Scientific Journal of Impact Factor (SJIF): 5.71
e-ISSN (O): 2348-4470
p-ISSN (P): 2348-6406

International Journal of Advance Engineering and Research Development

Volume 5, Issue 06, June -2018

REAL POWER LOSS MINIMIZATION USING ARTIFICIAL NEURAL NETWORK

Pathak Smita

Abstract: *objective for this paper is obtaining adequate setting of reactive VAR support so as to minimize real power loss. A back propagation algorithm (BPA) based network is trained to represent the system as ANN model. Training data for an Artificial Neural Network is generated using N-R method of load flow solution. Training data encompasses adequate amount of reactive VAR support for a variety of load pattern and real power loss associated with each setting which happens to be minimum for given input load pattern. Algorithm is developed for 6 bus, 7 line test system .This can be done for 30 bus data also.*

Index Terms— *ANN, Reactive Var, BPA, Active power loss.*

I. INTRODUCTION

REDUCTION of power generation cost is one of the current interested issue of power utilities, therefore, an optimal control to minimize power transmission loss is required. Minimization of loss and improvement of bus voltage profile these are two major objectives in satisfactory operation of power system operation. OPF has been found to be capable of handling these aspects at a time. In order to minimize loss appropriate distribution of reactive power generation in a power system should be guaranteed. This can be achieved by adjusting the reactive power control variables namely tap setting, PV bus voltage, shunt capacitors and inductors. This paper focuses on finding shunt capacitor value to minimize real power loss.

A large number of algorithms have been developed for the solutions for optimal reactive power dispatch and losses minimization. The algorithms can be classified according to either the AC load flow methods or the optimization techniques applied to determine the optimal reactive power flow. The most popular AC load flow method is the Newton-Raphson technique. This technique is highly precise and accurate, but it has some disadvantages, such as complexity and lengthy execution time. The second method which is the fast decoupled load flow (FDLF) has been accepted in recent years by the utility industries as a fast and appropriate approach to obtain power flow solution [1]. However, these techniques still lack one of the most important criteria in any system planning, which is speed. Intelligent systems are the ultimate means of achieving an accurate and global solutions for the VAR related problems in power system. Some of these are evolutionary programming, ANN, Genetic Algorithms, PSO etc.

Q. H. Wu et al [2] proposed an evolutionary based approach able to undertake global search with a fast convergence rate and feature of robust computation and passes an inherent capability for parallel processing. Ref [3] developed PSO for reactive power and voltage control including voltage security assessment. Ahmed et al [4] suggested an OPF based on hybrid particle swarm optimization for loss minimization. Artificial neural network has also been found wide application in power system [1]. It is quite flexible in its application since it can be incorporated with other techniques to accomplish tasks as fuzzy logic technique. A set of training data is required to train the network.

This paper describes an ANN technique for predicting an optimum setting of reactive VAr support which will in turn minimize the real power losses in an electrical power system. The input data are the real and reactive load at every load bus while the corresponding targeted outputs are the reactive VAr support and real power losses associated with VAr. The variety sets of data were obtained by using Matlab's load flow program. The ANN was then trained using these data. The fully-trained ANN was then evaluated to confirm its perfection by performing regression analysis, indicating that the network is able to perform desired task reliably and accurately. The technique was tested on IEEE 6-bus system and a positive indication was observed.

II. ARTIFICAL NEURAL NETWORK

The concept of artificial neural network (ANN) is one of the best developments of the century**.** The functioning of ANN resembles the human behavior like intelligent guessing and pattern recognition.

An ANN is based on a collection of connected units or nodes called artificial neurons which loosely model the neurons in a biological brain. Each connection, like the synapses in a biological brain, can transmit a signal from one artificial neuron to another. An artificial neuron that receives a signal can process it and then signal additional artificial neurons connected to it.

A neural network is a computational structure inspired by the study of biological neural processing. It works on the basic principle on which human brain works. The human brain uses a web of interconnected processing elements called neurons. Each neuron receives signal from other neurons through special junction called synapses. The neurons of neural network are divided into subgroups or fields and elements in each subgroup are placed in a row or a column. Each subgroup is called to as layer of neurons in the network. The input layer of the neural network inspire input signals for the neurons in the next layer which may be output layer or hidden layer which process the information between input and output layers. Two neurons are connected with a weight which may be positive, negative or zero. The output of a neuron is weighted sum of its inputs modified by weights connected to it, which can be expressed as

$$y = \sum_{i=1}^{n} W_i X_i$$

where, y is the activation (output)
W_i is the weight of i^{th} neuron
X_i is the input to 1^{st} neuron

The output of neuron which is weighted sum of input is passed through an activation function which limits it to some threshold value.

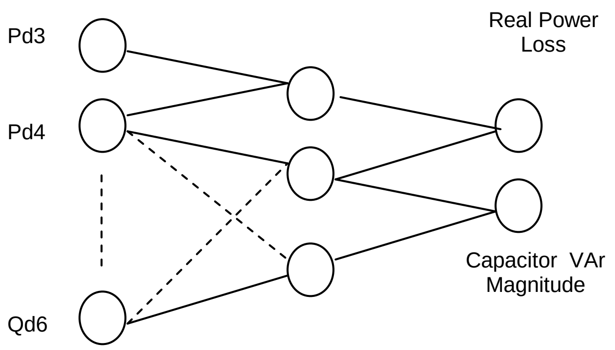


Fig. 1 Schematic Diagram of ANN

ANN has been proved to be a popular technique for providing solutions to variety of problem in power system. It is able to handle complex non-linear problems which are generally of complicated and ambiguous I behavior. Due to this feature it has gained attention by utilities and system engineers.

III. NETWORK ARCHITECURE

Network architecture developed in this paper for system consists of input layer, one hidden and output layer. Real and reactive loads are input variables which are applied to the neurons of input layer. The output layer consists of two neurons, one corresponding to the magnitude of reactive VAR at bus number and the other gives minimum loss for the given input and associated VAR. The proposed ANN scheme in this paper uses a multi layer feed forward network employing a back propagation learning algorithm. The scheme is illustrated in Fig. 1

GENERATION OF TRAINING SET DATA:

One of the significant component of ANN is to train the network with known inputs and known targets. The training and test samples have been obtained using a load flow program that employed a Newton-Raphson method. Real and reactive load at bus no. 3,4,5, & 6 were gradually increased up to 200% from the base case. For each loading conditions, the shunt capacitor was adjusted. The real power losses were observed and only the VAR setting that produced minimal real power losses was chosen as the first targeted output. For second targeted output, the real power loss associated with that VAR setting were selected. More than 35 patterns were generated from the load flow program in which 25 patterns were randomly selected for the training and remaining samples were used for testing purpose. The input data consists of 8 variables (i.e. 4 real and 4 reactive loads)

BACK PROPAGATION ALGORITHM TRAINING SYSTEM NETWORK: [5]

The network shown in Fig. 1 is trained using training instances generated by the cut-set method. The network is trained in the following steps.

Step 1: Select all weights initially as low random numbers

Step 2: A training instance is presented to the network of Figure 2.

Step 3: Output of each neuron is calculated using following equations.

$$O = \sum_{j=1}^{m} W_{j0} O_i (Non - sigmoidal)$$

$$Oj = \frac{1}{1 + e^{-net}}_{j} \quad \text{(Output of hidden layer neurons)}$$

j=1,2,…….,m

Where, ‘Net_j’ is given as follows

$$Net_j = \sum_{i=1}^{n} W_{ij} X_i$$

where i = 1,2,………,n

In above equations W_{j0} are the wights connected between jth hidden neuron and output neuron. W_{ij} are the weights connected between i^{th} input node and j^{th} hidden neuron. Xi is input variable at i^{th} node. These are load at various buses.
Step 4: Weights are updated using following relations.

$$\Delta W_{j0} = \eta \delta_i X_i$$

$$\delta = (T - O)$$

η is learning rate (0 < η<1), T, the target value of probabilistic insecurity index

$$\Delta W_{ij} = \eta \delta_i X_i$$

Where δ_i is error hidden layer and is given as follows

$$\delta_i = \delta W_{j0} O_i (1 - O_i)$$

X_i is the element of input vector [X], where

$X^T = [P_1,P_2,\ldots\ldots\ldots P_{NB}]^T$

Where, $P_1,P_2,\ldots\ldots\ldots P_{NB}$ are load at load buses.

Step 5: New training instance is presented to network and process is repeated from Step 3

Step 6: Calculate the value of ‘E’ if all the instances have been presented to the network.

$$E = \sum_{m=1}^{NT} (T^m - O^m)^2$$

where, NT denotes the total number of training instance. T^m and O^m are target values and output of ANN from m^{th} training instances respectively:

if $E \leq \varepsilon$ (tolerance), then stop

Otherwise, repeat from Step 2. This should be repeated till convergence or a maximum number of iterations have been conducted. Validation of the network is done by test instance.

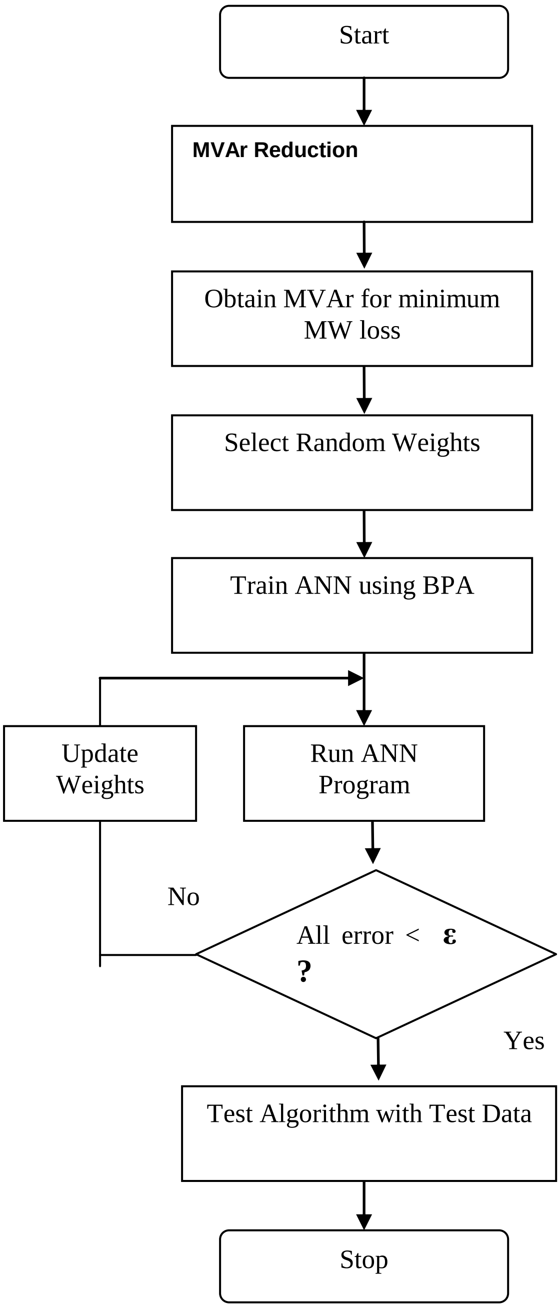


Fig. 2. Flowchart for ANN Process

IV. TRAINING AND TESTING

The training and testing processes were conducted using the ANN toolbox which is available in MATLAB. Two separated programs were written for training and testing. In this process, the training data was normalized within a specific range. This specific range is according to the type of transfer function used in the ANN network. If the transfer function is logsig, then the range of the normalized data would range between 0 and 1. on the other hand, if the transfer function is tansig, then the normalized data would range between 0 and 0.5 pu. As being previously mentioned, 30 training patterns were randomly chosen for training purposes. This training data was then fed to the network and the network was trained until it achieves a very small rms error. After that, the fully trained network was saved for testing purposes.

As mentioned earlier, the outputs of neural network are the shunt capacitor reactive VAR and the real power losses. Thus the network was trained and tested separately for each case. The testing process is carried out by feeding the trained network with series of unseen data. 10 input patterns were selected for testing purposes. A good and reliable network should produce a small rms error.

The performance of the developed network can also be justified by simply calculating the absolute error for every testing pattern. Further evaluation can be done by performing regression analysis. The correlation coefficient R closed to unity (1.0) indicates that the network performance is good and reliable. Unity value of correlation coefficient indicates that the actual and targeted outputs are exactly the same. The overall process is presented in the flow chart shown in Figure 2.

IV. RESULTS AND DISCUSSION

An ANN Based technique has been tested on 6-bus, 7-line IEEE test system[6]. The single line diagram of IEEE 6-bus test system is shown in Figure A1. Bus no.1 and 2 are slack and generator bus respectively. While bus no. 3, 4, 5 and 6 are the load bus. The reliability of the ANN will be tested on this bus system.

Shunt Capacitor is connected at Bus No. 4. For this system ANN has eight no. inputs with one hidden layer and two outputs. Training set is generated for different load and for different magnitude of shunt capacitor to find out the minimum real power loss using N-R method load flow solution. Every time 10% system load is increased and searching of new value of reactive power is performed corresponding to min. transmission loss, for the same load. Load is increased from base load to double of it. Various curves are illustrated in different figures (Fig. 3-6) indicating the chain in real and reactive power loss with increased system loading. Upper curves in each diagram shows without shunt capacitor and lower curve shows reduced transmission line loss obtained using adequate amount of reactive VAR compensation at Bus no. 4.A substantial reduction in line loss is obtained with adequate reactive power dispatch.

Voltage drop due to increase loading condition is also avoided when an attempt is made to minimize the real loss. This fact is shown in Figs 7 and 8. This results confirms to enhance voltage profile as well as static voltage stability limit with shunt capacitor support.

When only reactive load is increased at all the buses reduction in real power loss with capacitive VAR is significant. These effects are illustrated in Figs. 3,5. As shown in Figs. 7&8 voltage at bus No. 6 drops due to increase in load. It is possible to maintain the voltage at bus No. 6 almost at the desired level with reactive VARs at bus No. 4. Table -1 shows the real power loss output of ANN when an unknown load pattern is applied to the input. Actual loss is given in the next column. The error in the actual loss and as obtained using ANN is very small and is acceptable. Similarly table 2 shows the capacitive reactive power support for minimum power loss as obtained using ANN and with a load flow analysis. Error is given in the last column.

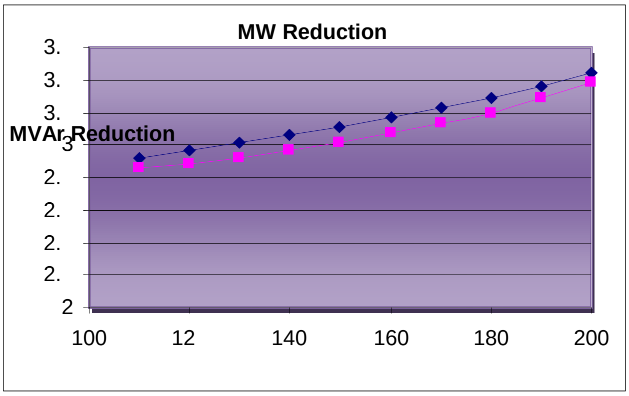


Fig. No. 3 Real Power loss with increase QL

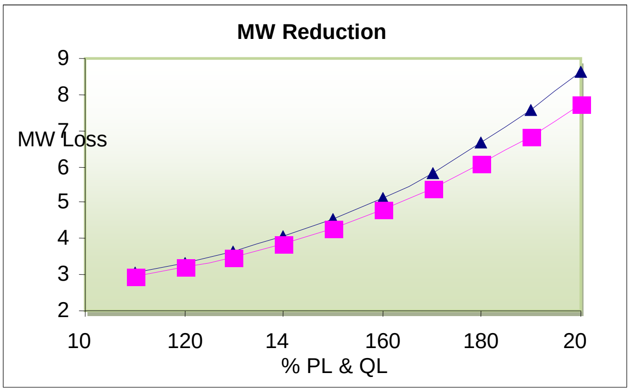


Fig. No. 4 Real Power loss with increase in system load

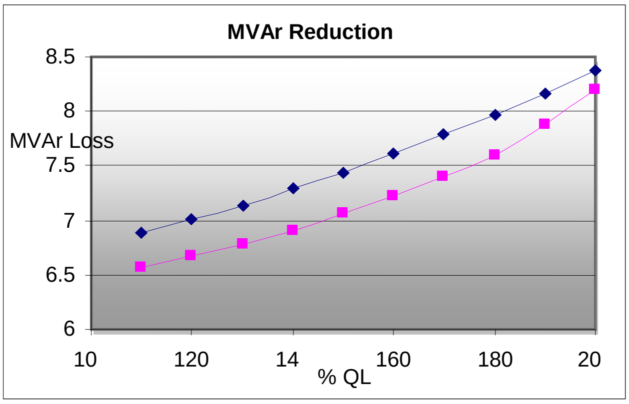


Fig. No. 5 Reactive power loss with increase in QL

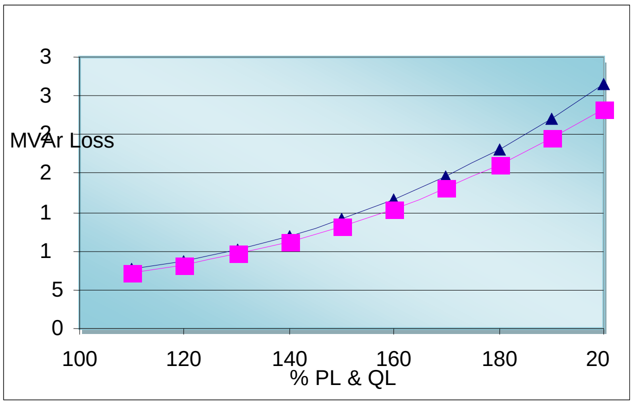


Fig. No. 6 Reactive power loss with increase in system load

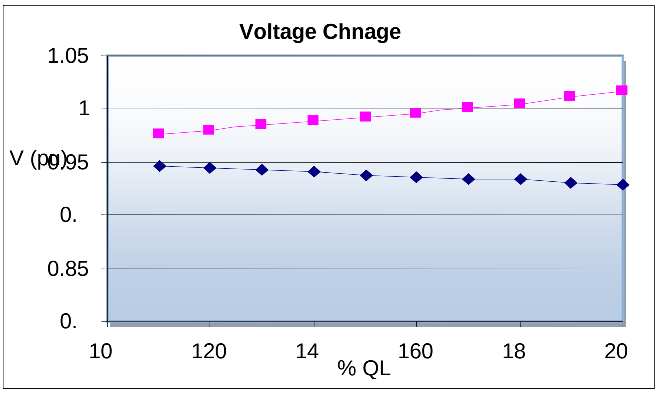


Fig. No. 7 Change in voltage in bus no. 6 with increased reactive load

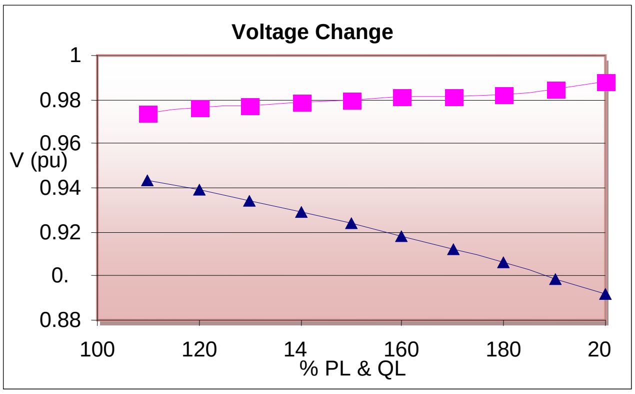


Fig. No. 8 Change in voltage in bus no. 6 with increased system load

Table - 1 ANN output for Real Power Losses

Sr No.	MW – Loss(pu)	ANN Output(pu)	Error
1	2.98	3.028158	0.048158
2	3.199	3.250994	0.051994
3	3.486	3.565676	0.079676
4	3.844	3.872722	0.028722
5	4.276	4.374944	0.098944
6	4.787	4.848311	0.061311
7	5.379	5.389997	0.010997
8	6.059	6.077855	0.018855
9	6.832	6.843038	0.011038
10	7.704	7.749131	0.045131

Table -2 ANN output for determining Shunt MVAR at Bus No. 4

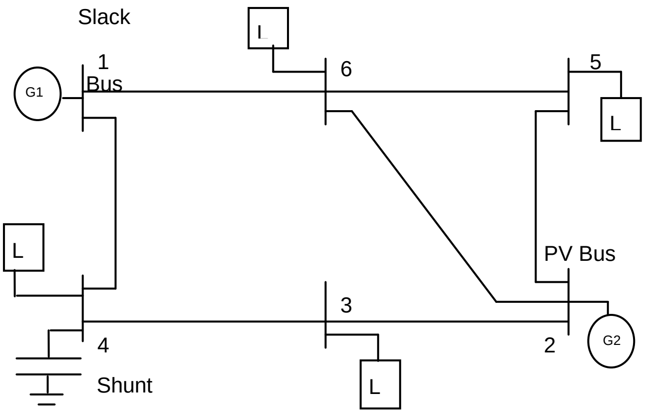
Sr No.	Targeted Output(pu)	ANN Output(pu)	Error
1	10	10.06693	0.066932
2	12	12.04062	0.040623
3	14	14.09937	0.099367
4	16	16.02052	0.020522
5	18	18.06116	0.061164
6	20	20.06213	0.062128
7	22	22.0986	0.098597
8	24	24.09373	0.093725
9	27	27.04552	0.04552
10	30	30.00613	0.006132

V. CONCLUSION

This paper presents the ANN technique for determining the magnitude of capacitive reactive VAR in order to minimize the real power losses in a power system. The proposed technique was tested on the IEEE-6 bus system and the result obtained indicates that the network is capable to perform its task with high accuracy. The application of ANN is feasible for online implementation, which can be utilized by system operators to perform their on-line monitoring and control.

APPENDIX-A

FigA1. IEEE Six Bus System



REFERENCES

[1] Ahmed A. A. Esmin, Germano Lambert-Torres, Antonio C. Zambroni de Souza, "A Hybrid Particle Swarm Optimization applied to Loss Power Minimization" IEEE Transactions on Power Systems, Vol.20, No. 2, May 2005. pp 859-866

[2] L. D. Arya, L. S. Titare, S. C. Choube, "Voltage Security Monitoring and Control Using Back Propagation Algorithm based Artificial Neural Networks" Journal of The Institution of Engineers (India), Vol.87, Jun 2006 pp 29-34

[3] P.R. Bijwe, D.P.Kothari and L.D. Arya, "Alleviation of line overload and voltage violations by corrective rescheduling" , IEE Proc. Part C, Vol.140, No.4, July 1993, pp. 249-253.

[4] Mohamed A. H. El-Sayed, Tarek M. Abdel-Rahman and M. Omar Mansour, "Reactive Power Control for Real Power-Loss Minimization" IEEE Transaction on Computer Application in Power, Jul 1998 pp16-21

[5] Q H Wu, J. T. Ma, "Power System Optimal Reactive Power Dispatch Using Evolutionary Programming" IEEE Transactions on Power Systems, Vol.10, No. 3, Aug 1995. pp 1243-1249

[6] Hirotaka Yoshida, Kenichi Kawata, Yoshikazu Fukuyama, Shinichi Takayama, Yosuke Nakanishi, "A Partical Swarm Optimization for Reactive Power and Voltage Control Considering Voltage Security Assessment" IEEE Transactions on Power Systems, Vol.15, No. 4, Nov 2000. pp 1232-1239

