



Voltage Profile Analysis in Power Transmission System based on STATCOM using Artificial Neural Network in MATLAB/SIMULINK

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ABSTRACT

This paper deals with Voltage Stability Analysis in a Power Transmission System with and without STATCOM using Artificial Neural Network in MATLAB/ SIMULINK. It is shown that trained Neural Network developed has excellent capabilities of forecasting which can be very useful in research. Voltage control and reactive power compensation in a weak distribution networks for integration of wind power is also represented in this paper. For dynamic reactive power compensation, when, STATCOM (Static Synchronous Compensator) is used at a point of interconnection of wind farm and the network; the system absorbs the generated wind power for maintaining its voltage level. Voltage level of the system changes on changing the values of resistive loads connected to transmission line and using these voltages on bus 1 and bus2 on different values of loads a neural network is developed after training which can forecast voltage on bus 1 and bus 2 of the transmission line on any values of the resistive load connected to transmission line.

Keywords

Artificial Neural Network (ANN), Dynamic Performance, Induction generators, FACTS, Matlab/Simulink, Transient Stability, Voltage Profile Analysis.

1. INTRODUCTION

In this paper artificial transmission line of 50KM is simulated and tested. STATCOM is placed at the receiving end for balanced load condition. The receiving end voltage fluctuations were observed for different loads. STATCOM are used to improve voltage and reactive power conditions in AC systems. An additional task of STATCOM is to increase transmission capacity as result of power oscillation damping. In This paper the reactive power compensation capability of STATCOM for wind power integration into a weak distribution network is evaluated. The 9 MW wind farm have conventional wind turbine systems consisting of squirrel-cage induction generators and variable pitch wind turbines[10]. Voltage profile of the system changes on variation of the values of loads connected to power transmission line and using these voltage values on bus 1 and bus 2 on different values of resistive loads a Artificial Neural Network is developed after training. Artificial Neural Network can now be used to forecast voltage values on bus 1 and bus 2 of the transmission line on any values of the resistive load connected to transmission line at any instant. An Artificial Neural Network is a system based on the operation of biological

neural networks, in other words, is an emulation of biological neural system[22]. As its biological predecessor, an artificial neural network is an adaptive system. By adaptive, it means that each parameter is changed during its operation and it is deployed for solving the problem in matter. This is called the training phase[21]. Simulation results show that STATCOM devices significantly improve the performance of the wind farm and power network. This paper also presents Algorithm and Program in MATLAB for training of Artificial Neural Network for calculation of weights and biases and then using these weights and biases Program in MATLAB is presented for forecasting the voltage values on bus 1 and bus2 of the power network on different values of Loads L1 and L2 at different time.

2. SIMULATION OF TEST SYSTEM

The network consists of a 132 kV, 50 Hz, grid supply point, feeding a 33 KV distribution system through 132/33 KV, 62.5 MVA step down transformer. There are two resistive loads in the system L1 AND L2. The 33 kV, 50 km long line is modeled as line. A 9 MW wind farm is to be connected to the 33 kV distribution network. The total MVA loading on the system is 50 MVA; considering the T & D losses in the system it is over loaded and representing weak distribution network. Dynamic compensation of reactive power is provided by a STATCOM located at the point of wind farm connection.

The simulation is run in three different modes, as follows –

- i. Without wind farm and STATCOM,
- ii. With wind farm and without STATCOM,
- iii. With wind farm and STATCOM

3. SIMULATION

3.1 Without Wind Farm and STATCOM

In this mode the wind farm and STATCOM were skipped while running the simulation. Only the distribution system and two loads were kept in the model. The purpose of running the simulation in this mode is to ascertain that, the test system is a weak system. Only voltages at 33 kV Bus – 1 and Bus – 2 are measured.

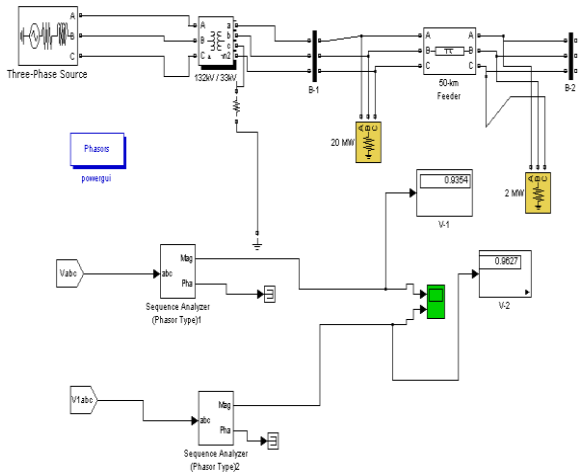


Fig 1: Simulink Model of the test system without wind farm and STATCOM

3.2 With Wind Farm and without STATCOM

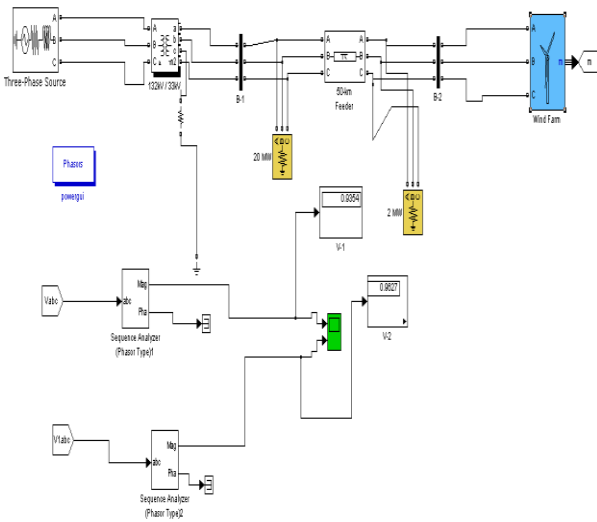


Fig 2: Simulink Model of the test system with wind farm and without STATCOM

In this mode of simulation the wind farm is connected to the weak distribution network in above mode. The purpose of running simulation in this mode is to try integration of 9 MW wind power in weak distribution network, without dynamic compensation of reactive power *i.e.* without using the STATCOM. Before tripping the wind turbine generators have drawn reactive power from the network.

3.3 With Wind Farm and with STATCOM

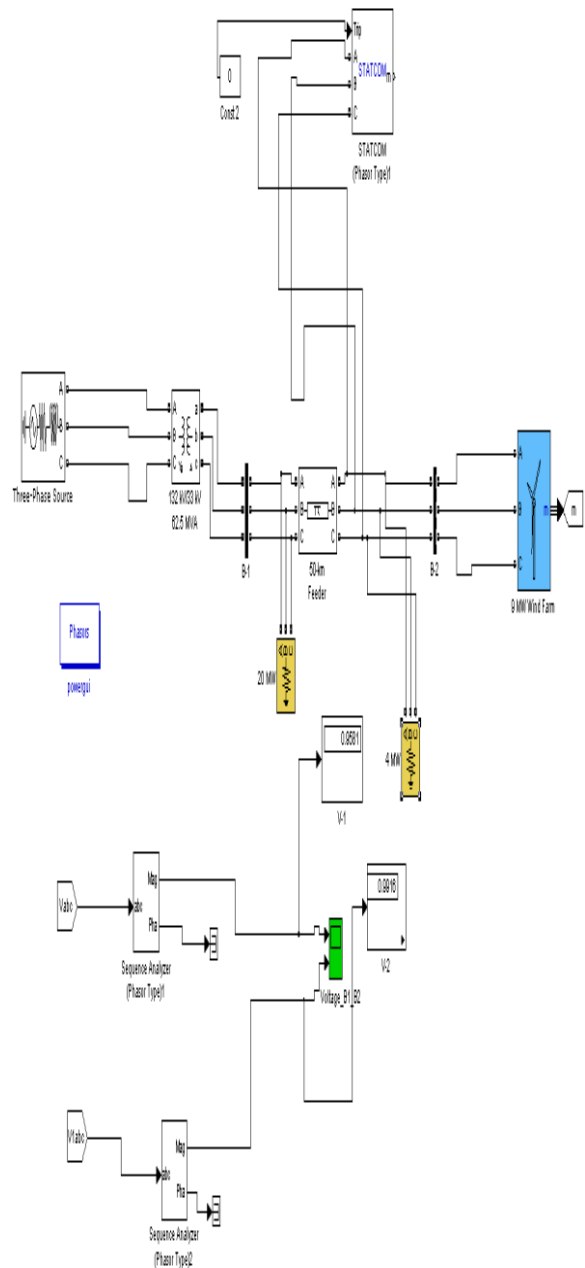


Fig 3: Simulink Model of the test system with wind farm and STATCOM

In this mode of simulation the wind farm with dynamic compensation by STATCOM is connected to the weak distribution network in above mode. The purpose of running simulation in this mode is to integrate 9 MW wind power in weak distribution network, with dynamic compensation of reactive power using the STATCOM.

4. ARTIFICIAL NEURAL NETWORK

Artificial neural networks born after McCulloch and Pitts introduced a set of simplified neurons in 1943. These neurons were represented as models of biological networks into conceptual components for circuits that could perform computational tasks. The basic model of the artificial neuron is founded upon the functionality of the biological neuron. By definition, “Neurons are basic signaling units of the nervous



system of a living being in which each neuron is a discrete cell whose several processes are from its cell body. One can differentiate between two basic types of networks, networks with feedback and those without it. In networks with feedback, the output values can be traced back to the input values. However there are networks wherein for every input vector laid on the network, an output vector is calculated and this can be read from the output neurons[23]. There is no feedback. Hence only, a forward flow of information is present. Network having this structure are called as feed forward networks. There are various nets that come under the feed forward type of nets. A multilayer feed forward back propagation network with one layer of z-hidden units. The Y output unit has W_{ok} bias and Z hidden unit has V_{ok} as bias. It is found that both the output units and the hidden units have bias. The bias acts like weights on connection from units whose output is always 1. This network has one input layer, one hidden layer and one output layer. There can be any number of hidden layers[22]. The input layer is connected to the hidden layer and the hidden layer is connected to the output layer by means of interconnection weights. The bias is provided for both the hidden and the output layer, to act upon the net input to be calculated [20].

5. TRAINING ALGORITHM

The training algorithm of back propagation involves four stages[18], viz.

1. Initialization of Weights
2. Feed Forward
3. Back Propagation of errors
4. Updation of the weights and the biases.

During first stage which is the initialization of weights, some small random values are assigned. During feed forward stage each input unit (X_i) receives an input signal and transmits this signal to each of the hidden units Z_1, \dots, Z_p . Each hidden unit then calculates the activation function and sends its signal Z_j to each output unit. The output unit calculates the activation function to form the response of the net for the given input pattern. During back propagation of errors, each output unit compares its computed activation y_k with its target value t_k to determine the associated error for that pattern with that unit. Based on the error, the factor δ_k is computed and is used to distribute the error at output unit y_k back to all units in the previous layer. Similarly factor δ_j is computed for each hidden unit z_j . During final stage, the weight and biases are updated using the δ factor and the activation .

x : input training vector

x : ($x_1, \dots, x_i, \dots, x_n$)

t : Output target vector

t : ($t_1, \dots, t_i, \dots, t_n$)

δ_k =error at output unit y_k

δ_j =error at hidden unit z_j

α = learning rate

V_{oj} = bias on hidden unit j

z_j = hidden unit j

w_{ok} = bias on output unit k

y_k = output unit k .

The training algorithm used in the back propagation network is as follows. The algorithm is given with the various phases:

5.1 Initialization of Weights

Step 1: Initialize weight to small random values.

Step 2: While stopping condition is false, do Steps 3-10.

Step 3: For each training pair do steps 4-9.

5.2 Feed Forward

Step 4: Each input unit receives the input signal x_i and transmits this signals to all units in the layer above i.e hidden units.

Step 5: Each hidden unit($z_j, j=1, \dots, p$) sums its weighted input signals.

$$z_{-inj} = v_{oj} + \sum x_i v_{ij} \quad (1)$$

applying activation function

$$Z_j = f(z_{-inj}) \quad (2)$$

and sends this signal to all units in the layer above i.e. output units.

Step 6: Each output unit (y_k) sums its weighted input signals.

$$y_{-ink} = w_{ok} + \sum z_j w_{jk} \quad (3)$$

and applies its activation function to calculate the output signals.

$$Y_k = f(y_{-ink}) \quad (4)$$

5.3 Back Propagation of Errors

Step 7: Each output unit receives a target pattern corresponding to an input pattern, error information term is calculated as

$$\delta_k = (t_k - y_k) f'(y_{-ink}) \quad (5)$$

Step 8: Each hidden unit (z_j) sums its delta inputs from units in the layer above

$$\delta_{-inj} = \sum \delta_j w_{jk} \quad (6)$$

The error information term is calculated as

$$\delta_j = \delta_{-inj} f'(z_{-inj}) \quad (7)$$

5.4 Updation of Weight and Biases

Step 9: Each output unit (y_k) updates its bias and weights ($j=0, \dots, p$)

The weight correction term is given by

$$\Delta W_{jk} = \hat{\alpha} \delta_k z_j \quad (8)$$

and the bias correction term is given by

$$\Delta W_{ok} = \hat{\alpha} \delta_k \quad (9)$$

$$\text{Therefore } W_{jk}(\text{new}) = W_{jk}(\text{old}) + \Delta W_{jk}, \quad W_{ok}(\text{new}) = W_{ok}(\text{old}) + \Delta W_{ok} \quad (10)$$

Each hidden unit ($z_j, j=1, \dots, p$) updates its bias and weights ($i=0, \dots, n$)

The weight correction term

$$\Delta V_{ij} = \hat{\alpha} \delta_j x_i \quad (11)$$

The bias correction term

$$\Delta V_{oj} = \hat{\alpha} \delta_j \quad (12)$$

$$\text{Therefore, } V_{ij}(\text{new}) = V_{ij}(\text{old}) + \Delta V_{ij}, \quad V_{oj}(\text{new}) = V_{oj}(\text{old}) + \Delta V_{oj} \quad (13)$$

Step 10: Test the stopping condition.

The stopping condition may be the minimization of the errors, number of epochs etc.

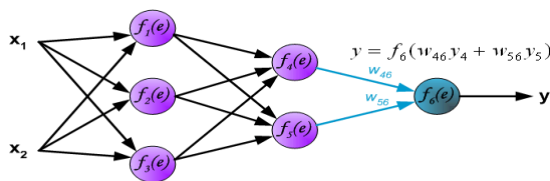


Fig 4: Feed Forward Networks

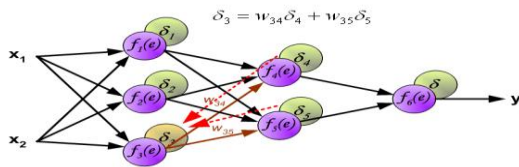


Fig 5: Back Propagation of Errors

6. MATLAB PROGRAMS FOR ANN 6.1

Program for Training of Neural Network

From SIMULINK Model of IG with STATCOM shown in Fig. 3 value of voltage at bus -1 is taken different time(s) from display block of the simulation at different values of Load (L1(MW), L2(MW)) and Time(s). These values of L1, L2, Time(s) are also mentioned in Table 1. Now from these different values of L1, L2 and Time(s) a neural network is trained through a x : which is a input training vector as mentioned in Training Algorithm explained in section 5. Input training vector in this case is L1, L2 and Time(s). Output target vector t is Voltage V1(p.u) at bus -1 in this case. Weight W and v are initialized to small random values. W_0 and V_0 are bias. Iterations done in this program are 990000000.

```
clc;
clear;
W=[-3.2184; -12.5463; 0.6328];
```

```
W0=[9.5708];
v=[0.8153 -0.0614 0.9105; 6.6872 19.4263 0.2000; 0.1294
0.0324 0.2064];
vo=[0.4346 0.8483 -0.4499];
x=[.020 .020 .040 .040 .040 .040 .008 .008 .015 .015 .030
.030 .035 .035 .002 .002 .004 .004;
.004 .004 .010 .010 .015 .015 .025 .025 .002 .002 .002
.002 .002 .002 .010 .010 .020 .020;
.005 .010 .005 .010 .005 .010 .005 .010 .005 .010 .005
.010 .005 .010 .005 .010 .005 .010];
t=[.9458 .9272 .8163 .7078 .9836 .9403 .8986 .7718 .9614
.9593 .9088 .8813 .8867 .85 .9952 .9842 .9253 .8014];
epoch=1;
alpha=.3;
while(epoch<990000000)
    for I=1:18
        for i=1:3
            zin1=0;
            for j=1:3
                zin1=zin1+x(j,I)*v(j,i);
            end
            zin(i)=zin1 + vo(i)*1;
            z(i)=1/(1+exp(-zin(i)));
        end
        yin1=0;
        for i=1:3
            yin1=yin1+z(i)*W(i,1);
        end
        yin1=yin1+W0;
        y(I)=1/(1+exp(-yin1));
        delta1=(t(I)-y(I))*(y(I))*(1-y(I));
        for i=1:3
            delin(i)=delta1*W(i,1);
            del(i)=delin(i)*z(i)*(1-z(i));
        end
        for i=1:3
            for j=1:3
                delv(i,j)=alpha*x(i,I)*del(j);
                v(i,j)=v(i,j)+delv(i,j);
            end
            delvo(i)=alpha*1*del(i);
            vo(i)=vo(i)+delvo(i);
        end
        for i=1:3
            delW(i)=alpha*z(i)*delta1;
            W(i,1)=W(i,1)+delW(i);
        end
        delwo=alpha*1*delta1;
        W0=W0+delwo;
    end
    epoch=epoch+1;
end
y
epoch
W
W0
v
vo
```

Output of the Training Program are Weights (W and V) and Bias (W_0 and V_0). Now using these values of Weights and Bias in Neural Network at any values of L1, L2 and Time (s) and values of voltage V1(p.u) can be easily forecasted through a program in MATLAB explained in section 6.2.



6.2 Program for Forecasting Voltage

Now using this MATLAB Program at values of L1,L2 and Time (s) values of voltage V1(p.u) is forecasted. In Table 6.7 voltage V1(p.u) is calculated through both with SIMULINK and Neural Network and Percentage error is calculated.

```

clc;
clear;
W=[-30.0447;
   -16.8708;
    96.2814];
Wo=[5.8332];
v=[25.0426 47.8485 72.5170;
   68.8580 71.6322 150.2044;
   115.7327 -42.5198 13.4404];
vo=[-4.6538 -2.9692 -7.5148];
x=[.010;.008;.010];
I=1;
for i=1:3
    zin1=0;
    for j=1:3
        zin1=zin1+x(j,I)*v(j,i);
    end
    zin(i)=zin1 + vo(i)*1;
    z(i)=1/(1+exp(-zin(i)));
end
yin1=0;
for i=1:3
    yin1=yin1+z(i)*W(i,1);
end
yin1=yin1+Wo;
y(I)=1/(1+exp(-yin1));
y
    
```

7. SIMULATION RESULTS

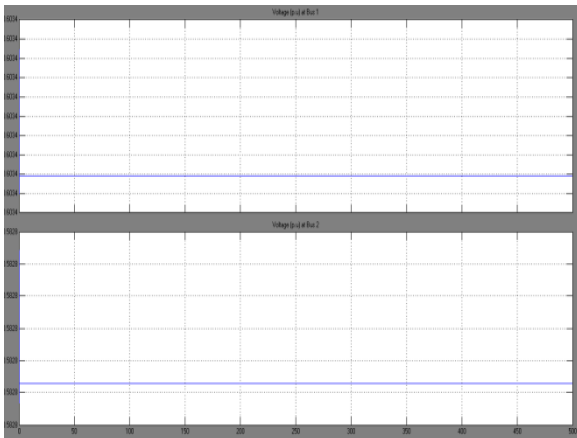


Fig 6: Voltage profile at bus 1 and 2 without Wind Farm and STATCOM.

From this Fig. it seen that the voltage at 33 kV Bus – 1 is 0.6034 pu. Where as the voltage at 33 kV Bus – 2 is 0.5828 pu.

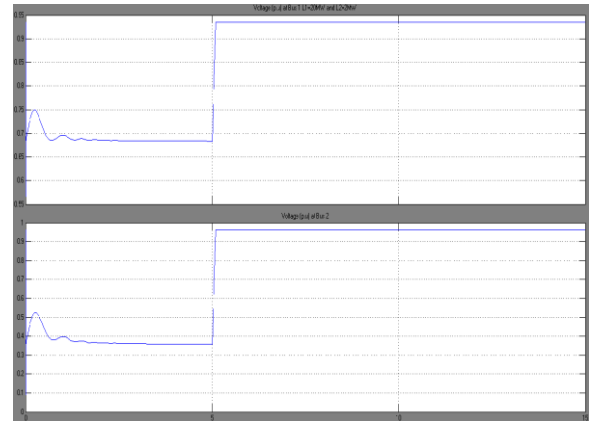


Fig 7: Voltage profile at bus 1 and 2 with Wind Farm and without STATCOM for L1=20 MW and L2=2 MW.

Before tripping the wind turbine generators have drawn reactive power from the network. As a result the voltage at 33 kV Bus – 2 as well as Bus – 1 is decreasing, thereby causing under voltage tripping of wind turbine generators. Fig. shows the voltages at 33 kV Bus – 1 and 33 kV Bus – 2.

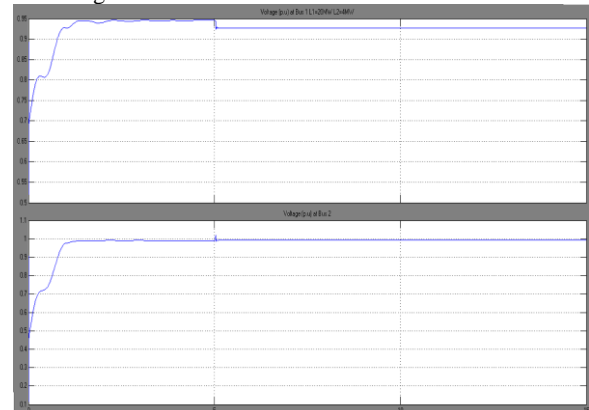


Fig. 8: Voltage profile at bus 1 and 2 with Wind Farm and STATCOM when L1=20MW and L2=4MW.

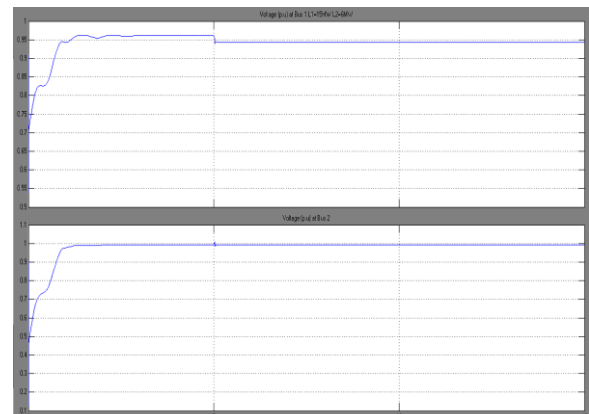


Fig.9: Voltage profile at bus 1 and 2 with Wind Farm and STATCOM when L1=40MW and L2=10MW

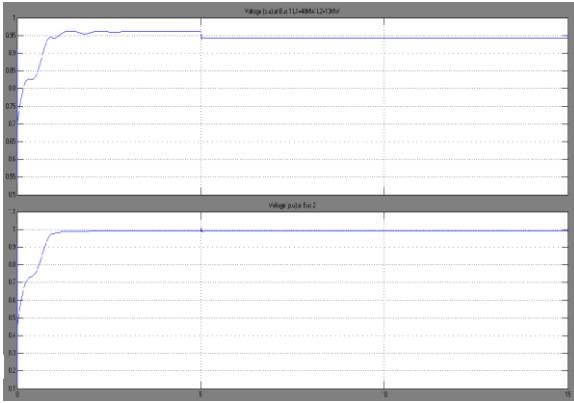


Fig.10: Voltage profile at bus 1 and 2 with Wind Farm and STATCOM L1=15MW and L2=6MW

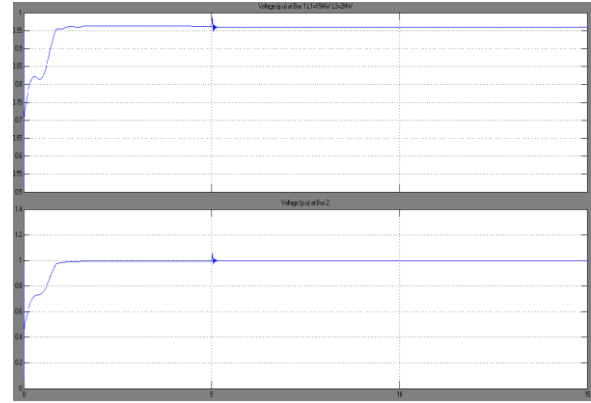


Fig.13: Voltage profile at bus 1 and 2 with Wind Farm and STATCOM L1=15 MW and L2=2 MW

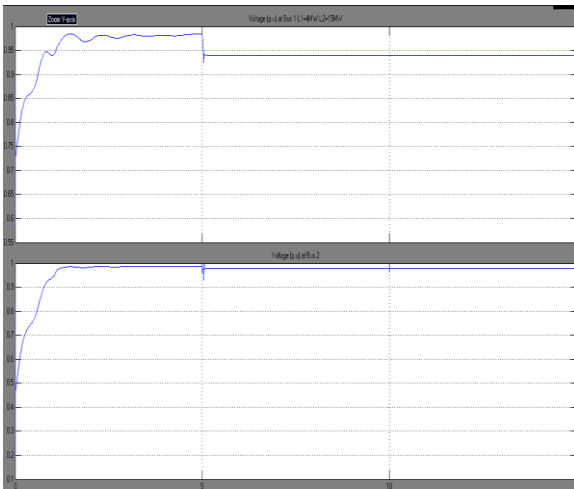


Fig. 11: Voltage profile at bus 1 and 2 with Wind Farm and STATCOM L1=4MW and L2=15MW

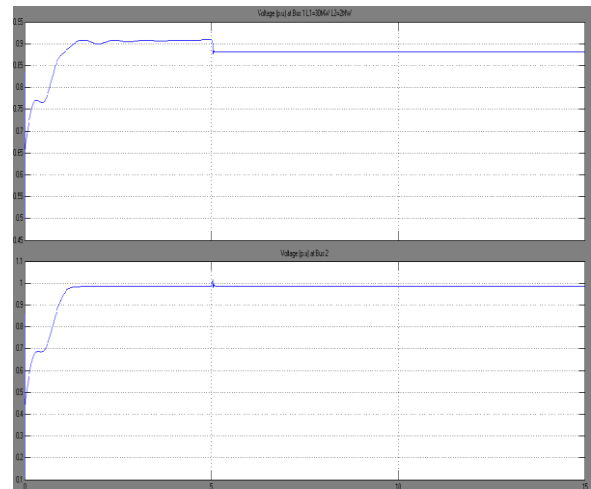


Fig.14: Voltage profile at bus 1 and 2 with Wind Farm and STATCOM L1=30MW and L2=2MW.

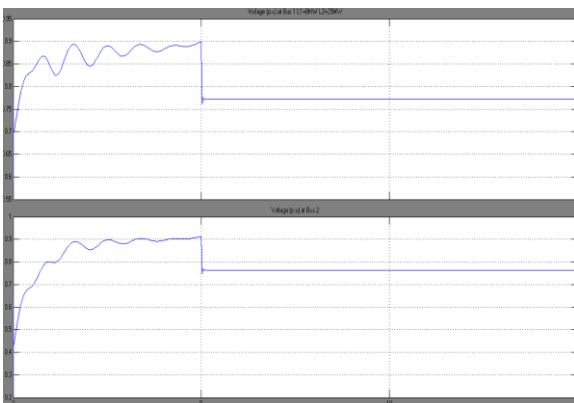


Fig.12: Voltage profile at bus 1 and 2 with Wind Farm and STATCOM L1=8 MW and L2=25 MW

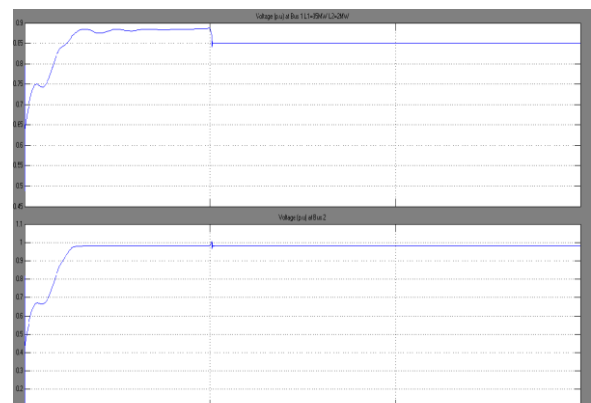


Fig.15: Voltage profile at bus 1 and 2 with Wind Farm and STATCOM L1=35MW and L2=2MW.

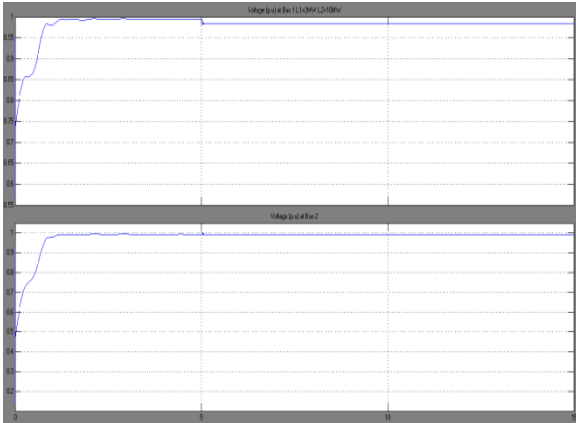


Fig.16: Voltage profile at bus 1 and 2 with Wind Farm and STATCOM L1=2MW and L2=10 MW.

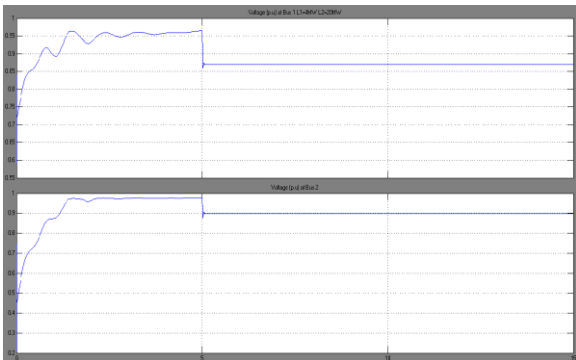


Fig.17: Voltage profile at bus 1 and 2 with Wind Farm and STATCOM L1=4 MW and L2=20 MW.

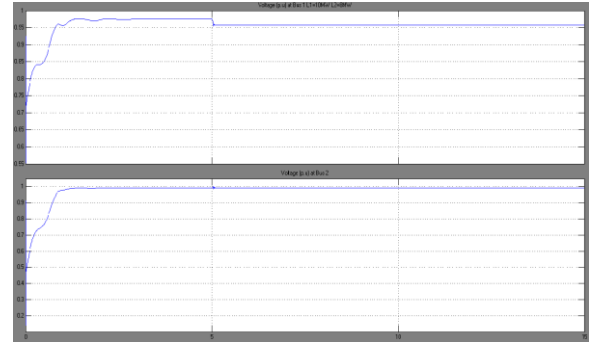


Fig.18: Voltage profile at bus 1 and 2 with Wind Farm and STATCOM L1=10MW and L2=8 MW.

Output of Program in MATLAB for training of Neural Network is as under:

```
y = [0.9558 0.9359 0.8182 0.7089 0.9725 0.9428
0.9083 0.7672 0.9763 0.9671 0.9222 0.8920
0.8800 0.8365 0.9746 0.9595 0.9095 0.8109]
```

```
epoch =99000000
```

```
W = [-30.0447
-16.8708
96.2814]
```

```
Wo = 5.8332
```

```
v = [25.0426 47.8485 72.5170
68.8580 71.6322 150.2044
115.7327 -42.5198 13.4404]
```

```
vo = [-4.6538 -2.9692 -7.5148]
```

Table 1. Values of Voltage on bus 1 and bus2 obtained through Matlab/Simulink and through Neural Network

Sr. No.	Value of Load L1 and L2 (MW)	Time (s)	Voltage at Bus 1 and Bus 2 obtained through SIMULINK (p.u)		Voltage at Bus 1 and Bus 2 obtained through ANN (p.u)		Error (%)	
1	L1=20, L2=4	5	.9458	.9904	.9558	.9507	-1.05	4
2	L1=20, L2= 4	10	.9272	.9916	.9360	.9420	-.9	5
3	L1= 20, L2= 4	15	.9272	.9916	.9360	.9420	-.94	5
4	L1= 15, L2= 6	5	.9616	.9914	.9611	.9554	.05	3.63
5	L1= 15, L2= 6	10	.9432	.9918	.9415	.9475	.180	4.46
6	L1=15, L2= 6	15	.9432	.9918	.9415	.9475	.18	4.46
7	L1= 40, L2= 10	5	.8163	.9512	.8188	.5162	-.30	4.57
8	L1= 40, L2= 10	10	.7078	.8435	.7104	.4692	-.36	44
9	L1= 40, L2= 10	15	.7078	.8435	.7104	.4692	-.36	44
10	L1= 4, L2= 15	5	.9836	.9866	.9464	.9292	3.78	5.8
11	L1=4, L2= 15	10	.9403	.9782	.9014	.9169	4.13	4
12	L1=4, L2= 15	15	.9403	.9782	.9014	.9169	4.13	4
13	L1= 8, L2= 25	5	.8986	.9126	.9088	.6214	-1.13	31.9
14	L1= 8, L2= 25	10	.7718	.7641	.7703	.5774	.194	24.4



15	L1= 8, L2= 25	15	.7718	.7641	.7703	.5774	.194	24.4
16	L1=15 , L2= 2	5	.9614	.9936	.9763	.9752	-1.54	18.5
17	L1= 15 , L2= 2	10	.9593	.9982	.9672	.9708	-.823	27.44
18	L1=15 , L2= 2	15	.9513	.9982	.9672	.9708	-.82	27.44
19	L1=30 , L2=2	5	.9088	.9861	.9225	.9182	-1.50	6.88
20	L1=30 , L2=2	10	.8813	.9869	.8926	.9039	-1.28	8.4
21	L1= 30 , L2=2	15	.8813	.9869	.8926	.9039	-1.28	8.4
22	L1= 35 , L2= 2	5	.8867	.9830	.8811	.8775	.631	10.7
23	L1= 35 , L2= 2	10	.85	.9823	.8377	.8568	1.44	12.7
24	L1=35 , L2=2	15	.85	.9823	.8377	.8568	1.44	12.7
25	L1=2,L2=10	5	.9952	.9932	.9747	.9710	2.05	2.2
26	L1=2,L2=10	10	.9842	.9929	.9595	.9659	2.50	2.71
27	L1=2,L2=10	15	.9842	.9929	.9595	.9659	2.50	2.71
28	L1=4,L2=20	5	.9253	.9347	.9094	.8519	1.71	8.8
29	L1=4,L2=20	10	.8014	.7894	.8097	.8281	-1.03	-4.9
30	L1=4,L2=20	15	.8014	.7894	.8097	.8281	-1.03	-4.9
31	L1=10,L2=8	5	.9759	.9920	.9654	.9596	1.07	-.8
32	L1=10,L2=8	10	.9581	.9916	.9461	.9525	1.25	3.9
33	L1=10,L2=8	15	.9581	.9916	.9461	.9525	6.25	3.9

8. CONCLUSIONS

This paper presented an analytical study about the dynamic power compensation capability of STATCOM for the integration of wind power in a weak distribution network. The study reveals that integration of wind farm in a weak distribution network is possible due to reactive power compensation by STATCOM. STATCOM prevents large deviations of bus voltage due to reactive power drawn by wind turbine generators. Simulations carried out confirm that STATCOM could provide the fast acting voltage support necessary to prevent the possibility of voltage reduction. A Neural Network is also developed in this paper which after training can forecast voltage values on bus 1 and bus 2 of the transmission line on any values of the resistive load connected to transmission line at any time duration. The developed Artificial Neural Network can further be used for further research.

9. REFERENCES

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