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UTILIZATION OF ARTIFICIAL NEURAL NETWORK FOR ELECTRICAL TRANSMISSION SYSTEMS PLANNING

M.M. Salama[1] , Ebtisam M. Saied[1], M.S. EL-Bages[2]

1- Associate professor of Electrical Engineering.
2- Assistant Professor of Electrical Engineering.
Electrical Dept., Faculty of Eng., Shoubra
108 Shoubra St., Cairo, Egypt.

Gasir M. Atta

Electrical Engineer.

Irrigation Barrage Directorate
EL- Kanater, Egypt.

Abstract

In transmission system planning, where new load growth, new generation sites and perhaps a new voltage level are to be considered, a computer aided method of visualizing new circuits in a network context is needed. This problem is solved before, using many traditional techniques. These techniques are heuristic and optimization techniques. DC linear programming optimization technique (DC L.P.O.T) is used in this paper as a traditional technique.

Artificial Neural Network Technique is suggested as a new and fast method to solve the planning problem as the potential benefits of Neural Networks extend beyond the high computation rates provided by massive parallelism. A feed-forward Propagation Network Train is used.

1. Introduction

Network planning is an important part of power system planning. Its task is to determine an optimal network configuration according to load growth and generation planning scheme for the planning period so as to meet the requirement of delivering electricity safely and economically [1].

An extensive effort has been started for the solution of the planning problem utilizing both mathematical programming techniques (optimization tools) and digital computer [2]. In order to develop practical and successful solution methods, accurate planning models as well as powerful mathematical programming solution tools must be involved [3]. (DC L.P.O.T) is used solving power system planning problem as it uses only active power Mw forecasts, and the error introduced by using the load flow approximation is acceptable in these studies [4],[5].

Artificial Neural Networks have been studied for many years in the hope of achieving human-like performance in many fields. Back-propagation Neural Network is suggested for studying the transmission system planning. This network composed of neurons (nodes) distributed in layers. Node elements are connected via weights that are typically adapted during use to improve the performance. As the trained propagation networks tend to give reasonable answers when presented with input that they have never seen. Typically, a new input will lead to an output similar to the correct output for input vector used in training similar to the new input being presented [6]. The Back-propagation training is used on a Set of input/target of the network (target is a set of solutions that has been obtained from the linear programming application on the network with many various corresponding inputs.

2. Theoretical Formulations

2.1 DC Linear Programming Optimization Technique Formulations

The objective of the mathematical model is minimizing the discounted capital and operating costs associated with the system expansion over the planning horizon. The constraints associated with this model are essentially the physical and economical

The mathematical simulation model utilized in this method at any iteration is: -

$$\text{Min.}\quad F=\sum_{i=1}^{m1+m2} C_i\{\max(|P_i|,|P_{i+nl}|)\} \qquad (1)$$

Subject to: -

1- Power balance constraint equation at bus i.

$$\sum_{k\in k(i)} P_k = w_i \qquad (2)$$

$$i = 1, 2, \ldots, N-1$$

2- Loop equation for loop i.

$$\sum_{iek\ 1(i)} X_i P_i = W_i \qquad (3)$$

$$i = 1,2,\ldots,nlv$$

3- Line limit constraint for line i.

$$\max(|P_i|,|P_{i+nl}|) \le P_i^{\max} \qquad (4)$$

$$i = 1,2,\ldots,nl$$

Where: -

- N : number of buses.
- $m1 + m2$: number of lines existing and new.
- C_i : linearized cost coefficient of line i.
- P_i : the magnitude of power flow in line i (existing or proposed).
- P_{i+nl} : the magnitude of power flow in line i in reverse direction .
- k_i : set of lines connected to bus i.
- W_i : net power at bus i .
- $k1(i)$: set of existing lines in loop i.
- nlv : number of basic loops.
- $p_i^{\max}$: maximum power flow in line i depending on (right – of-way).
- X_i : reactance of line i.
- nl :total lines existing and new.

2.2 Neural Network Formulations.

Figure 1 shows a two-layer neural network. A Feed-forward back-propagation with a sigmoid logistic non-linear function F (x) is used [6].

$$F(x) = \frac{1}{\ldots} \qquad (5)$$

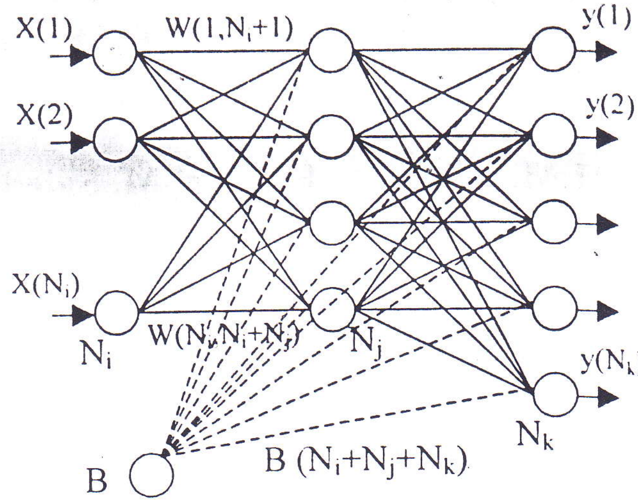

Figure 1. A Two-layer Neural Network

Step 1: Initialize weights, set all weights and node offsets to small random values.

Step 2: Present a continuous valued input vector $x_1, x_2, \ldots, x_{N_i}$ and specify the desired outputs d_1 , d_2, …., d_{N_k} .

Step 3: calculate actual outputs, use the sigmoid nonlinearly form equation (5) above and calculate the outputs y_1 , y_2 , ………, y_{N_k}

Step 4: Adapt the weight (w), using the recursive algorithm.

$$W_{ij}(t+1)= w_{ij}(t)+\eta\,\delta_j x_i. \qquad (6)$$

$$i = 1,2,\ldots,N_i \qquad j = N_j+1, N_j+2,\ldots,N_j+N_j$$

In this equation w_{ij} (t) is the weight from hidden node i or from an input to node j at time t, x_i is either the output of node i or is an input, η is a gain term, and δ_i is an error term for node j. if node j is an output node, then

$$\delta_i= y_i(1-y_i)(d_i-y_i) \qquad (7)$$

Where: -

- d_i : the desired output .
- y_i : the actual output.

If node j is an interval hidden node, then

$$\delta_i=x_i(1-x_i)\Sigma\delta_k w_{ik} \qquad (8)$$

Where k is overall nodes in the layers above node j. Internal node thresholds are adapted in a similar manner by assuming the connection weights on links from auxiliary constant-valid inputs.

momentum term is added and weight changes are smoothed by

$$W_{ij}(t+1) = W_{ij}(t) + \eta\delta_i x_i + \alpha(W_{ij}(t) - W_{ij}(t-1)) \qquad (9)$$

Where: $0 < \alpha < 1$.

Step 5 Repeat by going to step 2 until convergence occurs.

3. Applications and Results

3.1 DC Linear Programming Applications and Results

Consider an expansion of the six-bus system used by Garver [4] and subsequently by villasona [5]. In the system shown in figure 2,the goal is to design a transmission network that will supply the future load pattern without overloading any generators or transmission lines. Assume that busbar 1 is dispatched to 50 Mw and busbar 3 to 165 Mw. A new site (busbar 6) has been selected to build a new generating station dispatched to 545 Mw. The base is 100 Mw. The bus data is given in table 1,and the network data is given in table 2.

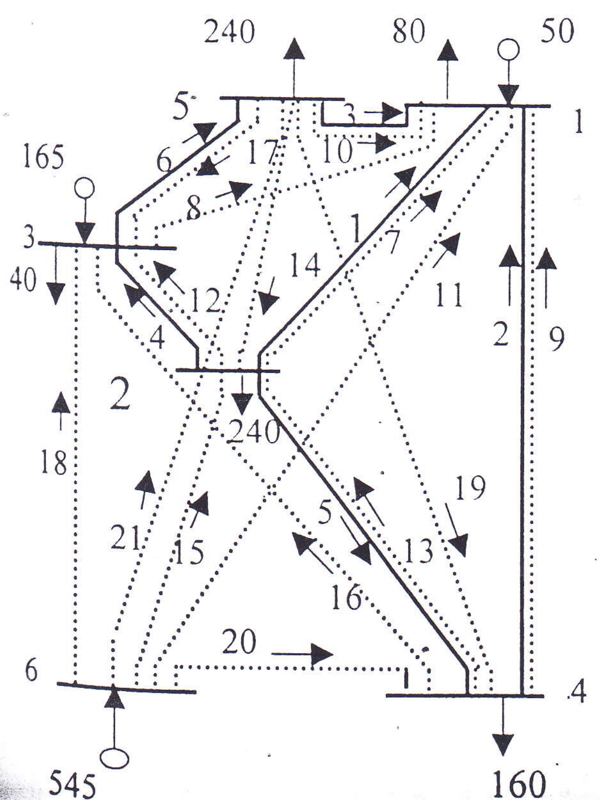

Figure 2. Initial Network Configuration.

Table 1. Generation and Bus Data

Busbar and site No.	Dispatch (Mw)	Load (Mw)	Net (Mw)
1. (existing)	. 50	80	-30
2. (existing)	0	240	-240
3. (existing)	165	40	125
4. (existing)	0	160.	-160
5. (existing)	0	240	-240
6. (new site)	545	0	545

Table 2. Paths and Transmission Line Data.

Line No.	Terminal No.	Length (mile)	X (pu)	Capacity (pu)
1	1-2	40	0.40	1.00
2	1-4	60	0.60	. 80
3	1-5	20	0.20	1.00
4	2-3	20	0.20	1.00
5	2-4	40	0.40	1.00
6	3-5	20	0.20	1.00
7	2-1	40	0.40	1.00
8	3-1	38	0.38	1.00
9	4-1	60	0.60	. 80
10	5-1	20	0.20	1.00
11	6-1	68	0.68	. 70
12	3-2	20	0.20	1.00
13	4-2	40	0.40	1.00
14	5-2	31	0.31	1.00
15	6-2	30	0.30	1.00
16	4-3	59	0.59	.82
17	5-3	20	0.20	1.00
18	6-3	48	0.48	1.00
19	4-5	63	0.63	.75
20	6-4	30	0.30	1.00
21	6-5	61	0.61	.78

Figure 3 illustrates the solution to the problem, the result of applying the DC L.P.O.T program to the system of figure 2,and shows the overload paths on which circuits should be considered to minimize the transmission investment cost.

The overload path solution in figure 3 indicates a need for 331.25 Mw of circuit capacity between buses 6 and 4, 213.75 Mw of circuit capacity between buses 6 and 2, and 61.25 Mw of circuit capacity between buses 3 and 5. Remain overload paths are not needed.

To plan transmission lines on the over load one followed by Garver [4] will be used. The purpose of this example is to illustrate how the facilities and overload networks interact and hence, circuits will be added one at a time in the overload path where the largest overload exists. After each new addition, the problem will be resolved. (Every circuit added is assumed to have a maximum capacity of 100 Mw). This procedure will continue until no overload remains in the network.

Using the round – up procedure above in the example of figure 3. The path 6-4 selected for the first insertion. The insertion was made for the maximum overload lines until no overload is occurred. Then final solution is shown in figure 4 and tabulated as case 1 in table 4. Taking the final solutions for thirteen variable patterns with different injected power values on the buses of the network shown in figure 2 as indicated in table 3 and the corresponding results are shown in table 4. Part I, table 4. Part II.

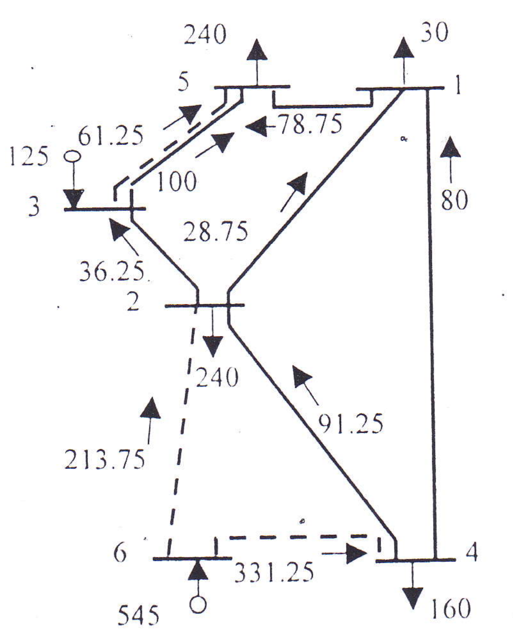

Figure 3. DC L.P.O.T Solution of the Six-Bus Problem.

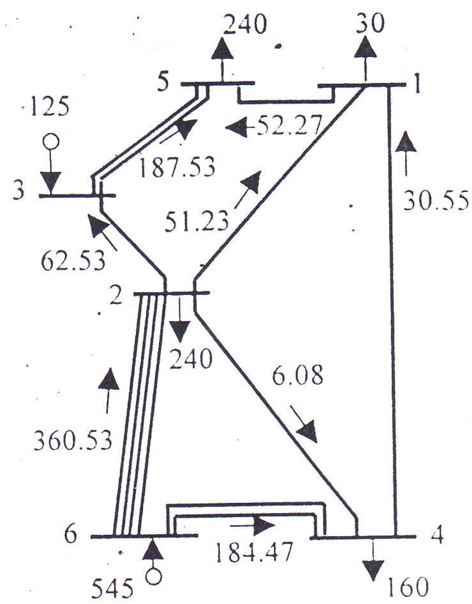

Figure 4. Final Solution of DC L.P.O.T.

Table 3. Patterns data for DC L.P.O.T

Pattern No.	Bus power (Mw)					
	Bus 1	Bus 2	Bus 3	Bus 4	Bus 5	Bus 6
1	-30.0	-240.0	125.0	-160.0	-240.0	545.0
2	-33.5	-250.0	133.5	-170.0	-250.0	570.0
3	-33.0	-264.0	137.5	-176.0	-264.0	599.5
4	-35.5	-280.0	150.0	-180.0	-275.0	620.5
5	-36.0	-288.0	150.0	-192.0	-288.0	654.0
6	-38.0	-270.0	148.75	-165.75	-280.0	605.0
7	-39.0	-312.0	162.5	-208.5	-312.0	708.5
8	-39.5	-330.0	159.5	-200.0	-335.0	745.0
9	-42.0	-336.0	175.0	-224.0	-336.0	763.0
10	-43.5	-340.0	175.0	-248.0	-340.0	796.5
11	-50.0	-365.0	160.0	-200.0	-390.0	845.0
12	-48.0	-384.0	200.0	-256.0	-384.0	872.0
13	-51.0	-408.0	212.5	-272.0	-408.0	926.5

Table 4. The output of DC L.P.O.T (part I)

Pattern No.	Line flow (Mw)				
	Line1	Line2	Line3	Line4	Line5
1	51.23	30.55	-52.47	62.53	6.08
2	54.00	32.90	-53.40	63.10	4.64
3	46.77	39.57	-53.34	73.16	-12.59
4	47.29	40.70	-52.49	72.51	-13.77
5	52.72	38.04	-54.67	56.50	-4.34
6	55.47	31.40	-48.87	82.38	8.36
7	57.11	41.21	-59.33	90.17	-4.71
8	51.24	41.39	-53.13	122.37	-10.85
9	61.55	44.38	-63.89	97.11	-5.07
10	52.61	33.06	-42.16	47.06	3.02
11	33.68	30.92	-14.60	6.53	-12.59
12	50.60	34.10	-36.71	54.07	-0.55
13	46.41	28.91	-24.32	18.66	3.05

Table 4. The output of DC L.P.O.T (part II)

Pattern No.	Line power flow (Mw)				
	Line 6	Line 15	Line 20	Line 18	Line 21
1	187.53	300.53	184.47	00.00	00.00
2	196.00	371.74	198.26	00.00	00.00
3	210.66	371.34	228.16	00.00	00.00
4	222.51	386.03	243.47	00.00	00.00
5	233.24	419.61	234.39	00.00	00.00
6	231.13	416.21	188.79	00.00	00.00
7	252.67	454.58	253.92	00.00	00.00
8	281.87	492.75	252.25	00.00	00.00
9	272.11	489.55	273.45	00.00	00.00
10	297.84	443.23	278.03	75.24	00.00
11	255.14	392.52	243.61	58.61	150.26
12	254.07	488.12	290.66	00.00	93.53
13	298.44	476.11	297.88	67.29	85.24

3.2 Artificial Neural Applications and Results

Applying on the neural network shown in figure 1. The number of input layer neurons, N_i =6, the number of hidden layer neurons N_J =8, and for the output layer neurons, N_k =10. A dummy neuron with fixed output = -1 has been added to generate additional weights between the Bias point and the hidden neurons, also between the Bias point and the output layer. $\propto$ = 0.8, η=0.87 and the square-error = .001.The network was trained by initially selecting small random weights. Weights were adjusted after every trail until weights converge. The convergence occurred after 34625 iterations. The input data for the neural network is the input of the patterns data for the L.P.O.T as shown in table 3 and the target data for the neural net is the solution results of the L.P.O.T as shown in table 4 part I and II. Table 5 tabulates the five patterns tested by the neural network technique. The output of these five tested patterns is indicated in table 6.

Table 5. Input bus power for patterns to be tested by neural network

Pattern No.	Bus power (Mw)					
	Bus1	Bus2	Bus3	Bus4	bus5	Bus 6
1	-30	-240	125	-160	-240	545
2	-48	-384	200	-256	-384	872
3	-51	-408	212.5	-272	-408	926.5
4	-52.5	-380	170	-226	-380	868.5
5	-55.0	-391	175	-235	-391	897

Table 6. Neural network test patterns output

Pattern No.	Line power flow (Mw)									
	Line1	Line2	Line3	Line4	Line5	Line6	Line15	Line20	Line18	Line21
1	51.95	30.35	-52.57	62.53	5.58	187.43	360.01	184.88	00.00	00.00
2	50.00	33.48	-35.76	54.99	-1.50	254.36	489.46	288.71	00.00	92.43
3	45.91	29.92	-24.35	18.68	3.65	299.54	276.11	297.88	67.29	85.24
4	32.18	27.59	-7.27	-3.46	-9.21	226.50	399.51	262.80	60.98	145.21
5	38.44	25.76	-9.2	7.05	-0.2	239.52	436.29	296.96	57.47	142.28

4. Conclusion

The main objective of this paper is to suggest an accurate method in planning stage. This suggested method is the utilization of feed-forward Backpropagation neural network for transmission system planning. DC.L.P.O.T is applied as a conventional method but because of its computation burden and time consuming, the neural network is suggested. Compared with the DC L.P.O.T method, back-propagation is faster, simpler and it can deal with inputs that it has never seen before giving results near to the actual values with a small error.

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Authors **M.M. Salama, Ebtisam M. Saied, M.S.EL-Bages and Gasir M. Atta**

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CORRESPONDENCE ADDRESS

General Secretary of MEPCON'2001.
Faculty of Engineering – Helwan
P.O. Technology, Postal No. 11792.
1 Sherif Street, Helwan, Cairo, EGYPT.

Tel. 202 – 5558413
Fax. 202 – 5558294
E-Mail: ohabdalla@ieee.org
Mobile: 012-2745855