Economic Dispatch Using Classical Methods And Neural Networks

Labed Imen[1], Boucherma Mouhamed[2] , Labed Djamel[3]

[1,3]Laboratory Of Electric Engineering, Department Of Electrical Engineering Constantine
University of Constantine 1(Algeria)
[1] labedimen4@gmail.com, [3]djamel_labed@yahoo.fr
[2]Laboratory Of Electric Engineering, Department Of Electrical Engineering Constantine
University of Constantine 1(Algeria)
[2]m_boucherma@yahoo.fr

Abstract

This paper presents the economic dispatch studies for electrical power systems using two approaches. In the first approach a classical method is used which is the gradient method, whereas, in the second approach a method that belongs to the field of artificial intelligence, which is the neural networks method, is used. In both cases system constraints like line losses and generators limits are included.

1. Introduction

The economic dispatch problem is the determination of generation levels, in order to minimize the total generation cost for a defined level of load, it's a kind of management for electrical energy in the power system in way to operate their generators as economically as possible [1].

So the main aim of the economic dispatch studies is including all variables having effect on costs, such as the electrical network topology, type of fuel, load capacity and transmission line losses .....ext).Indeed the generator cost is basically represented by four curves: Input/Output (I/O), heat rate, fuel cost and incremental cost curve.

The generator cost curves are usually represented by quadratic functions; each plant uses a quadratic cost function such as the Fuel Cost Curve[2].

In this work, the economic dispatch is studied using the gradient and the neural networks methods. Furthermore, a comparison between the results using the above mentioned methods is carried out at the end of this paper.

2. Economic Dispatch Formula

2.1. The cost function

The fuel cost function is usually approximated as a second order polynomial, it's the objective function we need to optimize[3][4][5]:

$$F_i\,(P_{Gi}) = a_i + b_i\,P_{Gi} + c_i\,P_{Gi}^2 \qquad (1)$$

Where:

i = generator *i,* one of the number of units.
F_i = operating cost of unit in $/h.
P_{Gi} =electrical power output of generator i in per unit on a common power base.
a_i ,b_i and c_i are the cost coefficients of the generator i.Expressed in units of dollars ($/h).

2.2. Equality constraints

The total generation must be equal to the demand plus the losses thus [4][5][6]:

$$\sum_{i=1}^{N} P_{Gi} = P_D + P_L \qquad (2)$$

Where:
P_D : total system demand.
P_L: total system loss.
N: total number of generators.

2.3. Inequality constraints

Each plant output is within the upper and lower generation limits inequality constraints [4][5][7].

$$P_{i(min)} \leq P_i \leq P_{i(max)} i = 1, \dots, N \qquad (3)$$

Where:
$P_{i(max)}$: maximum output of generator *i*.
$P_{i(min)}$: minimum output of generator *i*.
So the ED can be formulated as an optimization as follows:

$$Min \sum_{i=1}^{N_g} F_i(P_{Gi})$$
$$\sum_{i=1}^{N} P_{Gi} = P_D + P_L$$
$$P_{i(min)} \leq P_i \leq P_{i(max)} \quad i = 1, \dots, N$$

These three conditions must be realized in order to satisfy the economic dispatch studies [3] [4] [5][6].

3. Economic Dispatch Including Transmission Losses

The active power transmission losses may reach a rate of 20 to 30% of the total load demand, this is why we should take into account the active power transmission losses and including them into the demand[8].

3.1. Losses formula

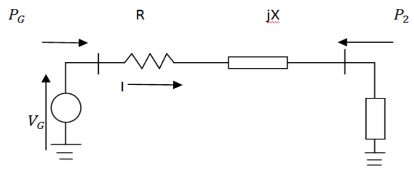

Fig.1. Radial line with one power generator and one load

$$P_{loss} = 3I^2R \quad (4)$$

Where:
R is the resistance of the line in ohms per phase.
The current I can be obtained by the following expression

$$|I| = \frac{P_G}{(\sqrt{3})V_G cos\phi_G} \quad (5)$$

Where:
P_G : The generated power load power including losses
V_G : The generated voltage magnitude (line-to-line)
$cos\phi_G$: The generator power factor.
Combining the two previous equations (4) and (5) we get:

$$P_L = \frac{R}{(cos\phi_G)^2|V_G|^2}\left(P_G{}^2\right) \quad (6)$$

We can write then:

$$\frac{R}{(cos\phi_G)^2|V_G|^2} = B \quad (7)$$

So losses can be expressed by the simple next equation:

$$P_L = BP_G{}^2$$

If a second or more than tow power generators are present to supply the load then we can express the transmission losses as the following equation through the B- Coefficients [10]:

$$P_L = \sum_{\substack{i=1 \\ j=1}}^{N} B_{ij}\, P_{Gi}{}^2 \quad (8)$$

Where:
B_{ij} are called the loss coefficients, which are assumed to be constant for a base range of loads.

3.2. Economic Dispatch

In the first place we need to put the three conditions of the economic dispatch:

$$F_{Total} = \sum_{i=1}^{N} F_i = \sum_{i=1}^{N}\left(a_i + b_i \ P_{Gi} + c_i P_{Gi}^2\right)$$
$$\sum_{i=1}^{N} P_{Gi} = P_D + P_L$$
$$P_{i(min)} \le P_i \le P_{i(max)} \ \ i = 1, \dots, N$$

The Lagrange function can be constructed as shown bellow [9][10]:

$$L = F_{Total} + \lambda\left(P_D + P_L - \sum_{i=1}^{N} P_{Gi}\right) \quad (9)$$

Where λ is called Lagrange multiplier.
As we know, to get the minimum of a function we have to derive it:

$$\left(\frac{\partial L}{\partial P_{Gi}} = 0 \ and \ \frac{\partial L}{\partial \lambda} = 0\right) \quad (10)$$

$$\frac{\partial L}{\partial P_{Gi}} = 0 = \frac{\partial F_{Total}}{\partial P_{Gi}} + \lambda\left(0 + \frac{\partial P_L}{\partial P_{Gi}} - 1\right) \quad (11)$$

$$\lambda = \frac{dF_i}{dP_{Gi}} + \lambda\frac{\partial P_L}{\partial P_{Gi}} = \left(\frac{1}{1-{\partial P_L}/{\partial P_{Gi}}}\right)\frac{dF_i}{dP_{Gi}}$$
$$= PF_i\frac{dF_i}{dP_{Gi}} \quad (12)$$

And in the other side :

$$\frac{\partial L}{\partial \lambda} = P_D + P_L - \sum_{i=1}^{N} P_{Gi} \quad (13)$$
$$\sum_{i=1}^{N} P_{Gi} = P_D + P_L \quad (14)$$

Where:
PF_i is known as the penalty factor of plant i and it's is given by [9][10]:

$$PF_i = \frac{1}{1-\frac{\partial P_L}{\partial P_{Gi}}} \quad (15)$$

The penalty factor depends on the location of the plant.
The minimum cost is obtained when the incremental cost of each plant multiplied by its penalty factor, is the same for all plants [9].
The incremental transmission loss is obtained from the next formula as:

$$\frac{\partial P_L}{\partial P_{Gi}} = 2\sum_{j=1}^{N} B_{ij}\, P_{Gi} \quad (16)$$

And we have also:

$$\frac{dF_i}{dP_{Gi}} = b_i + 2c_iP_{Gi} \quad (17)$$

We can find the iterative compact form:

$$P_i^{(K)} = \frac{\lambda^{(k)} - b_i}{2\left(c_i + \lambda^{(k)}B_{ii}\right)} \quad (18)$$

4. Neural Networks

4.1. Introduction

The origin of artificial neural networks comes from the biological neuron modelling test by Warren Mc Culluch and Walter Pitts. Initially Neural networks objective was: patterns recognition, classification.... then it becomes very interesting in all domains [11].

4.2. Neuron Model

Indeed; the simple architecture of a single neuron with a single layer is composed essentially:
First, the scalar input p which is multiplied by the scalar weight w to form the product wp this operation takes place at the integrator which is one of the important parts of the neuron; the result is again a scalar added to a scalar bias b to form the net input n.

The result n is then transformed by a transfer function f which produces the neuron output a [12][13].

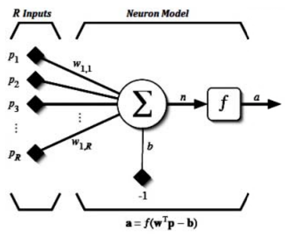

Fig.2. Artificial neuron model

$$n = \sum_{j=1}^{R} w_{1,j} p - b \qquad (19)$$

4.3. Neural Network Learning

Learning is a process by which the free parameters from a neural network are adapted, through a simulation process by the environment in which the network is contained [12][13][14].
The supervised and unsupervised methods are essentially the two types of learning for a neural network. In our case we are going to use the supervised learning where the training is controlled by an external agent which watches the answer that the network supposed to generate from the determined entrance. The supervisor compares the output of the network with the expected one and determines the amount of modifications to be made on the weights [12][13].
The supervised learning can be done through the three following Paradigms:

- Error correction learning
- Reinforcement learning
- Stochastic learning.

4.4. Error correction Learning

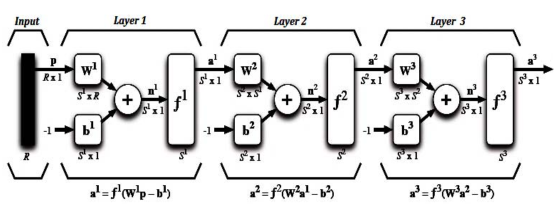

Fig .3. Representation of three layers network.

During the artificial neural network training by error correction the weights of the communication links are adjusted trying to minimize a function of cost depending on the difference between the desired values and the obtained one from the output network [12] [13].
It's required to determine the modifications on weights using the committed error; the correction error is calculated as the following expression:

$$\Delta w_{ki} = \eta y_j (d_k - y_k) \qquad (20)$$

Where,$\Delta w_{ki}$is the weight variation of the connection between the neurons j from the anterior layer and the output layer node k
d_k: The desired neuron output.
k,y_j and y_k are the output values produced in the neuron i and k respectively [12][13].
η : a positive factor denominated the learning rate$0 < \eta < 1$.
We can say that the new weight is proportional to the committed error produced by the network and the answer of the node j in the previous layer as shown in the following formula:

$$w_{kj}^{actual} = \Delta w_{kj} + w_{kj}^{anterior} \qquad (21)$$

And the total error is known as the mean square error expressed in the previous equation [13]:

$$Error_{\ global} = \frac{1}{2P} \sum_{P=1}^{P} \sum_{K=1}^{N} \left(y_k^{(p)} - d_k^{(p)} \right) \qquad (22)$$

Where:
N is the number of neurons in the output layer and P is the number of examples in the training sample.
Normally to minimize this criterion function, is employed learning rule given by the gradient descending [12][13].

$$\Delta w_{kj} = -\eta \nabla_{\mathrm{w_{kj}}} \left(\mathrm{Error_{global}} \right) \qquad (23)$$

If η takes a little, value the learning process is made smoothly which gives as result an increment in the time of convergence to a stable solution. In the other hand if η has an important value the speed of learning gets increased but there is the risk that the process has divergence and this causes the instability of the system [11][12][13].

5. Application and comparison of results

5.1. Data set

In this section we are going to apply the two methods on the test grid IEEE 30 – bus

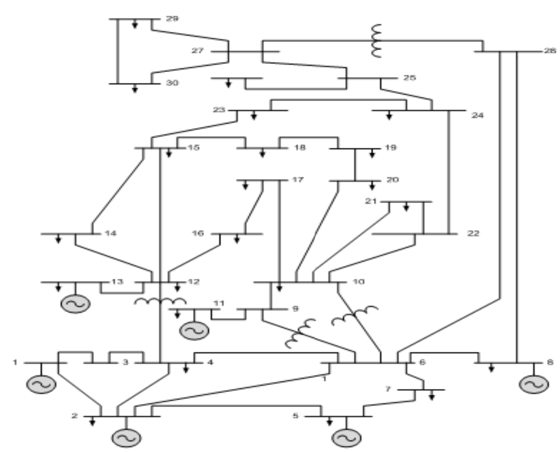

Fig .4. Single line diagram of IEEE-30bus

Table 1. The generators characteristics

Regulated Bus Data			
Bus No	Voltage Magnitude	Min.Mvar Capacity	Max Mvar Capacity
2	1.043	-40	50
5	1.010	-40	40
8	1.010	-10	40
11	1.082	-6	24
13	1.071	-6	24

Table 2. The generators characteristics

N°B	Ai	Bi	Ci	Pl	Pg min MW	Pg max MW
1	560	7.91	15.63e-4	3e-5	150	500
2	300	7.86	19.45e-4	9e-5	100	400
5	77	7.98	48.10e-4	12e-5	50	200
8	560	7.91	15.63e-4	3e-5	150	500
11	300	7.86	19.45e-4	9e-5	100	400
13	80	8	49.00e-4	13e-5	60	220

5.2. Results

5.2. 1.Classical method

Table 3. Economic dispatch with classical method

Total Demand (MW)	Generation (MW)					
	G1	G2	G3	G4	G5	G6
900	235.1	152.71	69.807	226.70	160.91	64.240
910	237.8	154.34	70.635	229.34	162.56	65.039
920	240.4	155.97	71.464	231.98	164.20	65.838
930	243.1	157.60	72.293	234.63	165.85	66.637
940	245.8	159.23	73.122	237.27	167.50	67.436
950	248.4	160.86	73.951	239.92	169.14	68.236
960	251.1	162.49	74.781	242.57	170.79	69.035
970	253.8	164.12	75.611	245.21	172.43	69.835
980	256.4	165.75	76.441	247.86	174.08	70.636
1000	261.8	169.01	78.102	253.17	177.37	72.237
1100	288.5	185.29	86.424	279.74	193.82	80.257
1200	315.3	201.56	94.772	306.41	210.25	88.299
1300	342.3	217.80	103.15	333.19	226.66	96.365
1400	369.4	234.02	111.55	360.08	243.05	104.45
1500	396.5	250.22	119.98	387.07	259.42	112.57
1600	423.8	266.40	128.43	414.17	275.78	120.70

Table 4. The total: Losses, Generation and Cost

Total losses (MW)	Total Generation (MW)	Total Cost ($)
9.5262	909.5262	9372.6
9.7319	919.7300	9460.2
9.9399	929.9400	9547.8
10.1500	940.1500	9635.6
10.3630	950.3600	9723.5
10.5770	960.5800	9811.5
10.7940	970.7900	9899.6
11.0130	981.0100	9987.8
11.2350	991.2300	10076.0
11.6840	1011.7000	10253.0
14.0660	1114.1000	11143.0
16.6700	1216.7000	12044.0
19.4980	1319.5000	12953.4
22.5490	1422.5000	13873.0
25.8230	1525.8000	14803.0
29.3210	1629.3000	15744.0

5.2.2. Neural network

Architecture and training phase

In our paper we are studying a fitting problem in other word a modelization problem this may explain the reason for which we have used a Levenberg Marquardt learning algorithm (trainlm); the network contains two layers:

- The first : hidden with 2 neurons.
- The second :is the output with 6 neurons
- The transfer function at the first layer is tansig.
- The transfer function at the second layer is purelin.
- The input 'p' is an [1x16] matrice .
- The target 't' is an [6x16] matrice.

Table 5. Economic dispatch with neural network Training phase

Total Demand (MW)	Generation (MW)					
	G1	G2	G3	G4	G5	G6
900	235.17	152.71	69.807	226.70	160.91	64.242
910	237.82	154.34	70.635	229.34	162.56	65.040
920	240.48	155.97	71.464	231.99	164.20	65.838
930	243.14	157.60	72.292	234.63	165.85	66.637
940	245.80	159.23	73.121	237.27	167.50	67.436
950	248.46	160.86	73.951	239.92	169.14	68.235
960	251.13	162.49	74.781	242.56	170.79	69.035
970	253.79	164.12	75.611	245.21	172.44	69.835
980	256.46	165.75	76.441	247.86	174.08	70.635
1000	261.79	169.01	78.102	253.16	177.37	72.237
1100	288.54	185.30	86.426	279.74	193.83	80.257
1200	315.38	201.56	94.775	306.41	210.25	88.300
1300	342.34	217.80	103.15	333.19	226.66	96.364
1400	369.40	234.02	111.55	360.08	243.05	104.45
1500	396.57	250.22	119.98	387.07	259.42	112.57
1600	423.85	266.40	128.43	414.17	275.78	120.70

Table 6. The total: Losses, Generation and Cost

Total losses (MW)	Total Generation (MW)	Total Cost ($)
9.5262	909.5262	9372.5
9.7319	919.7300	9460.1
9.9399	929.9400	9547.8
10.1500	940.1500	9635.6
10.3630	950.3600	9723.5
10.5770	960.5800	9811.5
10.7940	970.7900	9899.6
11.0130	981.0100	9987.8
11.2350	991.2300	10076.0
11.6840	1011.7000	10253.0
14.0660	1114.1000	11143.0
16.6700	1216.7000	12043.0
19.4980	1319.5000	12953.0
22.5490	1422.5000	13873.0
25.8230	1525.8000	14803.0
29.3210	1629.3000	15743.0

After the training phase the network is ready. Now we will introduce a real input matrice we can get from the electrical load curve for example. Let' see our results at real time.

Table 7. Economic dispatch with neural network at real time

Total Demand (MW)	Generation (MW)					
	G1	G2	G3	G4	G5	G6
905	236.49	153.53	70.221	228.02	161.74	64.640
915	239.15	155.16	71.050	230.66	163.38	65.439
925	241.81	156.79	71.878	233.30	165.03	66.237
935	244.47	158.42	72.707	235.95	166.67	67.036
945	247.13	160.04	73.536	238.59	168.32	67.835
955	249.80	161.67	74.366	241.24	169.96	68.635
965	252.46	163.30	75.195	243.89	171.61	69.435
975	255.13	164.93	76.025	246.54	173.26	70.235
985	257.79	166.56	76.856	249.19	174.90	71.035
1005	263.13	169.82	78.517	254.49	178.19	72.637
1155	303.29	194.24	91.014	294.40	202.86	84.677
1270	334.24	212.93	100.63	325.15	221.74	93.942
1390	366.68	232.40	110.71	357.38	241.41	103.64
1463	386.50	244.23	116.86	377.07	253.36	109.56
1533	405.57	255.56	122.77	396.01	264.82	115.25
1605	425.25	267.21	128.87	415.57	276.59	121.12

Table 8. The total: Losses, Generation and Cost

Total losses (MW)	Total Generation (MW)	Total Cost ($)
9.640	914.64	9416.4
9.840	924.84	9504.0
10.040	935.04	9591.7
10.250	945.25	9679.5
10.460	955.46	9767.5
10.686	965.68	9855.5
10.890	975.89	9899.6
11.110	986.11	10032.0
11.340	996.34	10120.0
11.790	1016.80	10297.0
15.487	1170.50	11637.0
18.637	1288.60	12680.0
22.226	1412.20	13781.0
24.583	1487.60	14458.0
26.983	1560.00	15113.0
29.608	1634.60	15791.0

6. Conclusion

In this paper the economic dispatch has been investigated using two different methods which are the gradient and the neural network methods. Both methods have been explored and tested. The comparison between these two methods shows that the neural networks method gives better results than the classical gradient method.

We can see clearly the utility and the importance of the neural network in this case by looking directly to accuracy and speed of results and the effect of this two characteristics on the optimization of fuel in very short time, that gives as more large space to compute the exact values of generated demand power in every point on the electrical load curve .

7.References

[1] S. Sivanagaraju and G. Sreenivasan ,"power system operation and control", Jul 2009 .

[2] Tim Anderson, Herman Migliore and Donald Ogilvie ,"Power System Economic Dispatch",Portland State Univesity.Aug 17, 2010.

[3] Kyung-Il Min, Student Member IEEE, and Young-Hyun Moon, Senior Member IEEE,"Function Merger Method for Economic Dispatch Considering Transmission Losses ", The International Conference on Electrical Engineering 2009.

[4] Vanitha, M. and K.Thanushkodi,"An Effective Biogeography Based OnOptimization Algorithm to Slove Economic Load Dispatch Problem", Coimbatore Institute of Engineering and Technology, Coimbatore, India, Journal of Computer Science 8 (9): 1482-1486, 2012.

[5] T. Bouktir,L. Slimani,and B. Mahdad,"Optimal Power Dispatch For Large Scale Power System Using Stochastic Search Algorithms", International Journal of Power and Energy Systems, Vol. 28, No. 2, 2008.

[6] Hongye Wang, Carlos E. Murillo-Sánchez, Ray D. Zimmerman, and Robert J. Thomas, Fellow, "On Computational Issues of Market-Based Optimal Power Flow",IEEE Transactions on power Systems, VOL 22, NO. 3, Augest 2007

[7] S. SUBRAMANIAN, Senior member*, IEEE* and S. GANESAN , "A Simplified Approach for Economic Dispatch with Piecewise Quadratic Cost Functions, International Journal of Computer and Electrical Engineering", Vol. 2, No. 5, October, 2010.

[8] EkbalAbd Al-Majeed ," Designing Program for Economic dispatch of Operation Power System",University of Technology, Baghdad, 2011.

[9] Rony Seto Wibowo, Mauridhi Hery Purnomo, and Dodiprastianto,"Determining Transmission Losses Penalty Factor Using Adaptive Neuro Fuzzy Inference System (ANFIS) For Economic Dispatch Application", Electrical Engineering Department, Sepuluh Nopember Institute of Technology ,java journal of electrical and electronics engineering vol.1,N°2 ,October 2003.

[10] Lukman K. WalsheT.R. Blackburn ,"Loss Minimization In Industrial Power System Operation", School of Electrical and Telecommunication Engineering University of New South Wales,KensingtonSydney, NSW 2052, Australia.

[11] DraidiAbdellah, LabedDjamel,"Power System Economic Dispatch Using Traditional and Neural Networks Programs",International Journal of Scientific & Engineering Research, Volume 3, Issue 4, April 2012.

[12] Enrique Castillo, Bertha Guijarro-Berdi ˜nas, Oscar Fontenla-Romero, Amparo Alonso-Betanzos,"A Very Fast Learning Method for Neural Networks Based on Sensitivity Analysis", University of Cantabria and University of Castilla-La Mancha;Journal of Machine Learning Research 7 (2006) .

[13] Eduardo Gasca ",Artificial Neural Network Institute of technology Toluca" ,Mexico.