur, making the network useless on new data sets

D. Telephone Switching System:

During the early years , the role of the telephone industry was to provide a worldwide network for speech communication. The first communication switching facilities were manually – operated switchboards. Numerous types of electromechanical system transformed this is the current variety of stored programme controlled electronic switching systems An example of this is the Alcartel 1000 S12 installed at the Nigerian Telecommunications PLC (NITEL), Iganmode Iyana Iyesi Otta secondary Exchange, Ogun state. It is principally used for the switched telephone network, providing access for both analogue and digital scribers.

Despite being very complex, telephone –switching service is comprised of a few basic network components, which are:

- ***a.*** ***User Equipment:*** telephones, computers and all other devices that provide a means of accessing the network.
- ***b.*** *Access Network:* users are connected to the main network by ire lives or radio links.
- ***c.*** ***Man Network:*** copper wire, microwave radio and optical fiber calls connecting all the nodes of the global network.
- ***d.*** ***Transmission Equipment:*** The means of which huge volumes of information are carried over the network.
- ***e.*** ***Switching Equipment:*** The hierarchy of local, national

E. Testing Modules:

The DSN has many modules with different function but the trunk testing module is used to perform tests for fault finding and checking the quality of service provided. It provides facilities for automatic or manual testing on about 30 trunks concurrently.

The test could be different forms:

a. To test a designated outgoing trunk
b. To test an analogue equipment
c. To test all trunks on a route.

F. *The Back propagation network:*

The input type in a

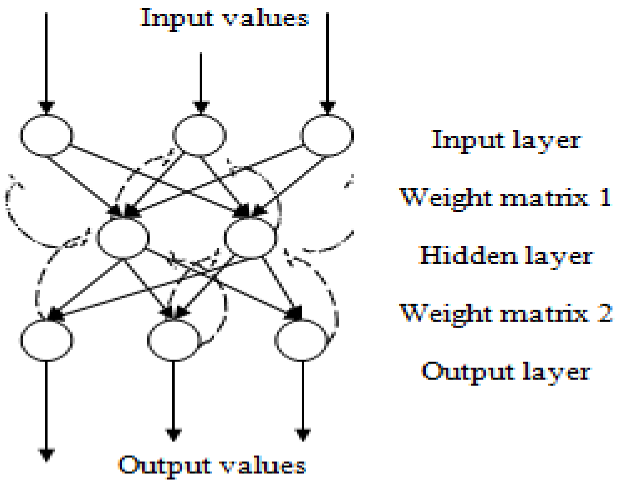


Figure.4 Back propagation Network

Back propagation net must be in a binary format and the network is able to deal with speech analysis. The Back propagation Network is trained using supervised learning which means the input and output need to be given to the network.[5] When training commences the network will look for patterns between different examples of inputs and outputs. So if the network is trained correctly you can simulate/test it and give it new unseen inputs. The network should then be able to generalise and say what it thinks the output will be for that input.

II. DATA COLLECTION

The test equipment employed at Nigeria Telecommunication (NITEL) Plc is Manufacture by Alcatel .It consist of centralized computer(Master Station)which control Remote Test unit(RTU) located within exchanges Each RTU connect to customer line via the exchange Test Access facility (TAF) .Once connection is establish, it is possible to performed parametric testing on the selected lines. The tests are performed on a variety of Dc and Ac measurements on individual lines.

The fixed tests consist of:-

- ***a.*** ***VAT:*** DC Voltage between the "tip" wire and ground
- ***b.*** ***VBT:*** DC Voltages between the "ring' wire and ground
- ***c.*** AC: AC Voltages
- ***d.*** ***RAB:*** Resistance between the "tip" and "ring' wires
- ***e.*** ***RBA:*** Resistance between the "ring" and "tip" wires
- ***f.*** ***RAT:*** Resistance between the "tip" wire and ground
- ***g.*** ***RBT:*** Resistance the "ring" wire and ground
- ***h.*** LED
- ***i.*** ***Input Volt:*** amount of current supplied into the exchange

A typical time for a routine test is approximately 9(nine) seconds for a Digital Exchange and 15 seconds for an Analogue Exchange[6]. It is possible to program the remote testing units to automatically line test for a given area store the results.

Table.3. Data Volume boundaries

Parameter	Minimum (Volts)	Maximum(Volts)
VAT	0	100
VBT	0	100
AC	0	100
RAB	0	100
RBA	0	100
RAT	0	100
RBT	0	100
LED	0	10
INPUT VOLT	48	53

A. *The Proble:*

Earlier, we discussed that the faults in most telecommunication lines are caused by discontinuity. This is when the signal sent from one end is not received at the other end due to one reason or the other. This can be traced on the Analog switch by testing each of the eight cables connecting the two ends.

When all the cables are tested, certain readings within the ranges specified in Table.3.1 are expected. Under normal conductions, the switch operates at 48-52volts. A reduction below 48v or an excess of 52v will affect the performance of the switch. The back propagation algorithm is used to train the network towards the 48v-52v boundaries. So, any reading not conforming to the required standard signifies a potential hazard.

B. *Data Collection Methods for Fault Detection:*

a. Reactive:

Faults are only acted upon when a customer reports a line problem to an operator. The operator will perfumed a demand test on a customer's line to identify any possible problems. After a problem has been identified, an electronic fault report is generated and stored in an electronic queuing system once the report makes its way to the head of the queue, it is then transferred to a maintenance engineer through their works Manager. A works Manager is a portable electronic device that connects to the Switched Network and allows an engineer to download information collected by the fault operator is then available to the engineer who will finally locate and rectify any problems.

b. Proactive :

Currents proactive methods employ a Dp scoring algorithm (Health Score). To obtain a Health Score, parametric values are required from the LTS data. A Health Score is calculated for each Dp within a given Exchange area. The highest DP Health Score are analyzed by an expert in the field to attempt to locate potential faulty areas. The analysis process consists of retrieving secondary network maps and identifying possible access sites for an engineer to investigate. After the expert is satisfied with the analysis and has located an access point for an engineer to investigate, a report is compiled and placed on a queuing system similar to the reactive method. A proactive engineer will then download the information to their works Manager devices and attempt to rectify the problem.

Table.4. Testing data

VAT	VBT	AC	RAB	RBA	RAT	RBT	LED	INPUT VOLT
103.5000	105.5000	95.5000	0	80.0000	100.0000	9.5000	1.5000	52.7
105.4000	98.1000	75.1000	115.1000	65.1000	100.0000	45.5000	11.5000	47.5
100.0000	45.9000	23.6000	83.1000	79.7000	96.9000	10.0000	0	50
75.9000	115.5000	99.0500	85.5000	100.0000	90.5000	49.5000	4.5000	53
99.9000	98.7000	102.5000	60.5000	45.7000	100.5000	15.5000	8.7500	46.5
99.5000	110.0000	80.0000	75.5000	105.0000	100.0000	7.5000	9.5000	55
99.9000	100.0000	114.1000	79.8000	83.2000	96.9000	52.1000	0.9000	52
58.1000	45.1000	63.0000	100.1000	121.0000	111.1000	55.0000	11.9000	55
33.1000	49.0000	71.2000	109.0000	88.0000	16.0000	50.0000	8.8000	53
18.5000	81.0000	16.9000	107.0000	10.5000	60.0000	48.0000	9.9000	51
33.3000	62.6000	76.5000	88.0000	68.1000	39.9000	67.1000	0.5000	49.5
36.5000	100.0000	109.1000	32.3000	77.3000	50.7000	40.3000	16.0000	52
13.0600	23.8000	60.0000	80.0000	115.0000	30.0000	46.0000	11.0000	49
77.8000	46.2000	89.0000	99.0000	10.0000	100.0000	62.0000	9.8000	55
17.1000	66.6000	45.0000	90.0000	72.1000	34.1000	33.0000	11.1000	47.9
92.9000	31.0000	115.0000	79.9000	33.1000	61.0000	70.0000	10.5000	56
98.1000	0	16.2000	49.3000	23.8000	79.7000	44.2000	13.9000	60.1
100.0000	100.0000	77.7000	44.2000	19.4000	12.3000	47.1000	3.3000	55.9
40.0000	100.0000	9.8000	115.0000	16.8000	71.0000	15.5000	3.2000	49
44.4000	80.1000	26.0000	3.6000	105.0000	50.0000	50.0000	3.3000	52
0.9500	80.0000	73.6000	33.6000	33.9000	102.0000	63.6000	42.8000	40.2
15.2000	38.5000	100.0300	50.1000	5.5000	20.0000	40.0000	80.0000	63.5
101.0000	70.0000	90.0000	111.0000	28.0000	12.0000	59.0000	2.8000	58
75.0000	7.0000	49.0000	110.0000	50.0000	18.3000	6.6000	4.0000	53
75.4000	106.2000	90.7000	13.8000	31.0000	50.0000	12.2000	2.2000	51
100.0000	40.0000	89.9000	8.1000	19.9000	75.4000	51.1000	5.5000	56
66.3000	23.7000	17.8000	30.0000	44.9000	54.6000	64.3000	7.0000	49.4
87.3000	94.4000	40.2000	3.6710	36.6000	73.0000	38.1000	3.8000	50
127.3000	100.0000	113.5000	0.6000	21.9000	99.3000	54.7000	0.1000	66.7
100.1000	99.0000	72.4000	77.1000	30.1000	17.2000	33.1000	6.2300	51.9
90.0000	85.0000	63.0000	77.0000	56.0000	100.0000	40.0000	8.0000	50
99.1000	73.6000	44.8000	14.3000	88.8000	93.7000	35.1000	7.0000	51
104.5000	98.1000	59.5000	100.0000	60.5000	105.0000	42.0000	2.5000	48.9
96.5000	100.0000	112.0000	80.5000	75.1000	98.4000	52.8000	9.8000	53.5
113.4000	107.6950	100.1000	88.9000	115.5000	75.2000	11.3000	2.2000	53
105.4000	0.5000	0	115.1000	66.6000	100.0000	57.0000	13.9000	46.1
100.0000	113.0000	120.9000	71.3000	66.9000	42.9000	49.5000	6.3000	51.9
0.1000	45.2000	33.9000	21.3000	100.1000	112.9000	50.9000	5.1000	47
110.0000	104.3000	99.5000	102.7000	75.2000	98.9000	6.2000	8.7000	47.6
100.5000	75.1000	80.5000	0	45.5000	115.5000	33.3000	0.5000	48

c. *Artificial Intelligent based System:*

The system being developed will utilized data collected from Remote Test Unit housed within exchanges The Al system will employ a structured architecture based on the network model. An effective model is necessary so the application of AI can be utilized to analyze the data in order to derive the information and knowledge necessary for a functional system.[7]

The model hierarchy is structured as follows

a) Exchange
b) PCP
c) Segment
d) Distribution Point
e) Telephone Number
f) LTS: Line testing system

A single exchange can accommodate tens of thousands of lines. Therefore the overall formulation of the model has a major significance on the operating speed of the system. Line monitoring on a regular basis is essential to increase the system efficiency.

d. *Feed- forward back propagation network training using MATLAB R12:*

We used data collection from an analog telephone switch to develop a model that will detect potential faults in the machine, when it encounters new set of data. With measurements of all the parameters that are required for optimal performance of the switch. The first step is to load the data into the workspace and perform a principal component analysis.[9]

Basically, eight input parameters were tested for. Thus, in the model, I have eight inputs and one desired output referred to as the target.

There are two layers in the model and structure.

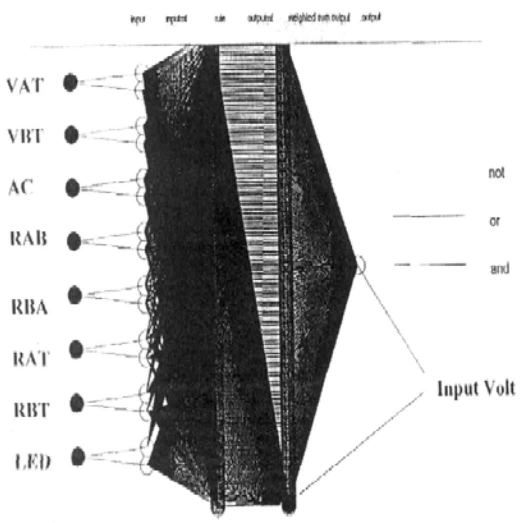


Figure.3 The structure of the Network in training

The structure depicted in figure 3 represents input variables, the bias points to the output variable, rule and weighted sum output.

Input variables: A layer of neuron receiving inputs directly from outside the network.

Weights: Weight functions apply weights to an input to get weighted inputs as specified by a particular function or connection straight.

The bias: A neuron parameter that is summed with the neuron's weighted inputs and passed through the neuron's transfer function to generate the neuron's output.

Rule: Methods of deriving the next changes that might be made in a network.

Weighted sum output: The result of applying a weight to a layer's output, whether it is a network output of another layer.

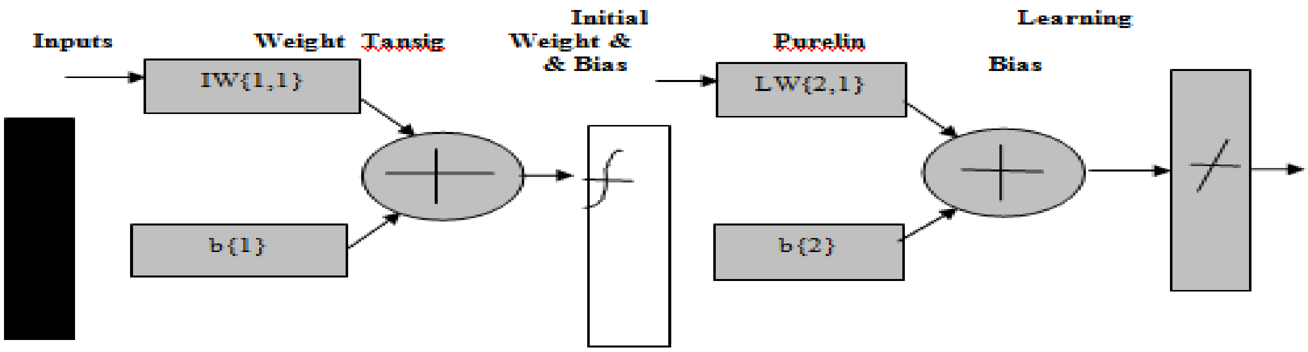


Figure.5The Model of the Network in training

The model in figure 5 depicts how the feed forward back propagation network created. The inputs are the data collected from the LST of the switch, initial weight and bias, which are the weights and bias state of the network before the training commenced. Tansig also known as Tan-Sigmoid Transfer Function generates outputs between –1 and +1 as the neuron's net inpxut goes from negative to positive infinity. The learning weight and bias are the weights and the bias state of values of the network after the tansig output is generated. Purelin is the final point output result generated from the learning weight and bias. It also generates outputs between –1 ansd+1.[10]

The components of the network model are linked together by the following syntax

Syntax

[Net, tr] = trainbr (net, Pd, T1, Ai, Q, TS, VV)

Info=trainbr (code)

C. Description:

Trainbr is a network training that updates the weight and bias values according to Levenberg-Marquardt optimization. It minimizes a combination of squared errors and weights, and the determines the correct combination so as to produce a network, which generalized well. The process is called Bayesian regularization.

Trainbr (net, pd, T1, TS, VV, TV) takes these inputs,

Net-Neural network
Pd-Delayed input vectors.
T1-Layer target vectors
Ai-Initial input delay conditions.
Q-Batch size
TS-Time steps
VV-Either empty matrix[] or structure of validation vectors

And returns,

Net- Trained network
TR-Training record of various values over each epoch:
TR.epoch-Epoch number.
TR.perf-Training performance
TR.perf-Training performance
TR.tperf-Test performance.
TR.mu-Adaptive mu value

The newff function provides the transfer function of the hidden and output layers.

With respect to this work, the hidden layer has 5 neurons, uses the tansigmoidal transfer function while the output layer has 1 neuron and uses the purelin transfer function.

D. Initializing Weights (INIT):

Before training a feed forward network, the weight and biases like synaptic junctions in the brain must be initialized. The initial weights and biases are created with the command init. This function takes a network object as input and returns a network object with all weights and biases initialized. The syntax for initialization:

Net=init(net);

a. Training the network:

There are two training styles under back propagation. In incremental training the weights and biases of the network are updated each time an input is presented to the network. In batch training the weight and biases are only updated after all of the inputs have been presented. The Levenberg-Marquardt algorithm is the training algorithm used. Its training function is trainbr. It ensures a faster convergence though it requires a lot of memory.

Training occurs according to the TRAINBR"s training parameters

Shown here with their default values:

Net.trainparam.shoow=50;
Net.trainparam.1r=0.05;
Net.trainparam.epochs=100;
Net.trainparam.goal=25;
Net=train (net, p, t);
A=sim (net, p);

The performance function employed is the mean square error (mse), which is set to learning function used, is **learngd**, which is invoked by setting the learning parameter (1r). Hence based on table 3.1, if the numerical representation of the telephone lines on a particular switch, for instance, is given as 103.5 105.5 95.5 0 80 100 9.5 1.5

with an input voltage of 52.7volts, this indicates that the telephone line would give a good performance result.

The complete set of the training inputs and outputs for the network can be found on table3 and table 4

III. RESULT ANALYSIS AND DISCUSSION

[20,1],{'tansig','purelin'},'trainbr');
net.trainparam.show=10;
net.trainparam.epochs=50;
randn ('seed', 192736547);
net=init(net);net=train (net,p,t);a=sim (net,p)

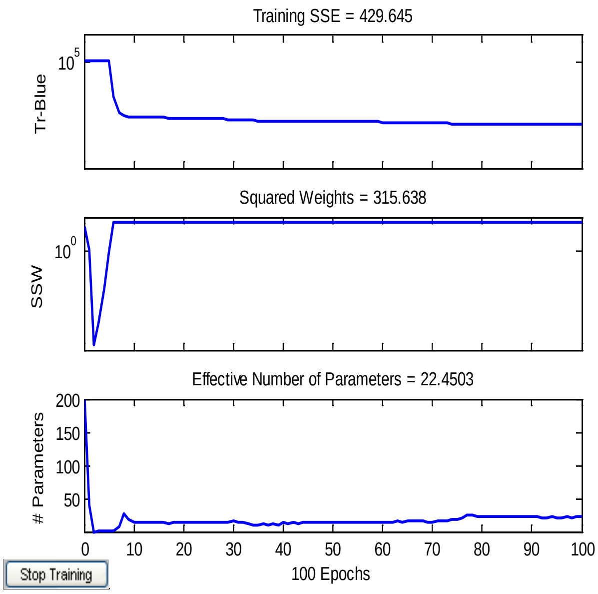


Figure.4 Graphical Representation of the trainbr result

When using trainbr, it is important to let the algorithm run until the effective number of parameters has converged. The training may stop with the message "Maximum MU reached". This is typical, and is a good indication that the algorithm has truly converged. You can also tell that the algorithm has converged if the sum squared weights (SSW) are relatively constant over several iterations. When this occurs you may want to push the "Stop Training" button in the training window.

A. *Post-Training Analysis (POSTREG):*

The performance of a trained network can measured to some extent by the errors on the training, validation and test sets, but it is often useful to investigate the network response in more detail. One option is to perform a regression analysis between the network response and the corresponding targets.[11] The routine postreg is designed to perform this analysis. The following commands illustrate how we can perform a regression analysis on the network, which we previously trained in the early stopping section.

A=sin (net,p);
[m, b, r]=postreg (a.t)
m=0.5651
b=22.4710
r=0.7871

Here we pass the network output and the corresponding targets to postreg. It returns three parameters. The first two, m and b, correspond to the slope and the y-intercept of the best linear regression relating targets to network outputs If we had a perfect fit (outputs exactly equal to targets), the slope would be 1, and the y-intercept would be 0. In this example we can see that the numbers are very close. The third variable returned by postreg is the **correlation coefficient** (R-value) between the outputs and targets. It is a measure of how well the variation in the output is explained by the targets. If this number is equal to 1, then there is perfect correlation between targets and outputs. In the result we have for this project here the number is very close to 1, which indicates a good fit. [12]

Below is a graphical summary derived from the postreg carried out for this training:

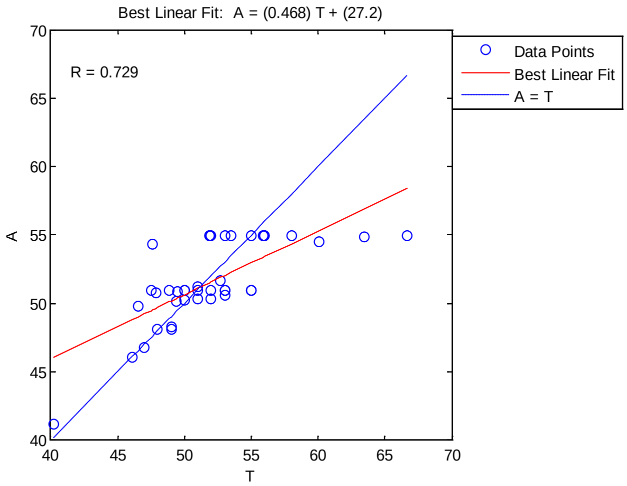
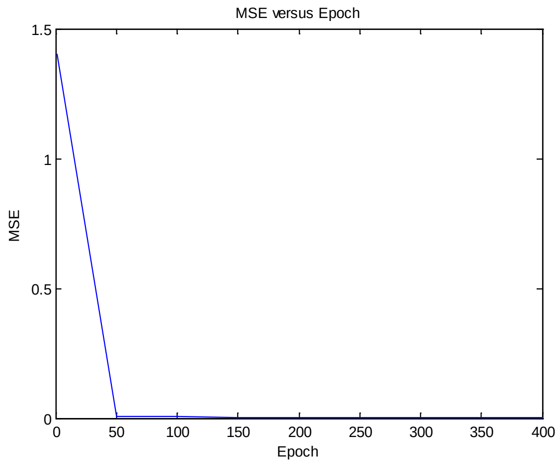


Figure.5 POSTREG of the trained network with correlation coefficient R

B. *Test Result Analysis for Matlab:*

When the training process was run, files were automatically created (using the tagged cross- sections) and loaded into the active matlab network. Each training process displays a dialog box user definable options corresponding to the type of training process being run. In this project, I trained the network one time. The dialog box was to use cross validation and train for 100 epochs.



Performance	***Value***
Correlation Coefficient R	0.729
Maximum MSE	1.2765
Minimum MSE	0.0065
Least Optimum Epoch	125

Figure.4.3 Mean Square Error (MSE) of epochs

The plot shows the learning curves for both the training and cross validation data sets. The table gives the epoch at which the training and cross validation means-squared errors (MSEs) were minimum, the values MSEs at the last epoch. The training MSE and cross validation MSE were collected for the epoch within the worksheet. From examining the learning curves, you can see that the MLP seems to have done a pretty good job of learning the telephone line data. To verify this conclusion, we need to run a testing set through the trained neural network model.

All training processes automatically save the weights at the minimum cross validation error (when cross validation is used) or at the minimum training error (when cross validation is used). These saved" best weights" was used to test the validity of the neural network model.

Table.4.2 Test Report

A	B	C	D	E	F	G	H	I
				IOUTPUT				
113.4	107.695	100.1	88.9	115.5	75.2	11.3	2.2	53
				50.2931595				
105.4	0.5	0	115.5	66.6	100	57	13.9	46.1
				50.6692047				
100	113	120.9	71.3	66.9	42.9	49.5	6.3	51.9
				51.9135666				
0.1	45.2	33.9	21.3	100.1	112.9	50.9	15.1	47
				50.1285515				
110	104.3	99.5	102.7	75.2	98.9	6.2	8.7	47.6
				51.8463783				
100.5	75.1	80.5	0	45.5	115.5	33.3	0.5	48
				55.8083267				

For the Test Report, I examined the various performance measures by comparing the desired output (MEDV Desired), and the actual network output (MEDV Output). I notice that in most cases, the output of the neural network model comes very close to the desired value**.**

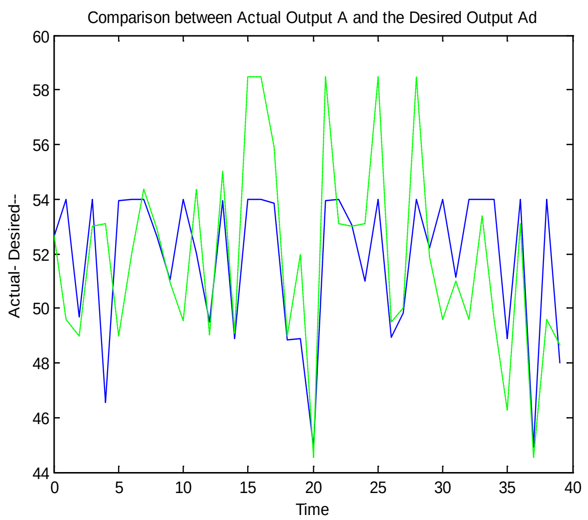
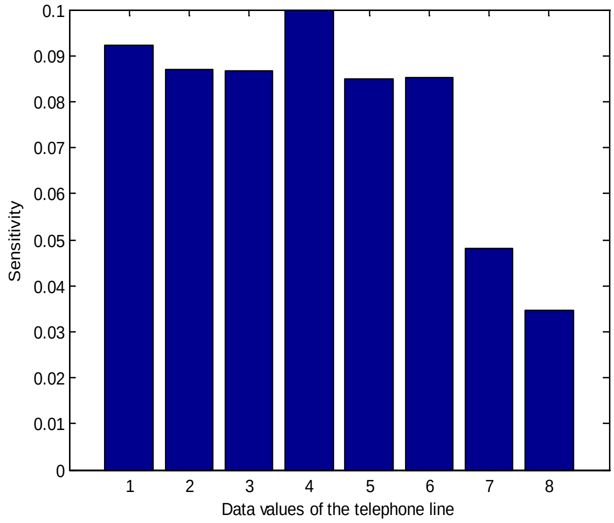


Figure.6 Evaluation of the Actual Network Output and Desired Output

C. Sensitivity Analysis:

We performed sensitivity analysis on the trained network to eliminate irrelevant inputs. The elimination of irrelevant inputs reduces data collection cost and can sometimes improve a network's performance. Furthermore, sensitivity analysis can give insights into the underlying between the inputs and outputs



Data Input	***Sensitivity Value***
VAT(1)	0.0922
VBT(2)	0.0869
AC(3)	0.0866
RAB(4)	0.1000
RBA(5)	0.0848
RAT(6)	0.0853
RBT(7)	0.0480
LED(8)	0.0347

Figure..6 Sensitivity of data inputs about the mean

Fig 5 shows Sensitivity about the Mean" testing process was used to analyze the trained network. It provides insight into what the network has actually learned in additions to exposing irrelevant inputs[12]

The Back propagation architecture, which picks on the feed forward sweep output error and makes it back sweep input and finally resulting into the desired output. This has helped to show that trial and error era in systems and programs do not apply in Neural Network. Overtime, the ANN will have the relationships between the data and the fault types that occur. Output from the ANN will then give an indication of the like occurrence of the fault, allowing the engineers to inspect a possible fault plant before the fault actually occurs.

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