Fault Location Estimator Design for Power Distribution System Using Artificial Neural Network

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Abstract
Fault location in distribution system is critical issue to increase the availability of power supply by reducing the time of interruption for maintenance in electric utility companies. Fault location estimator for power distribution system using artificial neural network is developed for line to ground, line to line, line to line to ground and three phases to ground faults in distribution system. To develop this estimator is one of rural radial power distribution feeder in Ethiopia, south west reign, Aba substation Tarcha line feeder is used as a test feeder. This feeder is simulated using ETAP software to generate data for different fault condition, with different fault resistance and loading conditions, which is the fault phase voltage and current. The generated data is preprocessed and put as an input for neural network to be trained. MATLAB R2016a neural network toolbox to train ANN and programming toolbox is used to develop graphic user interface for fault estimator. The feed forward multi-layer network topologies of neural network with improved back propagation, Liebenberg Marquardt learning algorithm is used to train the network. After the network is trained the mean square error performance, regression plot and error histogram analysis was made and found to have an excellent performance with regression coefficient 0.99929 , validation performance of 0.000102 and error histogram range 0.015 to 0.019. In this thesis for practical implementation the fault records at the test feeder is handled by intelligent electronic device (IED) installed at the substation feeders. The fault record of IED can be read by PCM600 tool using laptop or manually using IEDs human machine interface, this fault recorded data feed to the graphic user interface to estimate the fault location as well as the fault type. Finally it is found that artificial neural networks are one of the alternate options in fault estimator design for distribution system where sufficient distribution network data are available with narrow fault location distance range from the substation. This has benefits in assisting for maintenance plan, saving efforts in fault location finding and economic benefits by reducing interruption time.
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1. INTRODUCTION

The need for electricity is increasing in the world increasing and its expansion and installation is also increasing to reach each customer in both rural and urban. Through the installation of distribution lines, most of the customers in developing countries are getting electric access. But he access is not reliable due to the different causes, due to distribution system faults. These faults cannot be completely avoided due to natural reasons which are way beyond the control of mankind. In three-phase systems, a fault may involve one or more phases and ground, or may occur only between phases. The prospective short circuit current of a fault can be calculated for power systems. In power systems, protective devices detect fault conditions and operate circuit breakers and other devices to limit the loss of service due to a failure. Power distribution lines and transmission lines are the main link in power system to address the generated power to the customers. Fault occurs due to failure of insulation of the distribution system, bridging of energized phase conductors by objects, accidents etc. These events affect the value of the voltage and current on the distribution system and sometimes the entire power system. Electric power systems will always be exposed to the failure of their components. Fault location on power lines enables the technicians to pinpoint the location of a fault on power lines following a disturbance. If a fault location cannot be identified quickly and this causes prolonged line outage during a period of peak load, severe economic losses may occur and reliability of service may be questioned. The growth in size and complexity of power systems has increased the impact of failure to locate a fault and therefore heightened the importance of fault location research studies, attracting widespread attention among researchers in recent years.
Electric power utility companies basically must provide customers both large and small with adequate electric power and deliver the system load requirement. Modern society demands that electrical energy should be as economical as possible with adequate degree of continuity and quality. Reliability can simply be described as the ability of the system to provide an adequate supply of electrical energy for the period of time intended under the operating conditions encountered. The term power system reliability broad it also includes all aspects of the ability to the system to satisfy the customer load requirements.

2. Problem statement

The average fault location time and repairing time in city area is almost a half of the same time value in the rural areas. Operative maintenance team can do the fault location by systematic network topology changing in city area, which is impossible in radial power lines in rural areas. Usually, city is situated in the center of consumer and rural areas are in different directions around the center, so operative maintenance team is always in the space center during the normal power system function. In electric utilities power distribution system frequently observed that the power interruptions due to different reasons, mainly due to different type of electrical faults. As reports indicate 70% of faults is single line to ground fault. Existing distribution system fault location is done by patrolling the distribution line from the substation or the switching station in urban. By opening sections and closing breakers step by step till circuit breaker trips and identified the faulty sections, which makes the electrical equipment stress and time taking to get faulty location, finally it may leads to failure to the distribution system equipment's. From researcher points of view rural electrification faulty new distribution line will take more time to get the fault location as there is no means to know the fault location apart from visual inspection of insulators crack and conductors short. The maintenance time to clear the faulted line and restore the system is most of the time is too long, as records in the substations daily log sheet in EEU indicate on average 2-3 hours per day required to restore the rural feeder line. It is too exhaustive work to find the fault location with branched and lengthy power distribution lines. Long time interruption has significant impact in the daily social and economic activities of the customers. The main problem is getting the actual fault location is the big task, apart from the customers call for their information for power interruption.

3. Literature review

3.1 Knowledge based fault location techniques

Uncertainty of line parameter affecting variables, such as length of cables and unknown fault resistance, coupled with the complex structure of distribution management systems tends to make fault location through impedance and travelling wave techniques inaccurate. As a result of this, knowledge-based technique for locating faults has receiving attention from researchers in the last few years. In general, the technique requires information such as substation and distribution switch status, line measurements, atmospheric conditions, and information provided by fault detection devices installed along the distribution feeders. This information is analyzed using artificial intelligence methods to locate a fault.

3.1.1 Artificial Neural Networks (ANN)

The modern view of neural networks began in the 1940s with the work that shows networks of artificial neurons could, in principle, compute any arithmetic or logical function. The research study focus on fault location detection, the EMTDC simulation software is used in PSCAD environment. The root mean square fault voltage and currents are used as an input. The sigmoid transfer function is used between the input and hidden layers and the pure linear transfer function are used between the hidden and output layers the trained network initiates and determines the final output of the network. The result obtained is accurate, but the scope of the work is limited to short length low voltage distribution lines which has laterals and determined by the flags on branch's and no sub laterals. The studies present on detecting, classifying and locating faults on electric power transmission lines based on artificial neural networks. The methods employed make use of the phase voltages and phase currents as inputs to the neural networks. Feed forward networks have been employed along with back propagation algorithm for each of the three phases in the fault location process. Analysis on neural networks with varying number of hidden layers and neurons per hidden layer has been provided to validate the choice of the neural networks in each step.

3.2 Artificial neuron versus biological neuron

ANNs is based on the work of human brain by making the right connections can be imitated using silicon and wires as living neurons and dendrites. The human brain is composed of 100 billion nerve cells called neurons connected by axon. Stimuli from external environment or inputs from sensory organs are accepted by dendrites and create impulses. ANNs are composed of multiple nodes, which imitate biological neurons of human brain. The neurons are connected by links (weights) and they interact with each other. The nodes can take input data and perform simple operations on the data. The result of these operations is passed to other neurons. The output at each node is called its activation or node value. Each link is associated with weight. ANNs are capable of learning, which takes place by altering weight values. The main similarities between biological and artificial neural networks its building blocks are simple even though artificial neurons are much simpler than biological neurons they are highly interconnected.

3.3 Advantages of neural network

The following is a list of some of the advantages of ANNs:

Adaptively: ANNs have the ability to adapt their synaptic weights to reflect changes

Robustness: ANN has demonstrated the ability to perform even when the inputs are degraded or noisy.
Flexibility: ANN can be applied to several types of problems.
Generalization: when ANN properly trained, it can provide the correct response to untrained input

3.4 Artificial neural network model

Neuron can be either single input or multiple input neurons. For the single input neuron scalar input, p, is multiplied by the scalar weight, w and the bias, b is added to form network output, n that goes into a transfer function ,f , which produces the scalar neuron output, a.

The output of the single input neuron is calculated as$:= wp + b$,

$$\boldsymbol{a} = (n) = (wp + b) \quad (3.1)$$

3.4.1 Topologies of neural network

3.4.1.1 Feed forward neural networks

In feed forward neural networks, information moves only in the forward direction from the input layers, via the hidden layers to the output layers. Examples of feed-forward networks include the single-layer perceptron, multilayer perceptron, radial basis function, learning vector quantization network, probabilistic neural network and etc.

3.4.2 Feedback neural networks

In feed-back neural networks there is bi-directional data flow and data are also propagated from the outputs to the input layers. Feedback, networks are dynamic systems. When a new input pattern is presented, the neuron outputs are computed. Because of the feedback paths, the inputs to each neuron are modified, which leads the network to enter a new state. Examples of feed-back networks include Elman networks, recurrent network, etc.

3.5 Training artificial neural network

Neural network can train, and then improve its performance through training. Training is a process by which some parameters of a neural network i.e. synaptic weights and bias are adapted through a continuous process of stimulation in the environment in which the network is embedded.

Learning types in neural network

(a) Supervised Learning

The learning algorithm would fall under this category if the desired output for the network is also provided with the input while training the network. An input and output pair it is possible to calculate an error based on its target output and actual output. It can then use that error to make corrections to the network by updating its weights.

(b) Unsupervised Learning

Unsupervised learning, the weights and biases are modified in response to network inputs only. There are no target outputs available. This is especially useful in such applications as vector quantization.

(c) Reinforcement Learning

Reinforcement learning is similar to supervised learning, except that, instead of being provided with the correct output for each network input, the algorithm is only given a grade. The grade is a measure of the network performance over some sequence of inputs.

4. Distribution Network Simulation and Artificial Neural Network Training Process

Experiments for data generation

Extensive simulations were done in order to obtain data for fault conditions under different loading condition and different fault positions with different fault resistance values. The steady state simulation covered is to analyze the power flow in different loading condition of the feeder. Fault conditions involving different fault types namely single line-to-ground (LG), line to line (LL), double line to ground (LLG) and three line to ground (3LG.) faults were simulated on the test feeder respectively

4.1 Feeder Modeling

The distribution test feeder is modeled using ETAP (Electrical transient analyzer program) power station 4.0. It consists of distribution substations, radial medium voltage overhead line that distributes power to six rural villages at each taping point. There is section switches, three main laterals as well as sub laterals on branch two as shown in figure 4-1. Detail configuration of the line is mentioned in appendix B. There are 29 nodes in the feeder; these nodes are used to make faults at different length of the line from the substation. ETAP software version 11.4 with power station environment of 4.0 is used for simulation of distribution feeder for data generation. This software use IEEE/ANSI standards to do analysis in the simulation of electrical systems.

4.2 Transformer Models

The voltage source used for the test feeder was an external grid provided in the ETAP library. Two transformer models were made use of in this feeder. The transformer is the substation power transformer. The power transformers at the substation are 25/12.5/12.5MVA, 132/33/15kV transformer and 25MVA 132/15kV transformer. The parameters used are shown in appendix A. The parameters for the configuration of the transformers model are shown in figures (a) and (b)

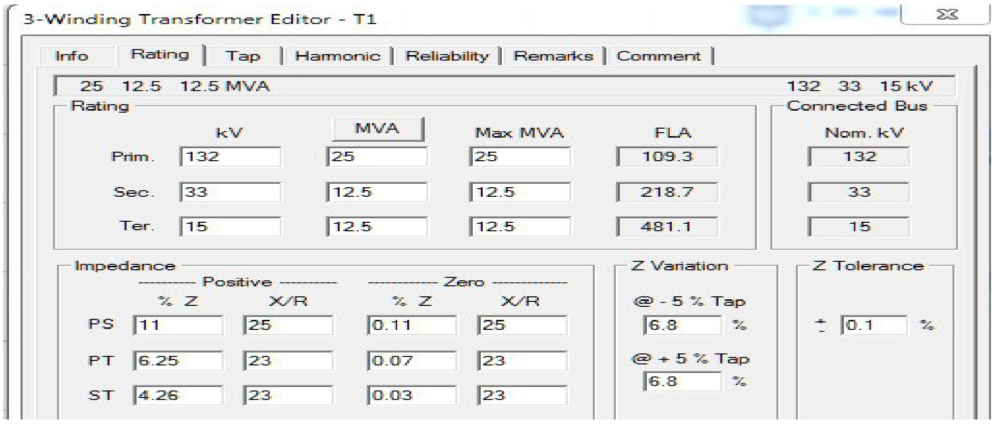


Figure 1show three winding transformer \

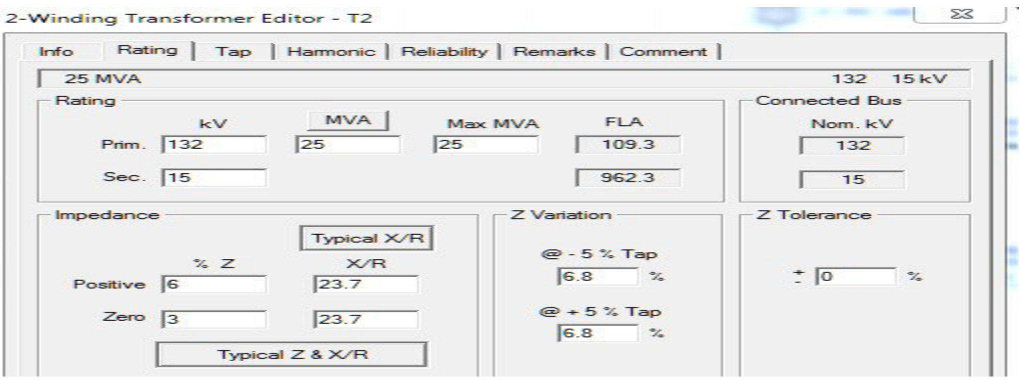


Figure 2 show two winding transformer parameter

4.2.3 Line Models

The geometric line modeling method is used in the ETAP power station software. The line configurations is three phase type horizontal with uniform spacing, the type of overhead conductor are used is aluminum with different sizes. The main feeder has a total length of 78.2km. The longest branch of feeder from the substation is 100.6km

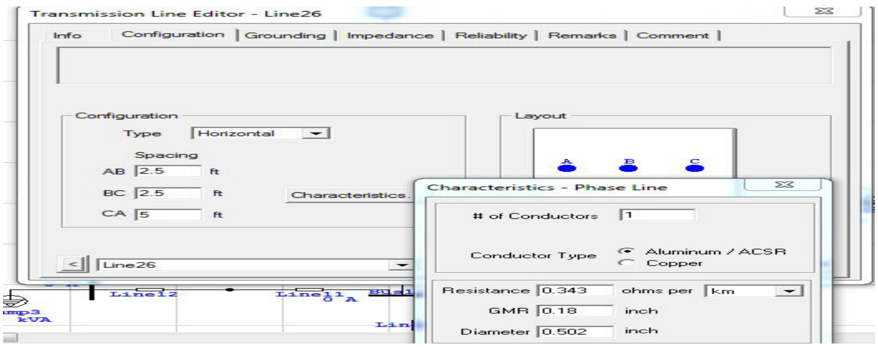


Figure 3 show configurations and modeling of test feeder in ETAP

Figure 4configurations and modeling of test feeder in ETAP

4.4 Load models

In the larger context of power systems, loads are usually modeled in an aggregated way rather than considering an individual appliance. Load may refer to an entire household, a city block, or all the customers within a certain region as mentioned in . In this thesis the village level block loads are considered. Loads on a distribution feeder can modeled as wye-connected or delta connected. The loads can be three-phase, two-phase, or single-phase with any degree of unbalance, and can be modeled as: constant real and reactive power (constant PQ), constant current, constant impedance, or any combination of the above. All models are initially defined by a complex power per phase and an assumed line-to-neutral voltage (wye load) or an assumed line-to-line voltage (delta load). The notation for the specified complex powers and voltages are as follows as described

4.5 Test feeder simulation and data generation

The following block diagram representation shows methodology followed to generate data that used as input to the neural network training.

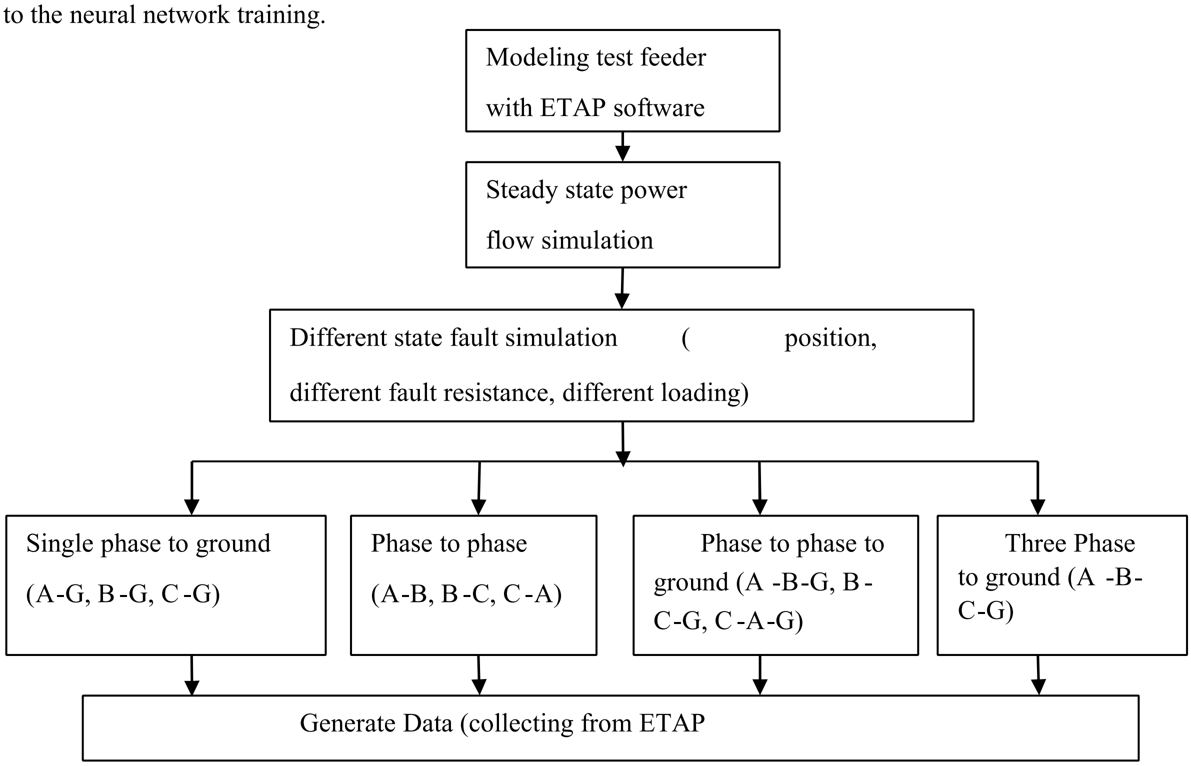


Table 1Summary of taps length, conductor types and distribution transformer quantity in the test feeder

Rural villages	MV line tap length	Conductor type and Area	Transformer rating used & Qty.	Circuit components
Abba	0.84km (from substation)	AAAC 95mm2	1x100kVA	DT and loads
			1 x50KVA	
Goriqqa	17.55km(from substation)	AAAC 95mm2	1	DT and loads
			1 x1250kVA	
Warra	26km(from substation)	AAAC 95mm2	1x100kVA	DT and loads
			2x50KVA	DT and loads
Lalla	35.10km(from substation)	AAC50mm2	1x100kVA	DT and loads
Hermana	41.30km(from substation)	AAC50mm2	1x100kVA	DT and loads
Tarecha maremiya	48km(from substation)	AAC50mm2	1x315kVA	DT and loads
Wsu tarcha campus	49.5km(from substation)	AAC 50mm2	2 x315 kVA	DT and loads
Tarecha city	55.63km(from substation)	AAAC 95mm2	8 x50kVA	DT and loads

Table 2 shows the plan for simulation of test feeder in fault condition

No.	Fault Condition.	Fault and System parameter
1.	Fault location (distance from substation(km))	3,6,9,12.. of the main feeder, and all the laterals and sub laterals (with three km increment, short length laterals by 1km increment)
2.	Fault types	single line-to-ground (LG), double line (LL), double line to ground (LLG), and three line to ground (3LG.)
3.	Fault resistance in ohm Ω	0, 0.5, 2.5, 5, 10, 25, and 50 for (LG)
4.	Loading	feeder loading of 0, 50%, and 100%

4.6 Artificial neural network training process

The neural network training process is an iterative procedure that begins by collecting data and preprocessing. At this stage, the data divided into training, validation and testing sets. Once the data is ready, we need to choose the appropriate network type and architecture. The training process mainly categorized into three steps: pre training, training and post training steps.

Pre training step

The steps that need to be performed before the network is trained can be grouped into three categories: selection of data, data preprocessing, and choice of network type and architecture.

(a) Selection of Data

Neural networks will only be as good as the data that is used to train it.

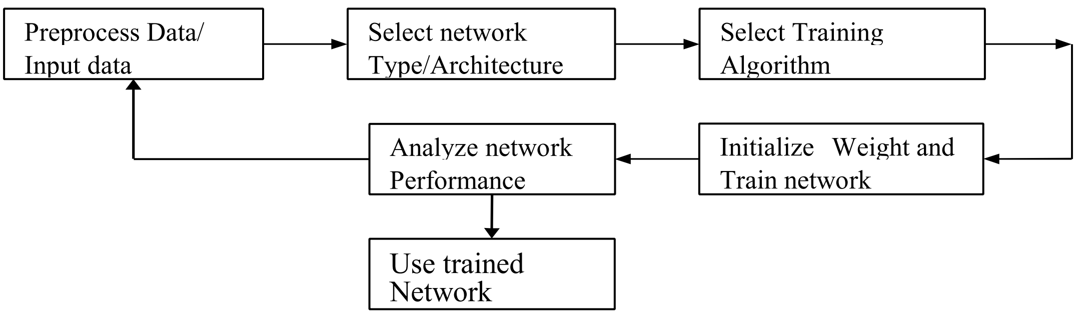


Figure 59 shows the block diagram for artificial neural network training process

(b) Data Preprocessing

The main purpose of the data preprocessing stage is to facilitate data for network training. It consists of such steps as normalization, nonlinear transformations, feature extraction, coding of discrete inputs or targets, handling of missing data and etc..

(c) Choice of Network Architecture

After exhaustive study the generally universal function approximates are selected. The radial basis network and the multilayer feed forward neural network are used. One of the improved back propagation learning algorithms, Levenberg Marquardt is used to train the network because of the most commonly used algorithm for neural network training.

4.6.1 Training the network

After the data has been prepared, and the network architecture has been selected, we are ready to train the network. Before training the network, we need to initialize the weights and biases.

4.6.2 ANN training for fault location

This section presents the fault location training process using the data of 2694 different type of fault simulation with different loading condition and different fault resistance values. This training process starts by preprocessing the data generated by the ETAP software. To make uniform the generated data with the actual intelligent electronic device (IED) fault reading values by dividing the simulated data to the corresponding voltage and current transformer ratios of the feeder line. Additionally to increase the efficiency of ANN in training both the input and output pair is normalized to the numbers between 1 and -1 by dividing both inputs and out puts to the maximum value. MATLAB R2016a neural network toolbox is used for training the neural network. In MATLAB, the implementation of neural networks is performed by means of matrix manipulation of the inputs, outputs, weights and biases vectors. Vectors from a training set are presented to the networks sequentially. The weights and bias of the network would be updated if the output of the network is different from the target dataset. The MATLAB neural network has the possibility to train the network either command line or graphic user methods. In this thesis graphic neural network training method is used for training the network for its simplicity in training process. In MATLAB software before training the data it randomly divided with 70% of data as training set, 15% validation set and 15% testing set. Training set used to compute gradients to determine the weight updates, validation sets used to check the trained network to be not to over fitting and testing sets used to test the trained network. The weights and biases are initialized by the MATLAB as default weights and the bias to random values between the input r The fault location estimator can be considered as function approximation problem. This problem can be solved by universal function approximation networks, like the radial basis and the multilayer feed forward network topology. The multilayer feed forward network topology can be trained using neural network fitting tool or customized neural network tool or using command line. The performance analysis of the trained neural network is based on their regression result, MSE, error histogram, and independent testing using a hold-out test dataset.

The well trained network can be used for further processing in fault location estimator design.

Network1 (6-21-4 ANN configuration)

This network is trained using the neural fitting tool with the *tansig* activation function between the input and the hidden layer and *purelin* between the hidden and output layer, with the 6 input neurons, 21 neurons in hidden layer and 4 neurons in output layer. Figure shows the overview of ANN training. The feed forward back propagation topology, two layer neural network is used. The Levenberg Marquardt variation back propagation learning rule is used. As there is no defined rule for the selection of number of neurons and layers in the hidden layer for back propagation algorithm, trial and error is made till well trained network is obtained.

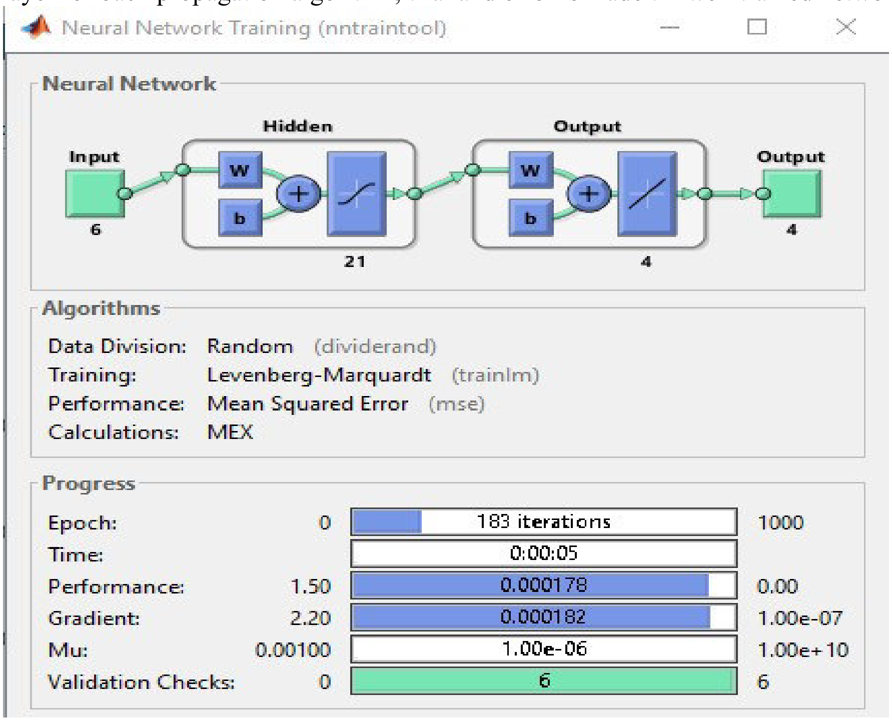


Figure 4-10 show overview of 6-21-4 neural network training process

During the training state of the network the gradient, the Marquardt adjustment parameter and the validation check is shown in figure below. As shown in the figure 4-10 the gradient value varies during training and finally 0.000182 at epoch 183. The validation check is made at different epochs and for continuous 6 validation checks made at epoch 177 to 183 and training stops. The training parameters during training are as follows: minimum gradient is 10^{-7}, performance goal set to 0 in order to achieve maximum possible training performance.

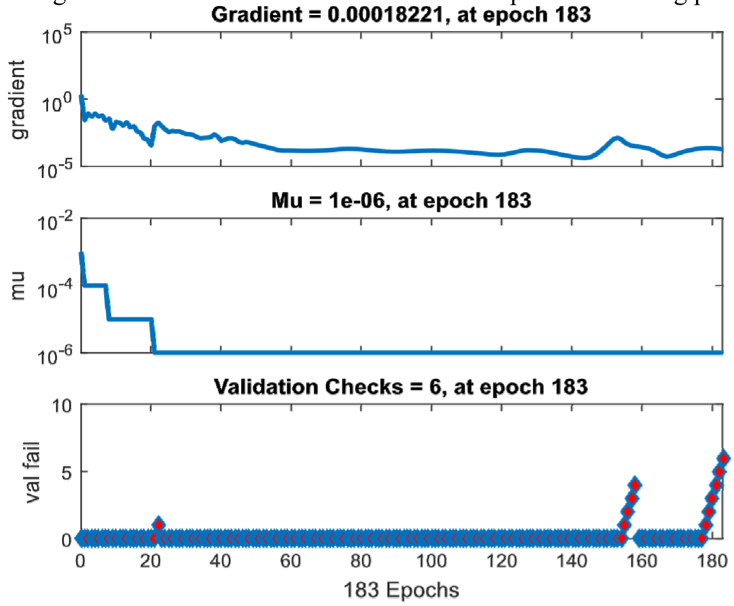
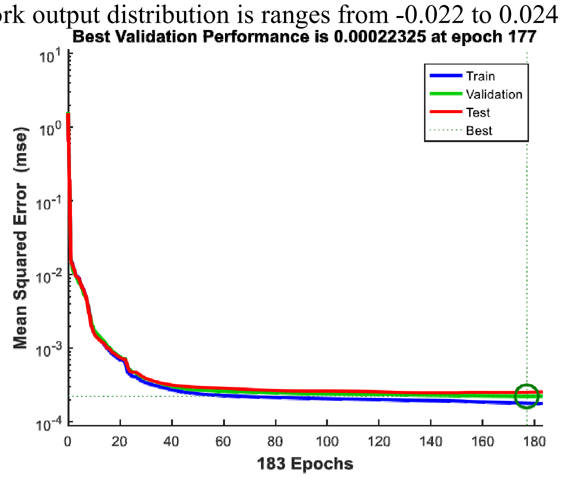


Figure 4-12 shows the training state of the 6-21-4 ANN configuration

The performance of the trained neural network was based on their regression result, MSE and error histogram values are shown in figure below. As shown in this figure the mean square error (MSE) of the validation data set at epoch 177 is 0.000222 and the error which is the difference between the target and network output distribution is ranges from -0.022 to 0.024 with most of the data concentrated near to zero.



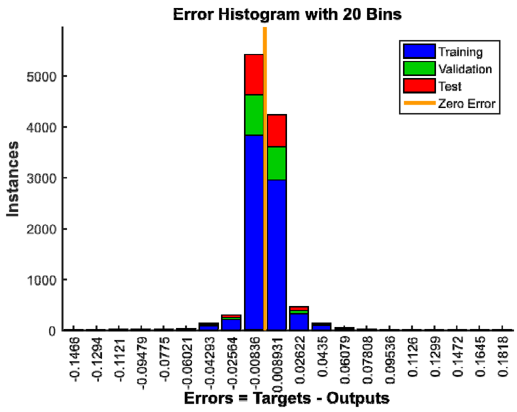


Figure show MSE performance and error histogram of 6-21-4 ANN configuration

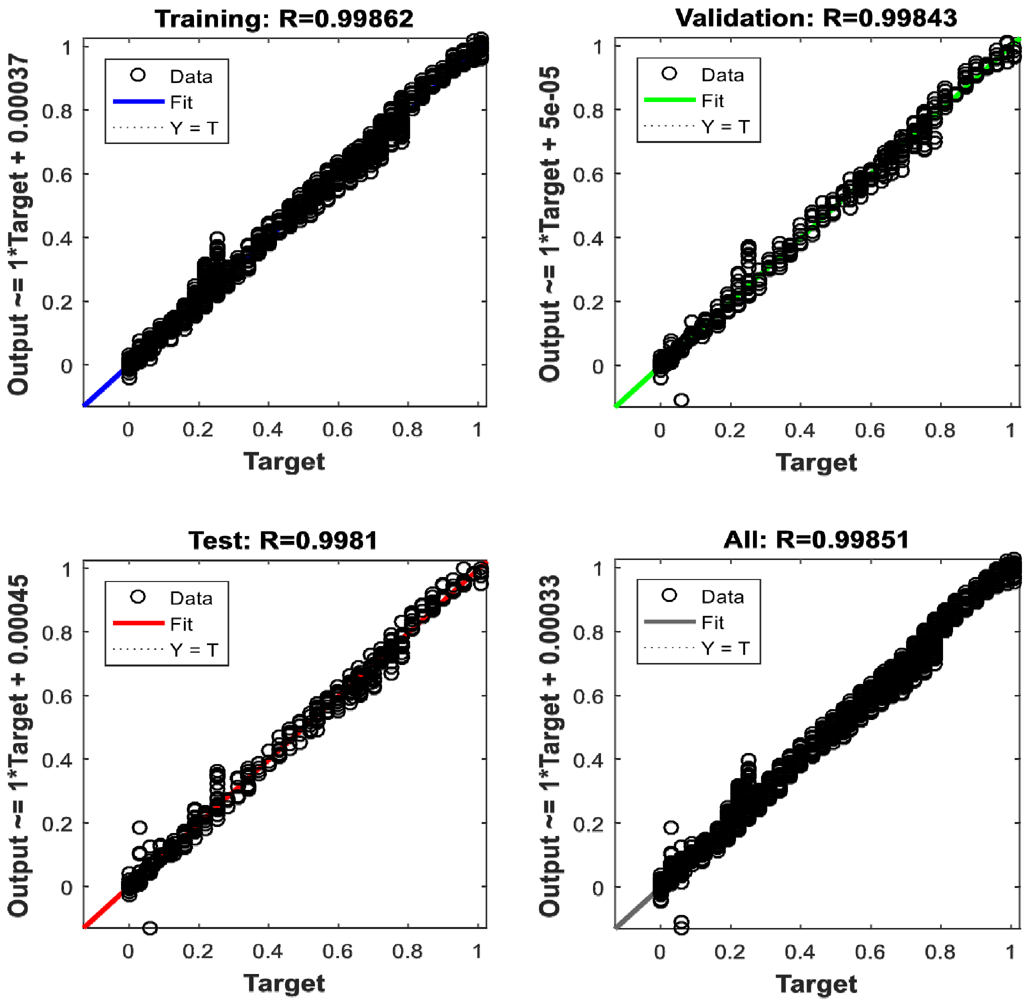


Figure 4-13 show the regression plot of 6-45-3 ANN configuration

Another performance measure of trained neural network is the regression plot of the trained network training set, validation set and testing set. The figure above shows the correlation of the trained network output and the target values of the train, test and validation as well as overall. The correlation coefficient (R) is a measure of how well the neural network's targets can track the variations in the outputs (0 being no correlation at all and 1 being complete correlation). The correlation coefficient in this case has been found to be 0.99851 which indicates good correlation.

Network2 (6-41-4 ANN configuration)

This network is trained using the neural fitting tool by increasing the neuron number in hidden layer, the *tansig* activation function between the input and the hidden layer and *purelin* between the hidden and output layer, with the 6 input neurons, 41 neurons in hidden layer and 4 neurons in output layer. Figure shows the overview of ANN training. the feed forward back propagation topology, two layer neural network is used. The Levenberg Marquardt variation back propagation learning rule is used. As there is no defined rule for the selection of number of neurons and layers in the hidden layer for back propagation algorithm, trial and error is made till well trained network is obtained.

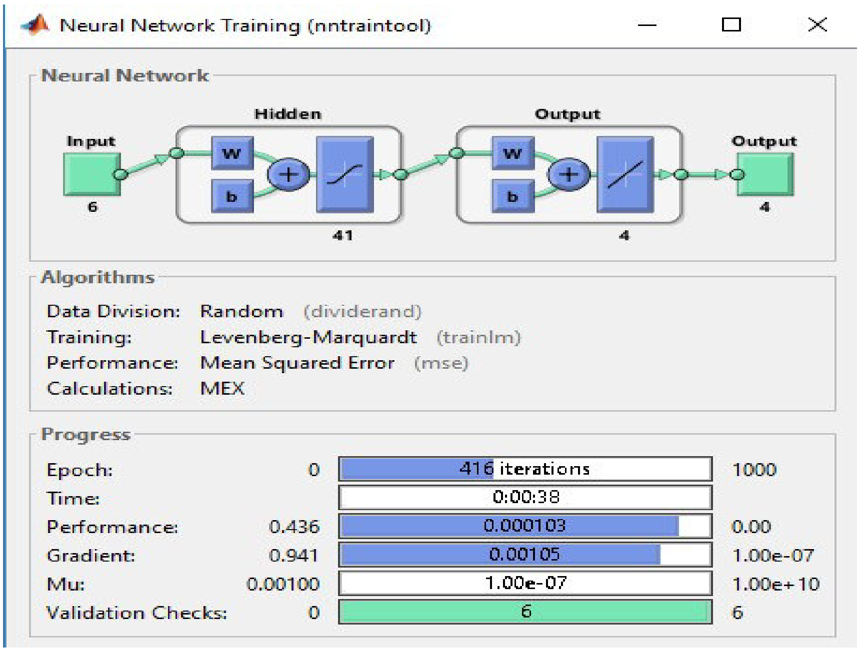


Figure show 4-14 overview of 6-41-4 neural network training process

The gradient, the Marquardt adjustment parameter and the validation check during training process is shown in figure below. As shown in the figure the gradient value varies during training and finally 0.0003555 at 301 epochs. The validation check is made at different epochs and for continuous 6 validation checks made at epoch 295 to 301 and training stops. The training parameters during training are as follows: minimum gradient is 10^{-7}, performance goal set to 0 in order to achieve maximum possible training performance.

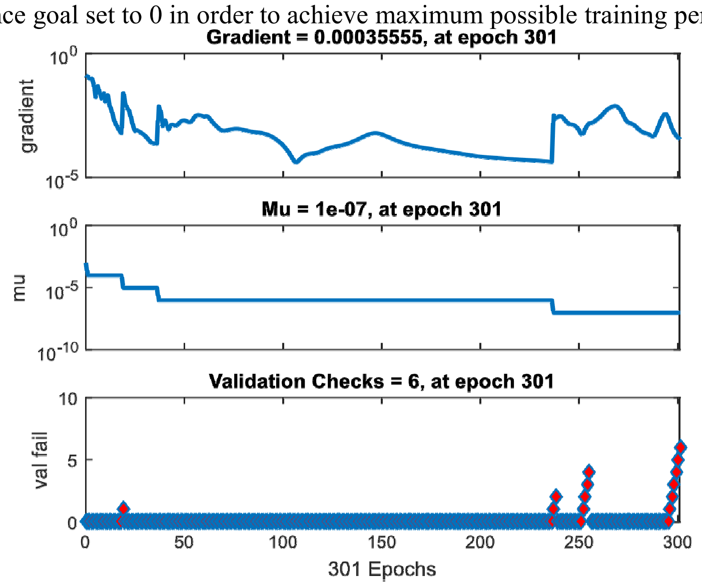


Figure 4-15 shows the training states of the 6-15-8-4 ANN configuration

The performance of the trained neural network was based on their regression result, MSE and error histogram values are shown in figure below. As shown in the figure the mean square error of the validation data set at epoch 295 is 0.000102 and the error which is the difference between the target and network output distribution is ranges from -0.015 to 0.019 with most of the data concentrated near to zero.

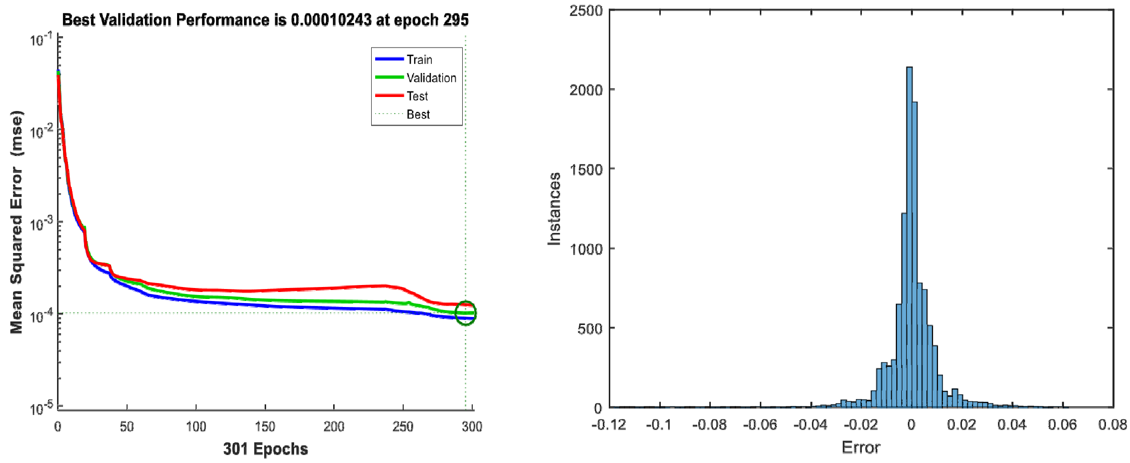


Figure 4-16 show MSE performance error and error histogram of 6-15-8-4 ANN configuration

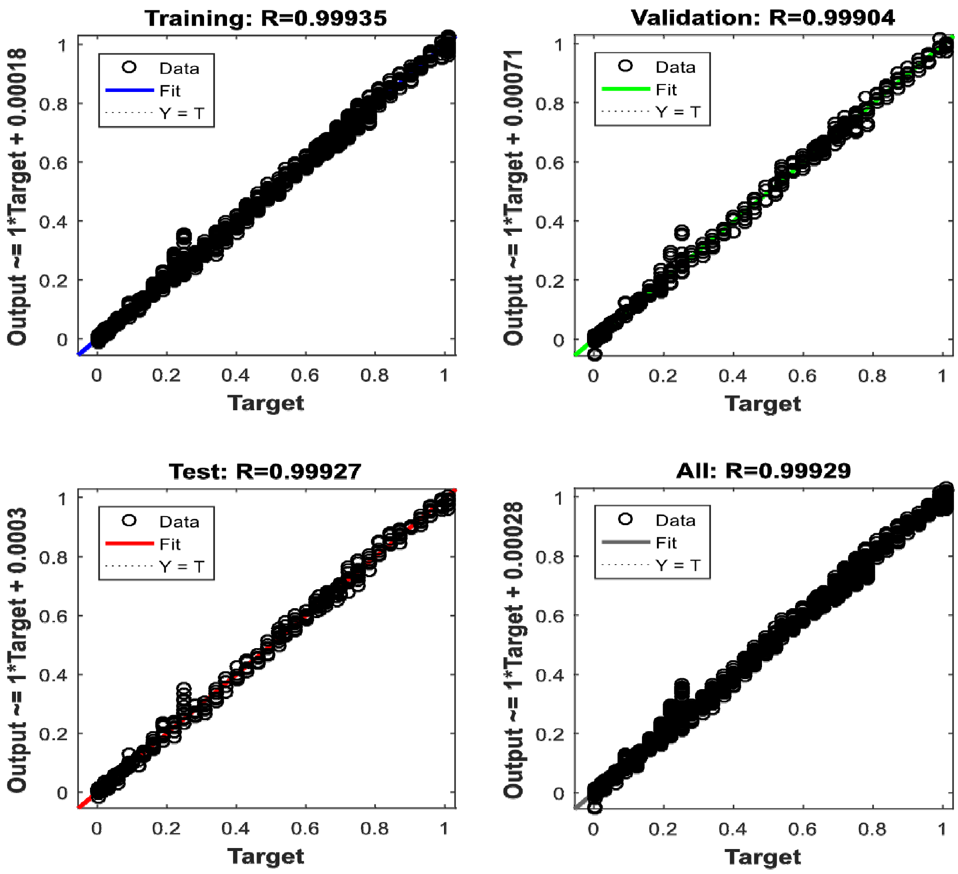


Figure 4-17 show the regression plot of 6-15-8-4 ANN configuration

Another performance measure of trained neural network is the regression plot of the trained network training set, validation set and testing set. The figure shows the correlation of the trained network output and the target values of the train, test and validation as well as overall of 6-15-8-4 ANN configuration. As shown in the figure the correlation of the overall trained network is 0.99929 which shows an excellent correlation.

Network4 (Radial basis network)

This network has two layers the *radbas* activation function and the *purelin* as shown in the figure below.

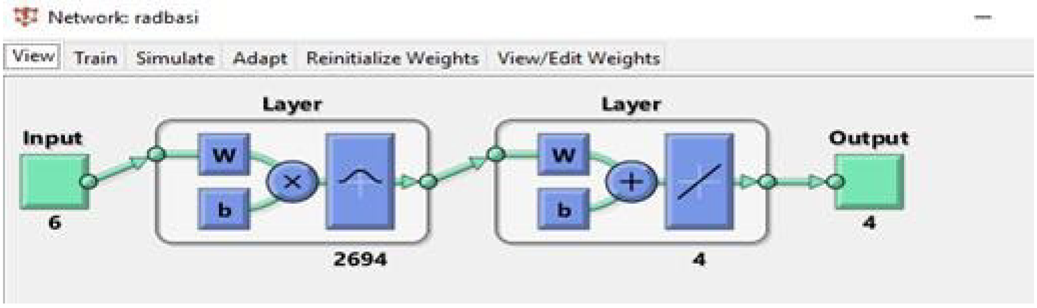


Figure 4-18 show Overview of radial basis neural network configuration

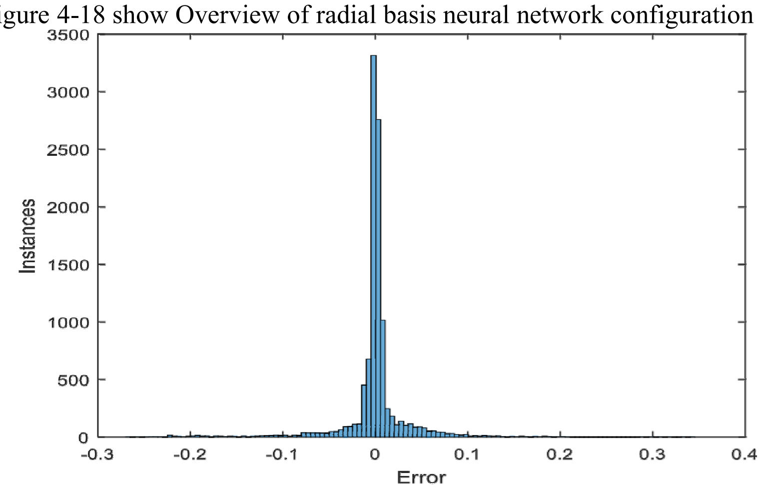


Figure 4-19 show the error distribution plot of the exact fit radial basis network

The radial basis function calculates the distance between the input and the initialized weight

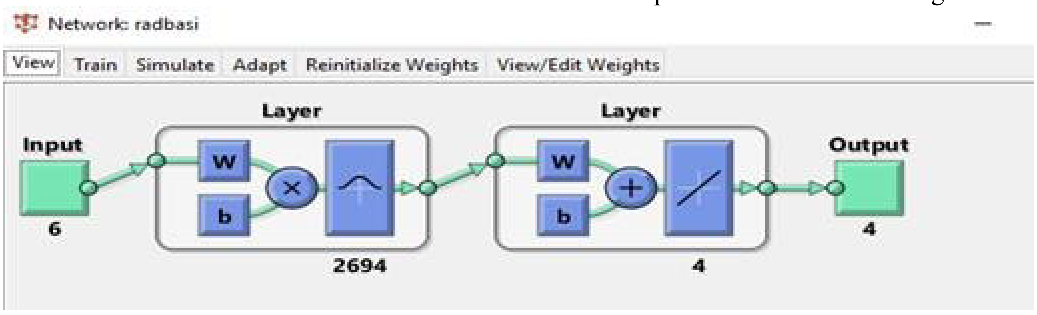


Figure 4-20 show Overview of radial basis neural network configuration

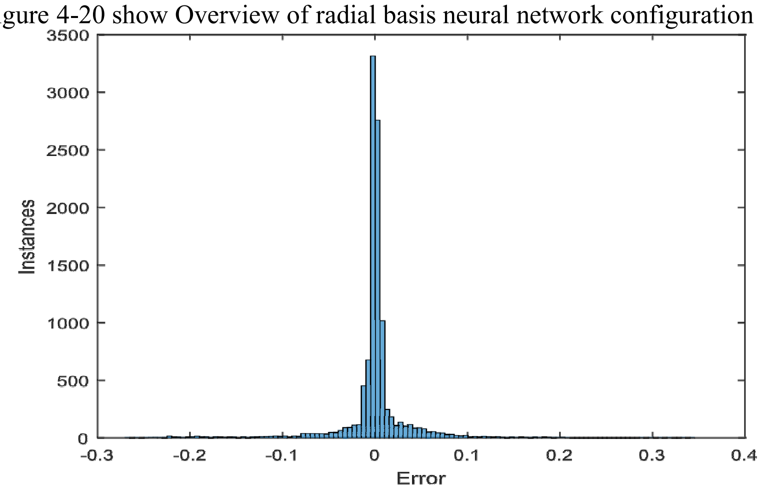


Figure show the error distribution plot of the exact fit radial basis network

The radial basis function calculates the distance between the input and the initialized weight and scaled by the initialized bias. the number of neurons used is the same as the number of total input used to train the network. one of the performance measures to see the exact fit radial basis is the error histogram as shown in figure above.

Discussion of results

To obtain well trained neural network, a number of different ANN configurations that are not presented here are made and four of ANN configuration are presented to show different configuration of ANN. Network1 (6-21-4 ANN configuration) two layer network, the MSE performance is 0.000222, the error ranges -0.025 to 0.024 and the overall correlation between the target and network output is 0.99851. Network2(6-41-4 ANN configuration) the two layer network, with increased number of hidden layer neuron by 20 additional neurons as compared to network1, the obtained the MSE performance is 0.0001438, the error ranges -0.017 to 0.02 and the overall correlation between the target and network output is 0.99908. Network 3(6-15-8-4 ANN configuration) the three layer network, with increased number of hidden layer by 1 additional layer and reduced number of neurons in hidden layer as compared to network2, the obtained the MSE performance is 0.000102, the error ranges -0.015 to 0.019 and the overall correlation between the target and network output is 0.99929. Network4 different type network used for training (exact fit radial basis network) this networks output is mainly affected by the initial weight initialization values. The error values ranges from -0.05 to 0.05 as shown from error histogram. As shown above the MSE, regression plot, validation performance of the three networks becomes improved as the number of neurons and layers in the network increase. As there is no defined rule for optimized number of neurons, layers in the neural network training based on the performance results of the above network the network configuration 6-15-8-4 is selected as final well trained network that used for the fault location estimator. The table below shows the comparison between trained neural network responses to the sample simulated faults location with the actual fault location. As shown in the table random sample new different type of faulty condition untrained 30 data given to the trained network and response of network to the new data is shown in table. As show in the table the maximum deviation in distance from the actual is 4.69km. The average distance, branches and sub branch location deviation from target is 0.269km, 0.099, and 0.038 respectively, as well as for fault type 0.092.

Table 4-5 show trained neural network response and actual fault location comparison

Actual fault location for sample simulation				Trained ANN network response to new data for different faults				Error (Difference between Actual target and network output)			
Distance (km)	Branch	sub branch	Fault type	Distance (km)	Branch	sub branch	Fault type	Distance (km)	Branch	sub branch	Fault type
9	0	0	9	8.82	0.28	-0.21	9.33	0.18	-0.28	0.21	-0.33
75	2	1	8	79.69	1.43	0.52	8.01	-4.69	0.57	0.48	-0.01
66	2	1	7	67.07	1.37	0.4	7	-1.07	0.63	0.6	0
22	1	0	8	26.28	0.76	0.16	8.01	-4.28	0.24	-0.16	-0.01
49	0	0	8	47.11	0.29	0.33	8.07	1.89	-0.29	-0.33	-0.07
34	0	0	7	33.37	0.66	0.35	7.03	0.63	-0.66	-0.35	-0.03
69	0	0	7	68.87	1.4	0.4	6.99	0.13	-1.4	-0.4	0.01
57	0	0	8	55.4	1.03	0.38	8.07	1.6	-1.03	-0.38	-0.07
6	0	0	7	5.96	-0.59	0.08	6.74	0.04	0.59	-0.08	0.26
96	2	1	7	94.15	1.9	0.44	6.94	1.85	0.1	0.56	0.06
65.8	2	0	2	65.82	1.05	0.33	2.16	-0.02	0.95	-0.33	-0.16
57	0	0	2	54.71	0.77	0.14	2.13	2.29	-0.77	-0.14	-0.13
60	0	0	2	60.67	0.96	0.3	2.22	-0.67	-0.96	-0.3	-0.22
78.2	0	0	2	74.06	1.37	0.51	2.21	4.14	-1.37	-0.51	-0.21
16	0	0	1	16.42	0.76	0.22	1.28	-0.42	-0.76	-0.22	-0.28
19	0	0	1	20.03	0.25	-0.06	1.1	-1.03	-0.25	0.06	-0.1
64	2	1	1	64.66	1.09	0.44	1.16	-0.66	0.91	0.56	-0.16
66	2	1	1	65.22	1.17	0.32	0.95	0.78	0.83	0.68	0.05
66	2	1	1	65.08	1.17	0.33	0.94	0.92	0.83	0.67	0.06
100.6	2	1	1	99.96	1.91	0.62	0.93	0.94	0.09	0.38	0.07
57	0	0	1	57.35	1.01	0.25	0.97	-0.35	-1.01	-0.25	0.03
3	0	0	3	4.52	0.04	-0.21	2.57	-1.52	-0.04	0.21	0.43
9	0	0	3	13.39	0.24	0.14	2.62	-4.39	-0.24	-0.14	0.38
12	0	0	3	11.41	0.04	-0.21	2.93	0.59	-0.04	0.21	0.07
54	0	0	1	52.9	0.93	0.2	1.11	1.1	-0.93	-0.2	-0.11
6	0	0	10	5.65	-0.04	-0.36	10.09	0.35	0.04	0.36	-0.09

As seen in the table most neural network response is similar to the actual target values for distance, branch and sub branch, but some of the values have deviation it might be due to lack of sufficient data representation from the active region of the data during training set selection.

Fault location estimator development and implementation

As detail discussion in the above sections on the distribution system simulation for data generation and neural network training process for test feeder to the desired fault location estimator design is covered. In the continuation of training process of ANN using the well trained NN to the fault estimator development. This development has the hardware and software implementations the overall hard ware and software combination layout is shown in figure. The major component in practical implementation is intelligent electronic device (IED), which is installed at the feeder in the substation. In this feeder ABB REF615 series IED is used for fault recording and protection of the distribution line and PCM600 IED software tool that used for reading the fault record using computer. The graphic user interface software is developed using MATLAB for interaction of the users with the fault estimator software developed.

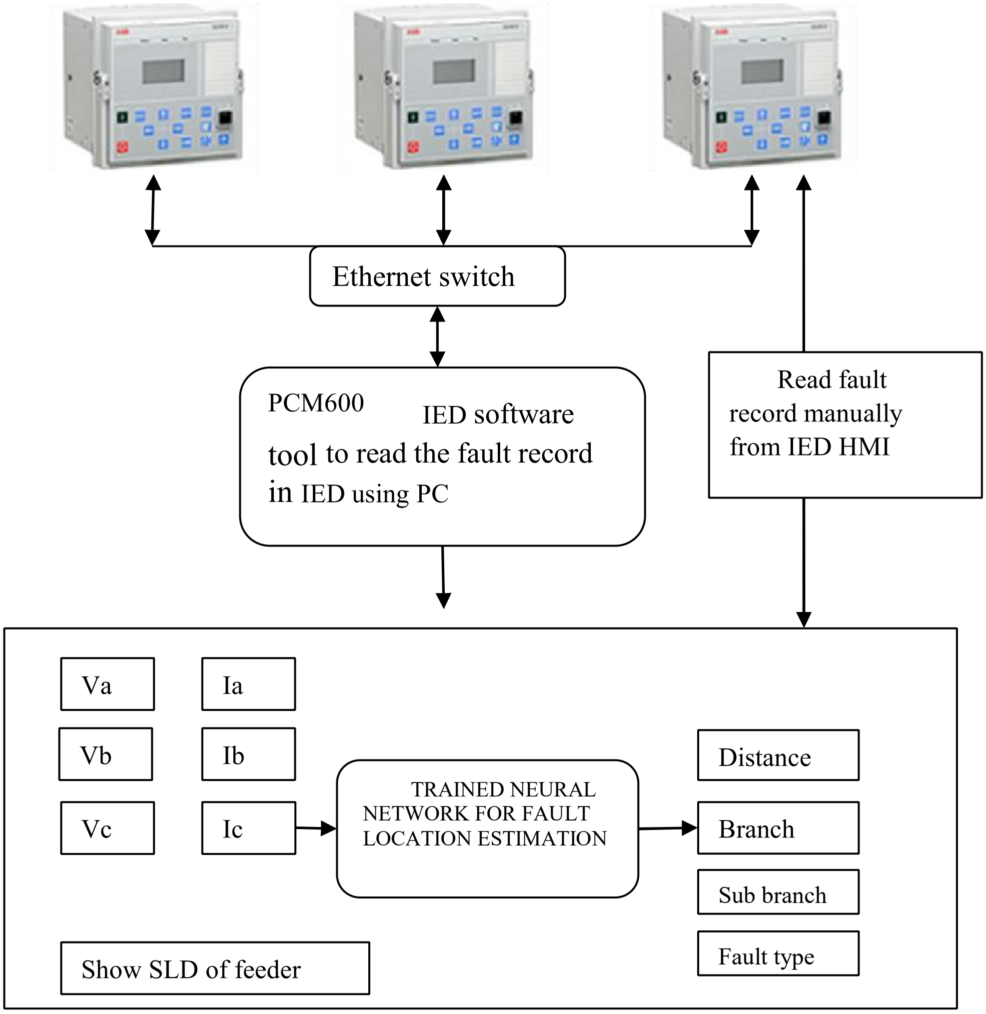


Figure 4-24 show general block diagram representation of overall fault location

Most of the feeders in Ethiopia have IEDs, made in ABB, AREVA, Micom which are most known electrical equipment manufacturing companies. So we can utilize this IEDs without additional cost for fault location estimator design.

Software development

The programming for the fault location estimator and fault type identifier is developed by MATLAB programming tool box. As shown in the figure show the fault record reading from the IEDs through PCM600 or manually using IEDs human machine interface (HMI),which is the maximum line current and the line to ground voltage is given as input to the graphic user interface input. The program behind checks all necessary data preprocessing and load the trained artificial neural network is ordered to simulate the given input and finally the output displays the estimate fault location by distance, branch and sub branch level and type of fault. The user interface is developed by the MATLAB graphic user interface tool box. The MATLAB generated code for the program is found in Appendix C.

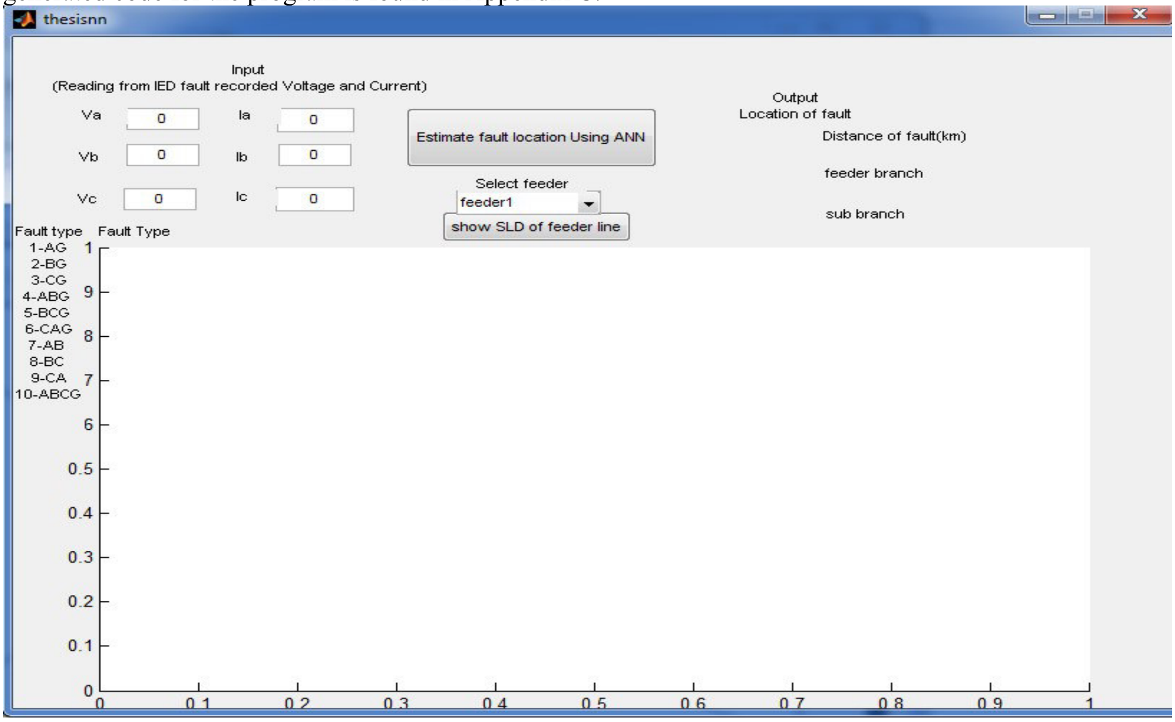


Figure 4-27 show the graphic user interface developed for fault estimator design

The fault record from IED the maximum current records and the phase voltage fault records will be given to the User interface and the output will be displayed on the right side of the window. The below window shows the input of fault record is given to the user interface and the output with the selected single line diagram of the feeder is shown.

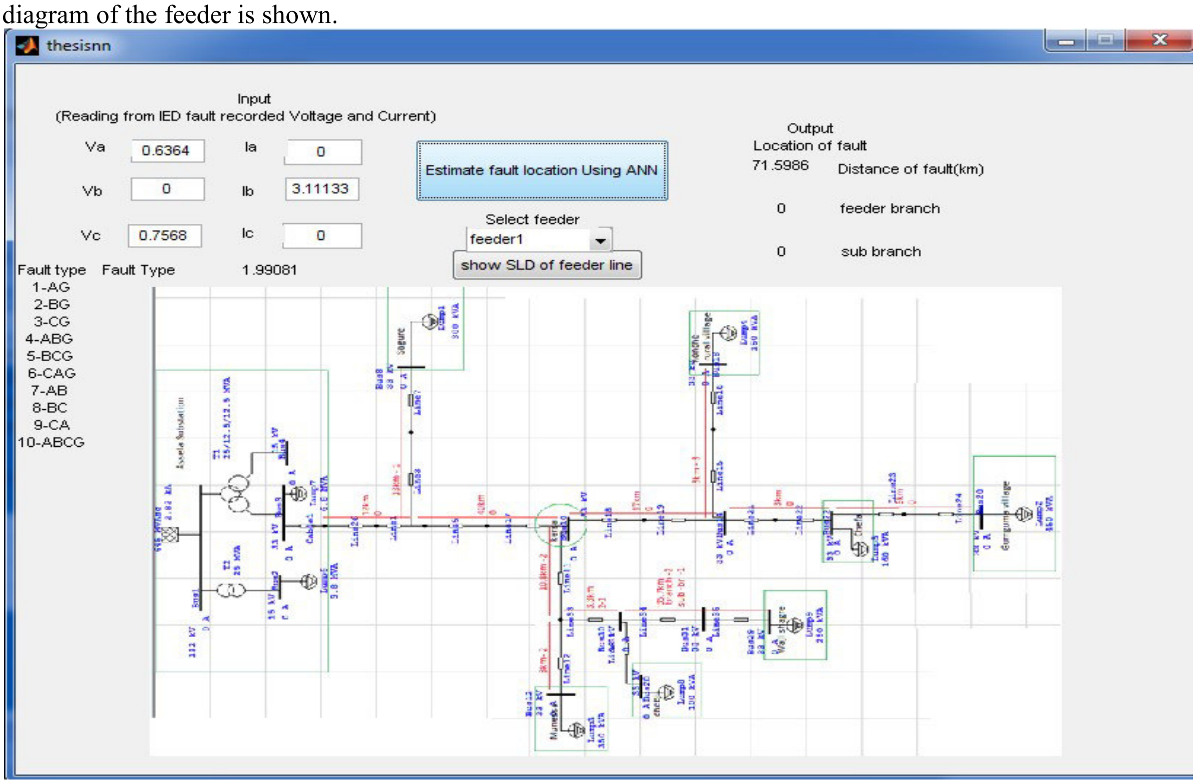


Figure 4-28 show the graphic user interface developed for fault estimator design, input fault data given and fault location shown as output

Conclusion

Fault location estimator for power distribution system using artificial neural network is developed for line to ground, line to line, line to line to ground and three phases to ground faults. To develop estimator, one of rural radial power distribution feeder in Ethiopia, south west reign Abba substation tarcha line feeder is used for design as the test feeder. Feeder is simulated using ETAP software to generate different fault condition, with different fault resistance and loading condition. MATLAB R2016a neural network toolbox to train ANN and programming tool box is used to develop graphic user interface for fault estimator. The fault condition generated data from ETAP software is normalized and this normalized data used as input for neural network to train neural network and to estimate the fault location with trained network efficiently. The feed forward multi-layer network topologies of neural network with improved back propagation; Levenberg Marquardt learning algorithm is used to train the network. The performance of the trained network is analyzed by mean square error, regression plot and error histogram. Different artificial neural network configurations are trained with variable hidden layer neuron and variable number of layers as well as varying different values of weight and bias initialization. Network configuration of ANN 6-15-8-4 is selected as final trained network for fault location estimator which was found as excellent performance with regression coefficient 0.99929, validation performance of 0.000102 and error histogram range 0.15 to 0.17 of network. Researchers can conclude that artificial neural network is one of the alternate options for fault location estimator design for distribution system where sufficient distribution network data are available with average error of fault location distance 0.296km, branch 0.09 and sub branch 0.038 from the actual location as well as fault type identification 0.092.

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